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Building stock modelling for energy benchmarking of schools in Brazil

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Abstract

This thesis aims to develop methods to obtain representative building stock models to benchmark the energy performance of Brazilian schools considering building-level and stock-level perspectives. A literature review regarding the main research gaps in operational building performance was carried out, contrasting both building and stock-level investigation perspectives. Then, an overview of the school building stock in Brazil outlined the main characteristics regarding the energy performance, and a representative building stock database was composed. The database was used to build a top-down building stock model, resulting in a model able to incorporate thermal satisfaction of occupants in the benchmarking classification through machine learning. Furthermore, a framework was proposed to model representative archetypes through entropy and cluster analysis. Artificial Neural Networks were used to model the energy benchmarking model. Results showed a manageable bottom-up model of the building stock able to perform a reliable representation of the actual stock performance. The bottom-up building stock model was used to predict the performance of the building stock performance under unseen conditions, i.e. future climatic conditions and different scenarios of air-conditioning. Five research articles were written to report the research. Conclusions of the thesis outlined the determinant factors that impact the energy performance of the school building stock in Brazil and the suitability of both top-down and bottom-up models to represent the building stock, according to specific purposes. The two stock modelling methods proposed employ different metrics to solve different problems. The top-down method provided a single performance scale to include occupants' aspects in buildings operational performance evaluation. The bottom-up method is adequate to rate the building performance under standard conditions. Thus, through the models proposed it is possible to evaluate further conditions, such as future climates, in the buildings-level perspective that potentially impact the energy consumption at a stock-level scale.

Keywords: energy benchmarking, building performance analysis, building stock, energy efficiency in buildings.

Resumo

Esta tese tem como objetivo desenvolver métodos de obtenção de modelos representativos do estoque de edificações para aferir o desempenho energético das escolas brasileiras, considerando as perspectivas a nível da edificação e a nível do estoque. Foi realizada uma revisão da literatura sobre as principais lacunas de pesquisa no desempenho operacional de edifícios, comparando as perspectivas de investigação encontradas. Em seguida, um panorama do estoque de edificações escolares no Brasil proporcionou o delineamento das principais características em relação ao desempenho energético e um banco de dados representativo foi composto. O banco de dados foi utilizado para construir um modelo de estoque de edificações de *top-down*, resultando em um modelo capaz de incorporar a satisfação térmica dos ocupantes na classificação de *benchmarking* por meio de aprendizado de máquina. Além disso, uma estrutura foi proposta para modelar arquétipos representativos por meio de entropia e análise de agrupamento. Redes Neurais Artificiais foram usadas para generalizar o modelo de *benchmarking* de energia. Os resultados mostraram um modelo gerenciável *bottom-up*, capaz de realizar uma representação confiável do desempenho real do estoque de edificações. O modelo *bottom-up* do estoque de edificações foi usado para prever o seu desempenho do sob condições ainda não vistas, ou seja, condições climáticas futuras e diferentes cenários de condicionamento de ar. Cinco artigos foram escritos para relatar a pesquisa realizada. As conclusões da tese delinearam os fatores determinantes que impactam o desempenho energético do estoque de edificações escolares no Brasil e a adequação de ambos os modelos *top-down* e *bottom-up* para representar o estoque de edificações, de acordo com finalidades específicas. Os dois métodos de modelagem de estoque propostos empregam indicadores diferentes para resolver problemas diferentes. O método *top-down* forneceu uma única escala de desempenho para incluir os aspectos dos ocupantes na avaliação de desempenho operacional dos edifícios. O método *bottom-up* se mostrou adequado para avaliar o desempenho do edifício em condições padronizadas. Assim, por meio dos modelos propostos é possível avaliar outras condições, como climas futuros, na escala da edificação como indivíduo, e que potencialmente impactam o consumo de energia na escala do estoque de edificações.

Palavras-chave: *benchmarking* energético, análise de desempenho de edificações, estoque de edificações, eficiência energética em edificações.

Resumo expandido

Introdução

O estado da arte revela a necessidade de um método robusto e confiável para avaliar o desempenho energético operacional dos edifícios existentes e que deva ser consistente com o contexto regional. O *benchmarking* energético é uma prática que consiste na comparação do desempenho de uma edificação com o consumo típico da tipologia avaliada (o *benchmark*). Usualmente, o *benchmark* é obtido por meio de um modelo do estoque de edificações e é usado para calcular o desempenho de referência que representa do estoque real. Atualmente, existem alguns métodos de modelagem de estoque de edificações que podem utilizar tanto abordagens *bottom-up* (que utilizam arquétipos ou edificações de referência que têm seu desempenho obtido por meio de simulação computacional) quanto abordagens *top-down* (que expressam o desempenho por meio da evidência e medições). Os arquétipos são úteis para métodos que carecem de divulgação de dados de políticas energéticas, enquanto as abordagens *top-down* podem explorar essas informações utilizando análises estatísticas. Apesar de os arquétipos serem empregados em métodos mais detalhados, existe uma lacuna em avaliar a representatividade dos arquétipos em relação ao estoque existente, ao mesmo tempo em que há carência de dados detalhados para proporcionar modelos unicamente baseados em análises estatísticas. Portanto, o problema de melhorar o *benchmarking* de energia e a modelagem de estoque de edificações que é abordado nesta tese pode ser delineado de acordo com as seguintes questões de pesquisa: Quais são os principais fatores que impactam o consumo de energia em edifícios escolares no Brasil? Como os aspectos subjetivos (como a satisfação térmica) podem ser considerados nas práticas de *benchmarking*? Como melhorar a representatividade do modelo de estoque de edificações?

Dessa forma, esta tese propõe uma ampla discussão sobre a modelagem de estoque de edificações aplicada ao *benchmarking* no Brasil. Para tal, uma tipologia de edifício foi estudada individualmente, uma vez que as características de um edifício estão intrinsecamente relacionadas com a sua função social. A tipologia alvo deste estudo foi o estoque de edificações escolares no Brasil, especificamente as escolas públicas de ensino fundamental e médio – que compreende a educação de pessoas de sete a dezessete anos. A justificativa para a seleção deste recorte deveu-se à importância da Administração Pública reconhecer a eficiência energética dos seus edifícios. Além disso, há um impacto da função social dessa tipologia de edificações escolares na sociedade. Nesse contexto, apenas o consumo de eletricidade foi avaliado.

Objetivos

Esta tese tem como objetivo geral desenvolver métodos de obtenção de modelos representativos do estoque de edificações para aferir o desempenho energético das escolas brasileiras, considerando as perspectivas a nível da edificação e a nível do estoque de edificações. Os objetivos específicos são:

- Identificar o estado da arte atual das abordagens de modelagem de estoque de edificações e os métodos de *benchmarking* por meio de revisão da literatura, considerando as diferentes perspectivas de análise energética em edifícios;
- Avaliar o estoque de edificações escolares no Brasil por meio de análise estatística, correlacionando as principais características do estoque de edificações com seu consumo de energia elétrica.
- Propor um modelo *top-down* para avaliar o desempenho do edifício-como-um-todo no método de *benchmarking*, incluindo abordagens subjetivas como a satisfação térmica dos ocupantes;
- Propor uma estrutura de modelagem de estoque de edificações *bottom-up* que use informações em nível de estoque para aprimorar a representatividade dos arquétipos e obter um modelo gerenciável do estoque de edificações;
- Avaliar a aplicabilidade do modelo *bottom-up* de estoque de edificações e por meio da avaliação dos efeitos das mudanças climáticas nos *benchmarks* gerais do estoque de edificações escolares no Brasil,

Método

Foi realizado um estudo baseado em epidemiologia energético para avaliar a distribuição (frequência e padrões) e os fatores determinantes do consumo de energia em edifícios escolares no Brasil. Cinco artigos constituem esta tese. O primeiro artigo apresentou uma revisão da literatura na qual foram identificadas as principais lacunas existentes no estado da arte sobre o tema, utilizando um método de revisão sistemática.

O segundo artigo apresentou informações sobre o estoque de edificações escolares e uma análise estatística das principais características do consumo de energia. O método utilizado para coleta de dados foi aplicação de questionário integrado a uma análise sistemática dos dados de consumo energético e informações das edificações escolares. Os resultados que caracterizam 417 edificações foram analisados por meio de análise exploratória de dados – empregando-se testes estatísticos não paramétricos de Kurskall-Wallis e Wilcoxon pareado para avaliar variáveis categóricas, modelo de distribuição para variáveis contínuas e frequência de palavras para variáveis descritivas.

O terceiro artigo propôs uma modelagem *top-down*, com base nos dados apresentados no segundo artigo, a fim de propor um método de *benchmarking* integrativo considerando aspectos subjetivos (satisfação com o ambiente construído) para o *benchmarking*. A categorização das variáveis foi feita por meio da discretização por igual frequência, e uma Rede Bayesiana foi utilizada como método estatístico de predição para o *benchmarking*, utilizando as probabilidades condicionais e relações entre variáveis selecionadas como meio de cálculo das probabilidades do resultado final. A avaliação do desempenho da Rede Bayesiana foi realizada por meio de uma validação cruzada e determinou-se a matriz de confusão da rede, bem como sua acurácia, taxa de erro e demais medidas de desempenho.

O quarto artigo propôs uma estrutura de modelagem *bottom-up* para se construir um arquétipo com menos incerteza para modelo de *benchmarking*. O arquétipo foi desenvolvido com base na entropia das variáveis que caracterizam o estoque de edificações, aplicando-se análise de agrupamento (método k-médias e Silhueta média para cálculo da quantidade de grupos) para seleção dos valores que compõem o modelo paramétrico. A entropia foi mensurada por meio da equação de Shanonn. Quanto maior a entropia da variável, mais valores foram adotados pela análise de agrupamento para serem inseridos na simulação paramétrica, de forma que o modelo seja capaz de representar melhor o estoque real de edificações. O arquétipo foi simulado utilizando o EnergyPlus e oito arquivos climáticos representando cada uma das zonas bioclimáticas brasileiras. Os resultados das simulações foram utilizados para formular o método de *benchmarking* por meio de uma Rede Neural Artificial (com 80% dos resultados das simulações), de forma a generalizar os desempenhos típicos em função das variáveis utilizadas como parâmetros para avaliação do desempenho do edifício. A avaliação do desempenho da rede neural foi realizada por meio de uma validação cruzada utilizando

20% dos resultados das simulações, e determinou-se tanto a raiz do erro quadrático médio quanto o coeficiente de variação da raiz do erro quadrático médio.

O quinto artigo apresentou uma aplicação prática do modelo de estoque construído no quarto artigo. O método empregado fez uso parcial do modelo apresentando no quarto artigo e, apesar de mais simplificado, simulou cenários climáticos futuros. Quatro arquivos climáticos utilizados na simulação foram adaptados utilizando o método *morphing* para incluir os cenários A2 do IPCC de previsão de mudanças climáticas para 2050 e 2080. Além disso, dois cenários de condicionamento de ar foram incluídos para representar situações futuras em que escolas teriam sistemas de condicionamento de ar em todos os ambientes.

Resultados e Discussões

Os resultados mostraram que as variáveis determinantes para o consumo de energia no estoque de edifícios escolares no Brasil foram: i) o número de alunos; ii) área construída; iii) tempo de operação; iv) especificações do sistema de climatização (tipo e quantidade) e v) o clima. Outros fatores como a satisfação térmica e a necessidade de melhorias desempenharam um papel importante, mas não foram decisivos. A questão da ciência dos diretores das escolas sobre o consumo de energia e a satisfação com outros aspetos de qualidade do ambiente interno (como a satisfação acústica e a satisfação com a iluminação) não foram relevantes para o desempenho energético. Além disso, as respostas da pesquisa mostraram que as escolas no Brasil não têm qualidade do ambiente adequada para aprendizado, e os ocupantes relataram uma necessidade urgente de melhor desempenho térmico, possivelmente resolvido com maior condicionamento de ar. Assim, o aparente baixo consumo de energia do estoque (se comparado a outros países) é um problema de pobreza energética somado à necessidade de melhor desempenho térmico nesses edifícios. Outro resultado importante é que a consideração de aspectos subjetivos é importante para permitir um *benchmarking* confiável. Um modelo probabilístico foi proposto neste trabalho para integrar variáveis qualitativas e quantitativas do estoque de edificações para realizar tal avaliação. A Rede Bayesiana apresentou resultados adequados. O método usado para aprimorar a composição do arquétipo (avaliação da entropia e seleção de valores da análise de agrupamento) forneceu um modelo de estoque de apropriado para representar adequadamente as condições de estoque. Este modelo de estoque baseado em arquétipos de suporte à análise de cenários hipotéticos para a população de edifícios, tais como implementação de estratégias de eficiência energética e desempenho em climas futuros.

Nesta tese, as duas abordagens de modelagem propostas resultaram em aplicações diferentes. A modelagem *top-down* se mostrou uma solução baseada em evidências para representar relações estatísticas e fornecer uma única escala de desempenho. Este modelo foi mais adequado para incluir os aspectos da satisfação dos ocupantes na avaliação do desempenho operacional dos edifícios. Por outro lado, o modelo *bottom-up* foi baseado nos dados do estoque para representar arquétipos; e usou inteligência artificial para generalizar a estimativa do *benchmark* de acordo com características da edificação. Este modelo é adequado para avaliar o desempenho do edifício em condições padronizadas. Como resultado, ambas as abordagens devem ser consideradas de forma diferente, porque medem indicadores diversos e resolvem problemas diferentes. Assim, ambas as abordagens são úteis e válidas porque avaliam questões distintas.

Considerações finais

A estrutura proposta para desenvolver o modelo de estoque de edificações *bottom-up* foi aplicado com sucesso em um estudo de caso considerando cenários futuros de dados climáticos e intervenções de instalação de ar-condicionado. Se o *status quo* for mantido, o estoque de edifícios escolares brasileiros experimentará aumento de 88% em seu consumo de energia médio até 2050 e 170% em 2080. Portanto, ações devem ser tomadas para proporcionar uma transição consciente para um estoque de edificações escolares mais energeticamente eficiente e confortável aos seus ocupantes.

As limitações do trabalho incluem: a quantidade de dados utilizada, uma vez que apenas um ano de dados de consumo de energia foi empregado (variações ano a ano devem ser exploradas); a restrição de aplicabilidade do modelo *top-down* apenas à amostra utilizada, uma vez que as probabilidades são intrínsecas aos dados e; a dependência subjetiva da modelagem da volumetria do arquétipo no modelo *bottom-up* em relação ao analista. Essas limitações podem ser sanadas em investigações futuras, para as quais sugere-se: ampliação da base de dados para inclusão de mais períodos e tipologias, e melhoria de composição do arquétipo utilizando ferramentas de modelagem paramétrica e programada.

Acronyms

ABNT – Brazilian Technical Standards Association (*Associação Brasileira de Normas Técnicas*);

ANN – Artificial Neural Network;

ANOVA – Analysis of Variance;

ASHRAE – American Society of Heating, Refrigerating and Air-Conditioning Engineers;

BN – Bayesian Network;

DEC – Display Energy Certificate;

EPC – Energy Performance Certificate;

EUI – Energy Use Intensity;

HVAC – Heating, Ventilation and Air-Conditioning;

IEA – International Energy Agency;

IEQ – Indoor Environment Quality;

IPCC – International Panel on Climate Change;

IPMPV – International Performance Measurement and Verification Protocol;

KPI – Key Performance Indicator;

LEED – Leadership in Energy and Environmental Design;

NBR – Brazilian Standard (*Norma Brasileira*);

RMSE – Root Mean Squared Error.

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1. Introduction

1.1. Context

The energy sector is one of the main responsible for the human impacts on the global environment. These impacts are related to greenhouse gas emissions due to energy generation, contributing directly to aggravate climate change (EBC IEA, 2013b). The International Panel on Climate Change (IPCC) established that reducing the overall energy use and looking for alternative energy sources are two urgent tasks to diminish the climate change effects and bring more sustainability to communities (IPCC, 2012). Moreover, the IPCC examines the impact of climate change effects in all sectors of society and the importance of mitigating such effects to bring balance between a healthy human society and the ecosystems on the planet.

Regarding the energy consumption in buildings, the Brazilian National Energy Report stated that this sector accounted for around 40% of the total electricity consumed in the country in 2020 (EPE, 2021). Therefore, actions to reduce the energy consumption in buildings are important due to the significant share of the building sector in the total energy consumption.

However, there are challenges in quantifying the energy consumption in buildings regarding the availability and amount of data in a standardised way. Such challenges difficult the long-term and stock-level energy analysis (HAMILTON *et al.*, 2015). The Annex 53 report of the International Energy Agency (IEA) established the six main factors that impact the energy consumption in buildings: climatic conditions, envelope, systems, operation and maintenance, occupant behaviour and indoor environmental quality (IEQ) (EBC IEA, 2013b). However, it is difficult to determine a systematic approach to consider all those factors simultaneously. Thus, there is a need to assess the building performance in a multidisciplinary approach. An insightful solution to assess the energy performance of buildings is to consider a group of buildings as a population and to apply statistical analysis through multidisciplinary evaluation – this concept is called energy epidemiology.

Energy epidemiology is an empiric-based approach that uses data obtained in actual world to assess energy usage in systems. This approach employs the epidemiology concept borrowed from medical science to seek connections and findings related to energy use in communities (HAMILTON *et al.*, 2013). Some studies that apply energy epidemiology have been carried out to improve energy efficiency in buildings (COFFEY *et al.*, 2015; HAMILTON *et al.*, 2017; VAN DEN BROM; MEIJER; VISSCHER, 2018). Due to the impact of socio-cultural particularities on the conditioning factors of energy consumption, there is a need for an individualised analysis of each cultural reality, once the building models and the methods of characterization of the building stock used in other countries cannot be directly applied in Brazil (BORGSTEIN; LAMBERTS, 2014).

The methodology of energy epidemiology finds answers to explain the patterns of energy consumption not only analysing the consumption log but also other related phenomena. Statistical analyses are employed to "enrich" the energy consumption database to search for cause-effect functions in groups of buildings under similar conditions. For example, Love and Cooper (2015) discussed this issue by combining data from different research approaches to create an interdisciplinary approach that took into account both technical and social issues. They reviewed three case studies and presented technical and social analyses, crossing quantitative and qualitative data and methods. As a result, the authors presented a new approach to social and technical research, recognising that energy use in buildings is both a social (because it makes use of an interactive person-environment resource) and a technical issue (due to system-environment and performance interactions).

Thus, on the one hand, there is considerable experience in studying energy performance from a building-level perspective. On the other hand, the statistical analysis of buildings in a stock-level perspective is gaining ground. Therefore, facing the energy consumption in buildings as a statistical phenomenon by grouping similar buildings into the "building stock" allows comprehensive epidemiological assessments. The building stock is represented through models – which allows test scenarios and detailed assessment of the building performance. In summary, analysing both building and stock-level perspectives of research may shed light on the building performance analysis in general. For example, a single solution can be explored in one building, but it can be an energy efficiency strategy for other buildings if they share similar conditions.

Hence, stock modelling techniques are necessary. A building stock is a database or inventory which records and represents as much information as possible at the level of individual properties (EVANS; LIDDIARD; STEADMAN, 2017).

Kohler and Hassler (2002) outlined important tasks for studying resources used in the building stock, such as quantifying energy, water and gas use, quantifying empty and occupied buildings, operating costs, logistics and mass flows, land use planning and conservation of historical monuments. In addition, building stocks are typically differentiated according to typologies to allow comparisons (comparing hospitals to hospitals, hotels to hotels, homes to homes, and so on).

A building stock represents an important tool to help increase energy efficiency. Among other criteria, Kavgic *et al.* (2010) established that the building stock must be able to:

- estimate a baseline of energy demand from existing buildings;
- explore the technical and economic effects of different efficiency improvement strategies (reduction of energy and CO_2 consumption), including the impact of new technologies; and
- identify the effect of strategies to improve efficiency in the built environment and the quality of the indoor environment.

A simplified example of stock composition was carried out by Mendonça (2012), who presented a method for characterising the stock of historic buildings in Florianópolis. Forty historic buildings were catalogued by compiling characteristics such as floor-plan area, relationship with the surroundings, colour and thickness of walls. Some conclusions were obtained by statically analysing the building stock, such as the low coefficient of determination between construction parameters and energy consumption, and the positive trend between the increase in glazed areas and energy consumption, but with weak correlations.

An advanced example is the project TABULA, which is a project to map and model the building stock in the European housing sector by aggregating information of location, floor-plan area, year of construction and consumption of electricity and gas. Episcope is an ongoing project that is part of TABULA, which aims to make energy retrofit processes more transparent and efficient in the European housing sector. In these projects, energy retrofit measures in residential buildings are identified and monitored, seeking to calculate scenarios for the stocks and portfolios studied, identifying the savings, construction and system combinations, and the renovation rates necessary to achieve the goals. The objective of the programmes is to help the countries of the European Union to achieve the goals for reducing the emission of carbon dioxide into the atmosphere (EPISCOPE, 2013).

Another advanced stock model is the 3DStock project, a tool developed by the Centre for Energy Epidemiology in the United Kingdom. This tool assesses the building stock in “three dimensions” through a digital model that associates building massing, materials, age, use, and energy and gas consumption.

The three-dimensional representation of the stock enables a longitudinal assessment, which considers the relationships among neighbouring buildings, surroundings, social aspects and even more advanced fluid dynamics modelling. Some conclusions presented by Evans, Liddiard and Steadman (2017) point out the significant influence of outliers on the typologies of offices, stores and workshops – which makes it impossible to create standards for understanding the use of energy – and less influence in schools, restaurants and coffee shops. In addition, 3DStock provides a detailed information model for thermal simulation. This simulation environment from 3DStock was developed by the same researchers and is called SimStock (COFFEY *et al.*, 2015). Although the 3DStock and the SimStock are advanced approaches, they are restricted to a single and small region (in a scale of a city or neighbourhood). Country-level models like this are still not supported by the current technology.

While quantifying human behaviour, thermal and energy loads and infiltration rates may be feasible at the scale of the building, it is impractical in large groups of buildings. Thus, it is necessary to summarise the stock of buildings into archetypes, which is the definition of parameters representing a group of buildings with similar properties (REINHART; DAVILA, 2016) through a single (or few) representative building model.

Schaefer and Ghisi (2016) analysed a residential building stock composed of 120 affordable housing in Florianópolis. The objective of the analysis was to evaluate the characteristics and determine reference models for energy performance simulations. A cluster analysis was used through hierarchical and non-hierarchical approaches, and two buildings were determined as reference models (archetypes). Computational simulations were used to validate the method and showed that the archetypes could adequately represent the building stock since the degree-hours obtained by means of computer simulation were similar to the sample means. Brøgger and Wittchen (2018) reviewed several studies that used inventory modelling to identify key representational elements. As conclusions, the authors point out that the representativeness of the archetypes must be improved, as sometimes it is not clear what makes the archetype or the building of reference representative. Furthermore, the authors point out that when efficiency measures are studied, the potential energy savings are usually calculated considering the total installed power, not the building systems and occupant behaviour, which leaves a gap considering the actual savings.

Alves *et al.* (2017) used archetypes to measure the potential for energy reduction due to energy efficiency measures. In order to understand the energy demand and provide information for intervention in existing buildings in Belo Horizonte (Brazil), the work proposed a framework to estimate the baseline of consumption of skyscrapers, based on the investigation of urban zoning, taxes information and field questionnaires from a stock. Results showed that the potential reductions were higher than the reductions observed *in-situ*, especially in lighting and cooling systems. In a following study, Alves *et al.* (2018) listed energy conservation measures and determined scenarios to calculate an energy-saving potential. Results showed an energy consumption reduction potential of up to 24% in relation to the baseline, considering the initial investment outlay, in 20 years.

Despite the fact that archetypes imply in loss of individual building details, the important differences between types of buildings are represented in the process.

The method proposed by Reinhart and Davila (2016) employs archetypes to simulate urban environments. In summary, archetypes are used to integrate 3D GIS models and compose an emulation of the neighbourhood-level environment to simulate the physics-based phenomenon (bottom-up model). The result is a manipulable model of part of a city. The method has been widely applied to study stock-level carbon-reduction strategies considering the building-to-building interactions (ANG; BERZOLLA; REINHART, 2020). The method relies on extensive and comprehensive information regarding the building stock allied to the digital model of the city.

Although the composition of the inventory is a critical issue to model archetypes, the use of archetypes can be helpful to both evaluate strategies to reduce energy consumption at the building stock level and assess typical conditions of actual buildings. By assessing typical conditions, it is possible to achieve typical energy performances of the building stock. Consequently, typical energy performance supports the process of energy benchmarking of buildings.

Energy benchmarking of buildings is the process of comparing the energy performance of a building to a reference (benchmark) (CHUNG, 2011). To make this a fair comparison, factors such as climatic conditions, floor-plan area, type of use, and systems must be taken into account. Energy performance benchmarking in buildings are widely used by government initiatives to measure operational energy performance on a large scale (BORGSTEIN; LAMBERTS, 2014; HONG *et al.*, 2014; LI; HAN; XU, 2014). In some countries, benchmarking is developed through government-determined information, intending to bring public pressure on the owners or managers in case of poor-performing buildings by encouraging them to improve performance. The most used performance indicator is the energy use intensity (EUI) – kWh/m².year or equivalent unit (BRADY; ABDELLATIF, 2017; FUMO; MAGO; LUCK, 2010).

Studies that evaluated methods to obtain the benchmark are increasing. Li, Han and Xu (2014) categorised benchmarking methods considering their complexity level (white, grey, or black-box approaches). A comprehensive review of the method is presented by Chung (2011):

i. Simple normalisation: a statistical analysis determines the benchmark by means of statistical measures (e.g., mean or median, or upper quantile for good practices). Further statistical analysis, such as histograms and correlation analysis, can be performed (BOEMI *et al.*, 2011; LI, 2008; SCOFIELD, 2013; SCOFIELD; DOANE, 2018; TAYLOR *et al.*, 2018);
ii. Regression analysis (or Ordinary Least Square, OLS): the benchmark is determined through a cause-effect function of the energy performance and relevant characteristics. A statistical regression model is employed (BORGSTEIN; LAMBERTS; HENSEN, 2016; HONG *et al.*, 2014a; PAPADOPOULOS; KONTOKOSTA, 2019; SABAPATHY *et al.*, 2010).
iii. Stochastic Frontier Analysis (SFA): a regression equation is also employed to determine the benchmark; however, there is a determination of a geometric element using data of high-performance buildings (BUCK; YOUNG, 2007; YANG; ROTH; JAIN, 2018).
iv. Data Envelopment Analysis (DEA): regression analysis is used to determine a boundary that includes all observations, and the benchmark is calculated using the distance of such dataset (CHUNG, 2011; LEE, 2008, 2009a).
v. Advanced methods: methods that take advantage of computational intelligence, for instance, geostatistical approaches (KOO; HONG, 2015; ÖSTERBRING *et al.*, 2018) and machine learning, such as decision tree and artificial neural networks (CHUNG; YEUNG, 2017; PARK *et al.*,

2016; RUZZELLI *et al.*, 2010; SEYEDZADEH *et al.*, 2018).

An example of a benchmarking system is the EnergyStar – an American organization linked to the EPA (Environmental Protection Agency) that establishes processes for continuous improvement of energy efficiency. Annually, the EnergyStar promotes and publishes energy benchmarks for buildings in the United States (ENERGY STAR, 2015). One of the practices that must be carried out during the energy management suggested by Energy Star is comparing a building performance to benchmarks, which consists of comparing the performance with similar buildings on the market, rating it a score from 0 to 100. The rating system (found in the Energy Star ® Portfolio Manager) establishes guidelines for energy management in buildings, such as standards, concepts, and best practices to be applied, as well as guidelines for performing benchmarking such as:

- Based on its past performance: comparing last month's performance with a baseline (12 months, for example);
- Average in the market: comparison with a standardised and average indicator published by a recognised agency;
- Best in the market: comparison with the upper quantile of the standardised indicator published by a recognised agency;
- Best Practices: Qualitative comparison against certain established practices considered to be the best in the industry. The Energy Star ® "Energy Program Assessment Matrix" is an example of a qualitative benchmarking tool.

Although some organizations have particular methods to establish benchmarks, the methods can – and should – undergo adaptations according to their context (LI; HAN; XU, 2014).

Hsu (2014) evaluated the relationship between building characteristics and their energy consumption in New York City using statistical regression models (ANOVA and Bayesian regression) on displayed performance information of the benchmarking policy. In this study, the author concluded that the level of building performance in previous evaluations has a more significant influence than any other parameter. One concluded that the benchmarking method could predict performance as properly as an energy auditing. Park *et al.* (2016) established six new efficiency rating categories by benchmarking commercial buildings in South Korea using electricity consumption data from 2012 to 2014 of 1,072 buildings. The authors used Pearson's correlation to verify the relevance of construction characteristics with energy consumption intensity and then establish new benchmarks using the Decision Tree method. ANOVA was used as a system for validating the benchmarks achieved. Chung (2020) explored a non-parametric least square model to improve benchmarking in Hong Kong to consider factors that the building manager can control.

In Brazil, Borgstein and Lamberts (2014) proposed a first benchmarking methodology for the country. The method was applied to bank branches and consisted of using archetypes to simulate typical conditions of buildings under several climatic conditions to develop a regressive model. The authors also obtained the typical electricity end-uses of the building stock of bank branches. Veloso *et al.* (2020) evaluated the building stock in Belo Horizonte through a statistical benchmarking approach. Although this method is accurate because it is evidence-based, it is restricted to the region of study.

In order to propose a country-applicable model, the CBCS (short for Brazilian Council for Sustainable Construction, in Portuguese: *Conselho Brasileiro de Construção Sustentável*) applied the same method developed by Borgstein and Lamberts (2014) to create benchmarking policies for office buildings in 2019 – the project DEO (short for Operational Energy Performance, in Portuguese: *Desempenho Energético Operacional*). In 2021, a project funded by Eletrobras and executed by CBCS improved the DEO initiative by including benchmark models of 15 typologies, including: bank branches (review), resorts, hotels, small hotels, big retails, small retails, grocery stores, restaurants, shopping centres, nursery schools, elementary and high schools, universities, hospitals, health care buildings, and data centres. Data from the project META (Technical assistance from the energy and mineral sectors) was used. The method employed regressive analysis of simulated archetypes obtained through a building stock model. Although benchmarking models were obtained, some limitations were drawn during the project development. For example, the evaluation of the representativeness of the archetypes considering the actual building stock, the response of the building stock to the benchmark model, and the consideration of subjective aspects on the benchmarking.

In this way, this thesis proposes a broad discussion about the building stock modelling applied to benchmarking in Brazil. For such an aim, the building typologies must be studied individually once the features and characteristics of a building are intrinsically related to its social function. The target typology of this study was the school building stock in Brazil, specifically the elementary and high public schools (Education of children from seven to seventeen years of age). Although public schools are planned to follow a standard design guided by the National Fund for Educational Development (in Portuguese "Fundo Nacional de Desenvolvimento da Educação", FNDE), many school buildings have particularities regarding the topography, size and budget. This makes the school building stock assorted and worthy of investigation. The justification for selecting such building stock was due to the importance of the Public Administration knowing the energy efficiency of their buildings. Additionally, there is an impact of the social function of this typology in society (BURMAN; MUMOVIC; KIMPIAN, 2014). Moreover, only electricity consumption was evaluated.

1.2. Problem

The state of the art reveals a need for a robust and reliable method to evaluate the energy performance of existing buildings, which has to be consistent with the regional context. Some methods for building stock modelling were proposed to achieve such aim, using archetypes or descriptive analysis of the stock. Archetypes are helpful for approaches that lack disclosure of energy policies data, while descriptive analysis can explore such transparency information. Although more advanced, 3D stock modelling is restricted to a specific neighbourhood due to the technological limitation and need for high-detailed information.

Hence, the problem of improving energy benchmarking and building stock modelling that is addressed in this thesis can be outlined according to the following research questions:

- *What are the main factors that impact the energy consumption in school buildings in Brazil?* There is a need for a descriptive analysis of the target building stock using a cross-sectional approach. By evaluating many subjects (buildings) of the same typology, it is possible to correlate the main building characteristics with their corresponding electricity consumption through a comprehensive statistical analysis.

- *How can subjective aspects (such as thermal satisfaction) be considered in benchmarking policies?* Taking user-related information into account in benchmarking evaluation guarantees trustful benchmarking accuracy. An efficient building is not only the one that consumes less energy but also the one which provides adequate environmental conditions by presenting low energy consumption. This is an issue that always has to be considered when operational energy performance is evaluated. Thus, integrating subjective aspects when evaluating energy efficiency is a challenge not considered in benchmarking models.
- *How can one improve the representativeness of the building stock model?* Since archetype-based benchmarking models are suitable for the Brazilian context, there is a need for a standard and replicable method to enhance the representative of archetypes in the stock modelling process. The current building stock modelling methods propose adopting data based on standards and legislations for some archetypes' parameters. Then, the actual representation of the building stock is limited because the actual stock does not always comply with standards and legislation guidelines. Nevertheless, the archetype simulation may lead to non-typical performances. Additionally, reducing uncertainty in the archetype composition is fundamental to guarantee that the benchmark is applicable for the building stock.

Therefore, this research is justified by integrating actual data in the comparative assessment of energy performance. In summary, we explore the school building stock in Brazil through an epidemiological approach, i.e. considering the buildings as a population and accounting for their diversity in features and behaviours.

1.3. Objectives

1.3.1. General objective

The objective of this thesis was to develop methods to obtain representative building stock models to benchmark the energy performance of Brazilian schools considering building-level and stock-level perspectives.

1.3.2. Specific objectives

Each specific objective is related to a main objective of each paper that composes this thesis and can be outlined as follows:

- Identify the current state of the art of the building stock modelling approaches and the benchmarking methods through a literature review considering both building-level and stock-level perspectives of energy analysis in buildings;
- Assess the school building stock in Brazil by means of a cross-sectional survey and a comprehensive statistical analysis that correlates the main features of the building stock with their electricity consumption. This objective was expected to compose a wide-ranging overview of the target building stock to be used in this study;
- Propose a top-down model to evaluate the whole-building performance in the benchmarking method, including subjective approaches such as thermal satisfaction;
- Propose a bottom-up building stock modelling framework that uses stock-level information to enhance the archetypes representativeness and obtain a manageable building stock model;
- Evaluate the applicability of the building stock model proposed and its validity by applying the building stock model obtained herein to address the effects of climate change in the overall benchmarks of the school building stock in Brazil.

1.4. Innovation

The innovation of this thesis is the mitigation of the gaps expressed in the Problem Section and can be outlined as follows:

- An innovative energy epidemiological approach of the school building stock in Brazil is reported through a comprehensive statistical analysis of the dataset. One employed an associative approach integrating real-world data from energy bills and evidence from survey applications to compose an innovative dataset of energy performance associated with environmental satisfaction. Several analyses between the energy performance and environmental satisfaction of occupants were outlined, as well as the necessity for improvements and energy management aspects;

- Using a machine learning technique (Bayesian Network), an innovative approach was proposed to integrate subjective aspects of the building performance with technical aspects in a probabilistic way. The data-driven method provides a reliable method for energy benchmarking mixed-mode buildings in warmer climates, identified as lacking in the literature. It brings metrics to evaluate building energy performance in countries where mixed-mode operation is predominant;
- The need for a standard structure to model the building stock led to the proposition of an innovative standardised framework to obtain a benchmark. The framework combines Information Theory through entropy and cluster analysis to determine the parameters of the archetype. The archetype is used to model an ANN that serves as the benchmarking tool;
- Additionally, the literature review paper is an innovative analysis focused on empirical studies about energy performance analysis in buildings. A systematic approach was used to survey the studies related to the operational building performance and a meta-analysis process established the relationship among studies.

Therefore, this thesis contributes to the understanding of the actual performance of buildings and it strengthens the state of the art of building stock modelling worldwide by proposing a technique to manage the uncertainties involved in representing the buildings as a group through manageable models.

1.5. Structure of the thesis

Apart from the Introduction, Discussions and Conclusion chapters, this thesis is composed of five chapters; each one presents a paper reporting the work performed during the doctorate. The papers were transcribed *ipsis litteris* to this thesis, just as they were published or submitted to journals, but with their layout adjusted to this document. Table 1.1 shows a summary of the papers, the journals in which they were published or submitted and the current status of each paper in the moment of the finalization of this thesis.

Table 1.1 – Articles that compound the core of this thesis

Title	Journal	Status
Building-level and stock-level in contrast: A literature review of the energy performance of buildings during the operational stage	Energy and Buildings	Published in January 2020
Mapping the energy usage in Brazilian public schools	Energy and Buildings	Published in June 2020
Integrating evidence-based thermal satisfaction in energy benchmarking: a data-driven approach for a whole-building evaluation	Energy	Submitted in May 2021, Under Review
Data-driven framework towards realistic bottom-up energy benchmarking using an Artificial Neural Network: application for Brazilian schools	Applied Energy	Submitted in July 2021, Accepted in August 2021
Impact of implementing air-conditioning systems on the school building stock in Brazil considering climate change effects: a bottom-up benchmarking	Building Simulation Conference	Presented and published in September 2021

All references were compiled at the end of this thesis for conciseness since several references are redundant in each Chapter. ABNT format was adopted for references. The conceptual model of this thesis is shown in Figure 1.1 and is explained as follows.

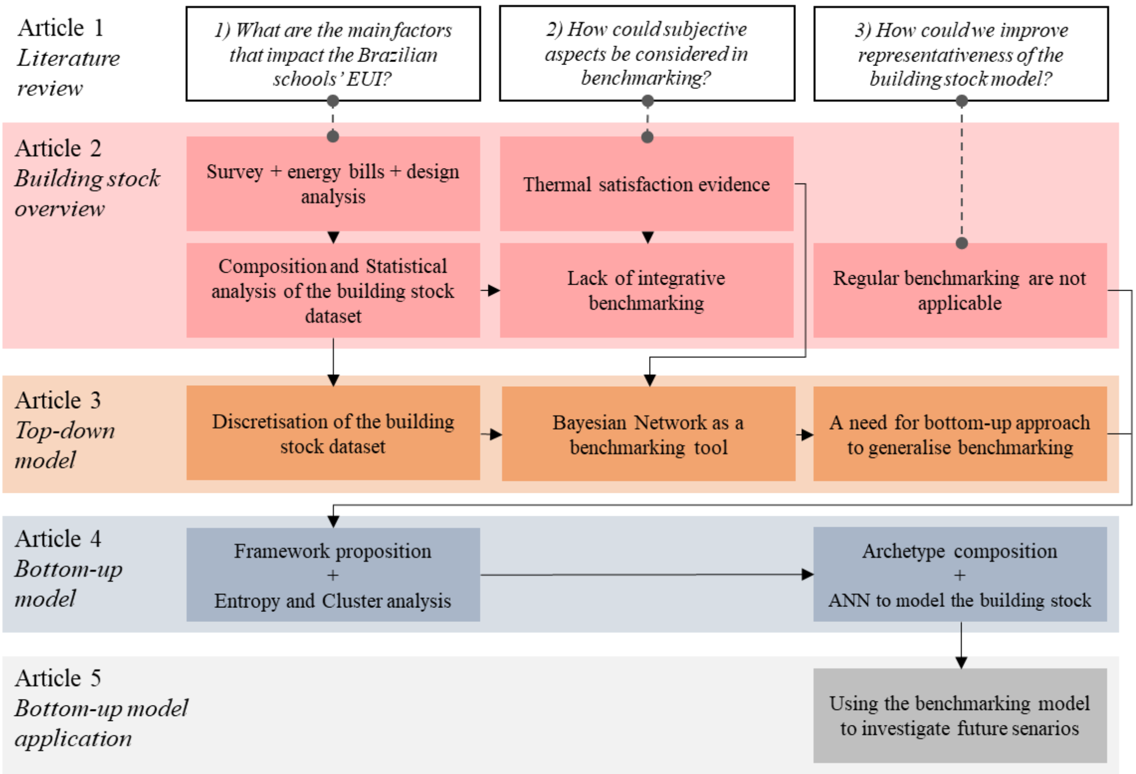


Figure 1.1 – Structure of the thesis.

The literature review presented in Chapter 2 enlightened the current state of the art of studies that assessed building energy performance evaluation during the operational stage. Complementary literature reviews are presented in each paper with updated studies regarding each subject since the paper was published in early 2020. The review process allowed the identification of two distinct approaches of study: a building-level perspective, which assumes that the energy analysis of the building is conducted at its specific level, considering the whole building as an individual; and a stock-level perspective, which considers the information from a group of buildings considering the variations among buildings.

The main methods and the time resolution assessed in the studies reviewed were summarised in the literature review, and conceptual models of each perspective of analysis (building-level and stock-level) were drawn. Conceptual models provided how the subjects addressed in studies connected with each other, and research insights prospected.

Then, from the extensive research of studies around the subject, it was possible to identify that benchmarking models lack in studying uncertainties in building stock representation, especially related to uncertainties due to operational performance.

Definition of representative benchmarks and verification of the application of benchmark models in actual building stocks were also pointed as limitations.

Subsequently, the school building stock was adopted as the target object of study. A survey was carried out to characterise the school building stock by means of requesting data from all 27 state education departments in Brazil. A questionnaire was applied to the school principals to raise information from actual schools to enhance the dataset and school's characterisation. Fifteen Brazilian states provided information about energy consumption, floor-plan area and other information on approximately 2,000 buildings, but only around 500 filled-in questionnaires were obtained. The final clean treated and complete dataset comprises the full characterisation of 419 schools, including information regarding location, energy consumption, building features, systems types and specifications, occupant behaviour patterns, satisfaction with the built environment and needs for improvements. The dataset was comprehensively investigated through statistical analysis by correlating the energy consumption of the buildings to their characteristics. All the process of gathering and analysing this dataset is presented in Chapter 3. The main results of this overview showed that most of the schools do not have HVAC systems in classrooms. Also, there is a significant difference in EUI from schools that have HVAC in classrooms compared to those with no HVAC. The EUI as a function of the number of students was more appropriate than the floor-plan area to achieve a reliable energy performance analysis. Comments from the principals emphasise a need for air-conditioning, and the low levels of satisfaction with the temperature proved that schools, in general, provide poor thermal conditions to the occupants. This fact led to a complementary research insight: a simple classification of energy performance might classify buildings with poorer indoor conditions as efficient, but they needed air-conditioning.

Henceforward, a model for integrating this thermal satisfaction evaluation needed to be proposed, and it is presented in Chapter 4 through a top-down benchmarking approach. The dataset obtained through the survey (Chapter 3) was used to construct a data-driven model that integrates occupant-reported thermal satisfaction into the whole-building evaluation – together with building features, location, and systems specification. A machine learning approach through Bayesian Network was employed to integrate subjective aspects of the building performance with technical aspects in a probabilistic way. Thus, a method for improving reliability in energy benchmarking of mixed-mode buildings in warmer climates was proposed, which was identified as lacking in the literature. Additionally, this method brought metrics to evaluate building energy performance in countries with predominant mixed-mode operation, i.e. high cooling demand and use of natural ventilation.

The difference between top-down and bottom-up analysis in the building stock model must be specified. While the top-down (data-driven) analysis employs an evidence-based approach and uses relationship among variables to predict an outcome, the bottom-up analysis employs deterministic equations to calculate a result of a physical phenomenon. Top-down approaches are restricted to the dataset but consider uncertainties inherent to reality since they are based on evidence – for example, a linear regressive equation can predict the energy consumption of a sample of buildings. Bottom-up methods calculate the phenomenon by means of physical iterations – for example, energy simulation is often used to determine thermodynamic processes and achieve thermal loads. To do so, archetypes are used. Literature reports that there is high uncertainty in collecting parameters of the simulation of archetypes, and a need for representative methods to extract information from the building stock is lacking.

Although the top-down approach is useful to evaluate building performance when a large evidence-based dataset is available, a bottom-up approach is useful to model a manageable building stock model. Since this approach is based on deterministic calculations, it is possible to determine the response of the performances of the buildings in the stock under conditions yet unseen.

In this thesis, both methods were proposed. A top-down method was proposed to integrate the subjective aspects reported by occupants in the benchmarking model, and a bottom-up method was proposed to reduce uncertainty regarding the archetype by approximating the archetype to typical conditions observed in the stock. Both methods used school buildings in Brazil as a test-bed dataset, but they can be applied to other typologies and other countries. The purpose was to contribute methods to model the building stock with high representativeness.

Therefore, in Chapter 5, a framework using a bottom-up approach was proposed to reduce the uncertainty of the archetypes. The framework combines Information Theory through entropy and cluster analysis to determine the parameters of the archetype. The archetype is used to model an ANN that serves as the benchmarking tool. Then, an actual sample of buildings is benchmarked, showing how the building stock responded to a benchmark application.

The motivation of the study came from the need for a standard framework to model the building stock in developing countries to obtain representative archetypes and, consequently, reliable benchmarks. The main innovation relies on the formulation that this framework was proposed: the schematic data-driven method was created to reduce uncertainty in modelling archetypes for energy benchmarking of buildings. Moreover, the study innovatively reported an actual building stock benchmarking evaluation on a large scale in Brazil. Important conclusions showed that the Brazilian school building stock had a tendency to inefficiency, and a specific study case pointed out that inefficient equipment might cause such inefficiency.

The development of this manageable building stock model allowed the further exploration of the model to test the response of the current building stock under future climatic conditions and considering the gradual implementation of HVAC in classrooms. This analysis is presented in Chapter 6. Through this analysis, it was found that the average EUI would increase around 88% compared to the actual EUI if HVAC systems were implemented today in classrooms. Moreover, there would be an increase of 43% of the EUI in 2080 due to climate change effects. Conclusions support that enhancing thermal comfort conditions in school building stock needs attention towards improving passive energy efficiency strategies and implementing active cooling systems.

Finally, Chapter 7 shows a discussion to link all papers' results and the contribution of the thesis by associating the results with other studies in the literature. The discussion is conducted to highlight the importance of the building stock modelling as well as the results of the case study evaluated: the school building stock in Brazil. Insights of the typical Brazilian school building conditions and their implications on their energy performance are discussed, together with the consequences on the occupants' conditions. Therefore, the concept of benchmarking is discussed to show the purpose of benchmarking and how this practice is related to energy efficiency in buildings.

At last, it is important to mention the impact of the COVID-19 pandemic in this study. A data collecting phase was planned to occur at the beginning of the school year in 2020 (March 2020). This phase would collect high-granularity energy consumption data (using smart meters) and thermal satisfaction evidence from students of around 12 schools. Since the pandemic outbreak in February 2020 in Brazil, lockdown measures stopped school activities, and collecting such data was not possible. An ongoing change in the thesis approach was needed, and Chapter 5 reflects the main change – instead of using monitored data, building energy simulation was used to obtain the energy performance of the stock. Actually, this improved the thesis by bringing a fresh outlook for the use of archetypes, which supported the development of a manageable building stock model.

As a final remark on this Chapter, one discusses the validity of the energy benchmarking application. In this thesis, two stock modelling methods were proposed: a top-down and a bottom-up method. The top-down method was an energy epidemiological solution based on evidence to model statistical relationships and provide a single performance scale. This method is suitable to include occupants' aspects in buildings operational performance evaluation. On the other hand, the bottom-up method started from the building stock dataset to model archetypes; artificial intelligence was used to generalise the benchmark prediction. This method is adequate to rate the building performance under standard conditions. As a result, both aspects are important to be considered and have to be considered differently because they measure different metrics and solve different problems. Thus, both methods are useful and valid, but they perform different evaluations.

2. Literature review

This Chapter is the transcription of the following paper:

Building-level and stock-level in contrast: A literature review of the energy performance of buildings during the operational stage
Authored by Matheus Soares Geraldi and Enedir Ghisi.
Published in Energy and Buildings (ISSN: 0378-7788), volume 211, in 2020, and catalogued through the DOI: https://doi.org/10.1016/j.enbuild.2020.109810

Abstract:
This paper aimed to review the literature of the past ten years about the energy performance of buildings during their operational stage. The focus of this review was empirical works that examined the energy use in real buildings. An overview of the literature survey is presented. A meta-analysis technique al- lowed the identification of two approaches of study: building-level analysis and stock-level analysis. The building-level analysis considers the building as the system of study. Otherwise, the stock-level analysis considers a group of buildings as the subject of study while the buildings are elements inside the system. Notable research topics were addressed involving performance gap, energy audit, retrofit savings assessment, Zero Energy Buildings (ZEB), benchmarking, regulations and strategies to overcome climate change. This literature review summarised the level of information of the studies by listing the granularity of the energy performance data according to the purpose of the study. Furthermore, a specific section was dedicated to assemble the methods and tools adopted. Finally, we proposed conceptual models for both approaches (building and stock-level) that outlined the main aspects and dynamics identified in this literature review. Thus, we obtained insights to be investigated in further studies.

1. Introduction

Reducing energy consumption is a well-known and urgent task since many studies have shed light on the impact of energy on climate change (BATES *et al.*, 2008). Assessing the energy use in buildings is essential since they are significant contributors to energy demand. In this regard, energy performance of buildings has become the focus of many studies.

De Wilde (2018) discussed the emerging field of the building performance analysis by gathering and organising the most common terms and relevant studies. There is a debate about the definition of building performance analysis because it could mean distinct concepts. Nevertheless, energy performance is usually related to the amount of energy consumed to provide adequate environmental quality and to achieve the building function.

Designing buildings that consume less energy should contribute to decreasing energy demand. However, in practice, this is not necessarily what has been observed. Newsham *et al.* (2009) analysed 100 LEED-certified buildings and concluded that only about 18-39% used less energy with a weak correlation between certification and energy performance in all of them. Furthermore, Scofield *et al.* (2009) re-analysed part of the Newsham's database and concluded that there is no statistical difference of the site energy between LEED-certified buildings and their matching CBECS (Commercial Building Energy Consumption Survey) office buildings.

Although these buildings were designed to be energy efficient, they might reveal different performance levels during the operational stage. Indeed, the energy performance predicted in the design phase rarely matches the measured performance. This phenomenon is defined as the "energy performance gap" (DE WILDE, 2014; GENG *et al.*, 2018; KHOURY; ALAMEDDINE; HOLLMULLER, 2017; SUNIKKA-BLANK; GALVIN, 2012) or just "performance gap" (BRADY; ABDELLATIF, 2017). The understanding of the causes and consequences of the performance gap have been the subject of many studies (DE WILDE, 2014; HORRIGAN; MURPHY; DONNELL, 2017; KHOURY; ALAMEDDINE; HOLLMULLER, 2017; SUNIKKA-BLANK; GALVIN, 2012), as well as some of the means to bridge the gap (e.g., BARTHELMES *et al.*, 2017; GENG *et al.*, 2018; LIM; ZHAI, 2017; MENEZES *et al.*, 2012). Data-driven models are often used to provide real-world data to enhance prediction models during the lifespan of the building (CHEN; TAN; BERARDI, 2018; WEI, Y. *et al.*, 2018). However, adopting data-driven models to predict the performance of another building could lead to significant bias (TARDIOLI *et al.*, 2015).

Buildings are complex systems composed of an arrangement of smaller systems, interacting with the occupants (D'OCA; HONG; LANGEVIN, 2018; DE WILDE, 2017). That concept has led to a definitive insight: "buildings don't use energy, people do" (JANDA, 2011). The IEA (International Energy Agency) EBC (Energy and Buildings Communities) annex 53 (EBC IEA, 2013a) defined six main factors that impact the energy consumption in buildings: (a) climate; (b) envelope (c) systems and equipment; (d) operation and maintenance; (e) user behaviour and; (f) indoor environmental quality. From this perspective, two well-defined dimensions could be depicted: (a), (b) and (c) are related to building dimension – i.e., where the building is, what it is made of, what is in the building; and (d), (e), (f) are related to human dimension – i.e., how people use them, how they maintain them, and their satisfaction, comfort and health levels in the building. Understanding the interface human-built environment could lead to a better prediction of energy use and make the energy efficiency actions more reliable and feasible.

In this way, the study of energy performance in the real world is as relevant as the development of advanced simulation tools (that reproduce complex physical/behaviour phenomena). Being conscious of how energy is used in practice can help to improve building simulation and, consequently, to enhance the construction of new, reliable and high-performance buildings (MENEZES *et al.*, 2012). Additionally, the study of energy use over the operational stage might support the improvement of the existing building stock through retrofits and campaigns for behaviour change (MA *et al.*, 2012). Ultimately, one can address the actual energy usage scenario demanded by buildings and support energy efficiency policies (HSU, 2014).

Despite the difficulty of evaluating energy performance of buildings at stock level, several studies addressed the topic in many different contexts. The literature review performed by Pereira *et al.* (2014) gathered energy performance information of schools in different countries, highlighting the differences in usage patterns. The study of Santim (2011) determined behavioural patterns associated with the energy used for heating in houses while correlating them with building characteristics. Ahn *et al.* (2017) analysed a large number of office buildings data and tried to establish correlations between energy consumption and building characteristics.

The emerging Display Energy Policies – which makes owners and managers declare the energy consumption in their buildings – and the advancing of Building Automation Systems are providing data to explore the real energy use in buildings. This fact induces that the energy performance analysis during the operational stage must consider the building stock to compare a building with its pairs (HSU, 2014). The energy epidemiological approach attempted to achieve reliable stock-level analysis by considering buildings as a population (HAMILTON *et al.*, 2013). Some studies were performed using such a methodology (HAMILTON, 2017; HAMILTON *et al.*, 2014), and the outcomes led to a discussion about the benefits of using energy efficiency policies.

Benchmarking is a convenient method used to assess the energy performance of existing buildings because it takes advantage of the comparison among pairs. The literature review of Chung (2011) presented mathematical benchmarking methods and discussed the applicability of benchmarking for increasing energy efficiency. Several studies discussed benchmarking, from a comparison among existing methods (BORGSTEIN, LAMBERTS; HENSEN, 2016; HONG *et al.*, 2014) to benefits of using this approach (HSU, 2014; MENG; HSU; HAN, 2017) and development of new methods (BORGSTEIN; LAMBERTS, 2014; MELEK, 2007; RUZZELLI *et al.*, 2010). Papadopoulos et al. (2018) innovated by analysing energy time series data of buildings to identify patterns using benchmarking of two typologies: commercial and residential buildings. Results showed that typologies respond differently regarding the energy disclosure policy, which reveals a need for a comprehensive framework considering building specificities.

In this way, some studies examined the performance at a building-level. The principal perspective of those studies is to analyse one facility/building performance and to establish baselines for comparison with itself. Ma *et al.* (2012) present a comprehensive state of the art of the methodologies available.

In this paper, the main objective was to conduct a literature review about the energy performance of buildings during the operational stage by differentiating the stock-level and building-level perspectives. This paper intended to discover the main targets of research in the operational stage in the past ten years and to describe the lead research purposes using relevant studies as examples. Also, this paper aimed to summarise the level of information and the methods and tools of the works reviewed. A final specific objective was to develop a conceptual model by linking the pieces of research reviewed and recognising the train of thought.

2. Results of the Literature Search

The search was carried out using a systematic review method. The main engine of the search was the Scopus platform. Several attempts were made starting with general terms (including “building energy performance” plus “operation” plus “use” plus “real”). The final argument of search is described below:

TITLE-ABS-KEY (buildin AND energy w/3 performanc* w/4 ("operation*" OR "use" OR "actual" OR "real") AND NOT (concret* OR material)*

We considered this argument satisfactory because it encompasses relevant and well-known papers and excludes non-associated studies. Similar arguments were used in other search engines (ScienceDirect and Google Scholar). Most of the results were redundant, but we added some complementary articles in the database. Henceforward, we employed the term “Operational Performance” to denote measured and in-use energy performance. This terminology was formalised by ISO 50001 (ISO, 2018). The literature survey resulted in 574 documents, including eleven review papers, and the reference date is 17 June 2019. Table 2.1 shows the top ten most cited articles.

Table 2.1 – Top 10 articles (out of 574) of the literature survey in Scopus.

#	Title	Authors	Journal	Year	Number of citations
1	Existing building retrofits: Methodology and state-of-the-art	Ma, Z., Cooper, P., Daly, D., Ledo, L.	Energy and Buildings	2012	405
2	Do LEED-certified buildings save energy? Yes, but...	Newsham, G.R., Mancini, S., Birt, B.J.	Energy and Buildings	2009	298
3	The gap between predicted and measured energy performance of buildings: A framework for investigation	De Wilde, P.	Automation in Construction journal	2014	281

Table 2.1 – Top 10 articles (out of 574) of the literature survey in Scopus (continuation).

#	Title	Authors	Journal	Year	Number of citations
4	Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap	Menezes, A.C., Cripps, A., Bouchlaghem, D., Buswell, R.	Applied Energy	2012	278
5	European residential buildings and empirical assessment of the Hellenic building stock, energy consumption, emissions and potential energy savings	Balaras, C. A., Gaglia, A. G., Georgopoulou, E., Sevastianos, Mirasgedis S., Sarafidis, Y., Lalas, D. P.	Building and Environment	2007	267
6	A review of sensitivity analysis methods in building energy analysis	Wei, T.	Renewable and Sustainable Energy Reviews	2013	255
7	Introducing the prebound effect: The gap between performance and actual energy consumption	Sunikka-Blank, M., Galvin, R.	Building Research and Information	2012	216
8	A hybrid decision support system for sustainable office building renovation and energy performance improvement	Juan, Y.-K., Gao, P., Wang, J.	Energy and Buildings	2010	190
9	Review of building energy-use performance benchmarking methodologies	Chung, W.	Applied Energy	2011	141
10	Quantitative energy performance assessment methods for existing buildings	Wang, S., Yan, C., Xiao, F.	Energy and Buildings	2012	131

The top 10 articles show diverse objectives: some studies go deep into performance gap (DE WILDE, 2014; MENEZES *et al.*, 2012; NEWSHAM; MANCINI; BIRT, 2009; SUNIKKA-BLANK; GALVIN, 2012; WEI, 2013); others present retrofit methodologies (MA *et al.*, 2012); and assessing energy performance methods are also included (JUAN; GAO; WANG, 2010; WANG; YAN; XIAO, 2012), as well as benchmarking (CHUNG, 2011). Figure 2.1 presents an overview of the search results, while Table 2.2 presents the top ten sources including their journal metrics.

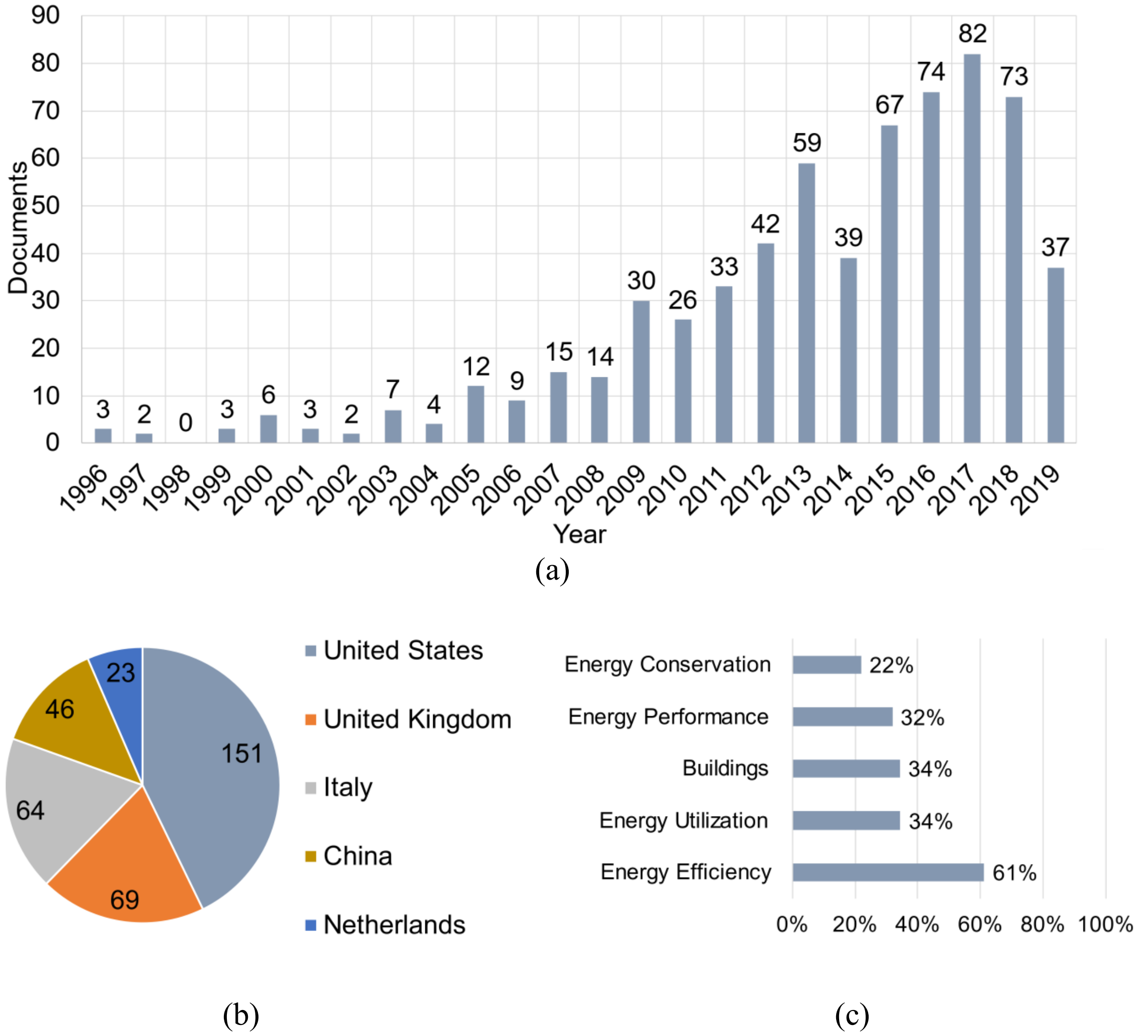


Figure 2.1 – Overview of the publications selected. (a) Number of articles published per year (in Scopus), (b) shows the top five Country/Territory with the corresponding number of documents, and (c) shows the top five keywords and the frequency of appearance.

Table 2.2 – Top 10 international journals.

Top 10	Source	Number of Documents	Source IF	Source SNIP	Source SJR
1	Energy and Buildings	98	4.495	1.826	1.934
2	Applied Energy	28	8.426	2.616	3.455
3	Energy Procedia	19	-	0.58	0.468
4	Building Research and Information	13	3.744	1.59	1.283
5	Building and Environment	12	4.82	2.198	1.879
6	Procedia Engineering	11	-	0.78	0.277
7	Building Simulation	10	2.238	1.06	1.186
8	Energies	10	2.676	1.16	0.612
9	Energy Efficiency	9	1.961	0.92	0.698
10	Energy	8	5.537	1.822	2.048

We noticed that “Energy and Buildings” and “Applied Energy” journals lead the publications in this field. It is remarkable that they lead not only the number of publications, but also the impact of the publications, once six out of the ten most cited articles were published in these two journals.

Nevertheless, we applied a systematic search method to carry out the literature review, and we only disregarded articles that focused either on simulations (i.e., optimization of simulation algorithms, propositions of methods for calculating, calibrating and validating simulations, and related subjects); or on human aspects in buildings (i.e., environmental comfort, such as thermal, acoustic or lighting comfort, and related subjects). Thus, the participation of these two journals in the analysis was not determined by the authors. Instead, we understood that the concentration of studies in “Energy and Buildings” and “Applied Energy” is an indicative that these journals are quite involved in the field and are leading the knowledge progress.

The interest in the field increased in the past ten years, and we refined our search to cover this period specifically. The countries that produced more studies (the United States and the United Kingdom) stand out for government programmes and incentives on energy use in buildings. The keywords most frequent were “Energy Efficiency”, “Energy Utilization” and “Buildings”.

First, the abstracts of the documents were reviewed using a meta-analysis way. From this process, it was evident that the studies on energy performance of buildings had two different main approaches: one focused on the building level and one focused on the stock level. So, we sought to distinguish the subject of study in those two approaches. Furthermore, some articles were excluded due to the disinteresting subject of study (especially because they used simulation or non-empirical data) resulting in 312 articles.

According to the content of each article, we could identify the primary purposes that the studies addressed, and we grouped them according to common terminologies. From the first reading of the abstracts, Table 2.3 shows the structure of the classification according to the preliminary meta-analysis.

Table 2.3 – Arrangement of the Identified purposes of research.

Approach	Identified Purposes of Research	Section
Building-level analysis	Performance Gap	3.1.1
	Energy Audit	3.1.2
	Retrofit Savings Assessment	3.1.3
	Zero Energy Buildings (ZEB) Evaluation	3.1.4
Stock-level analysis	Benchmarking	4.1.1
	Regulations and directives for the building stock	4.1.2
	Strategies to Overcome Climate Change Effects	4.1.3

The articles were fully reviewed to go deeper into each category of the meta-analysis. The initial hypothesis about the building-level and stock-level definition proved to be very important because different methods, tools and techniques according to the target of study were found. Furthermore, diverse outcomes and applicability were expected as well. In this regard, this literature review was structured according to building-level and stock-level differentiation. A discussion about the boundary for both topics is presented. We gathered the main objectives pursued by both topics, as well as the level of information employed, the methods and the tools applied.

3. Building-Level Analysis

In this section, we gathered studies that focused on energy performance at the building-level. This approach assumes that the energy analysis of the building is performed at its specific level, considering the whole building as an individual. The subject could be a facility with either one building or multiple (not many), for example, a school with all-in-one building or with one building for the classrooms and other for the administration.

3.1. Identified Purposes of Research

We grouped the studies that analysed the performance of buildings over the operational phase at building-level according to four purposes of research: performance gap, energy audit studies, retrofit savings assessment, and ZEB evaluation. We could say that a study is somehow always related to at least one of those topics.

3.1.1. Performance Gap

Several studies aimed to understand or proposed methods to overcome the performance gap. In order to comprehend performance gap phenomena, De Wilde (2014) defined types of variability and broke the performance gap down into first-principle predictions and measurements; machine learning and measurements; and predictions and display certificates in legislation. This study brought a comprehensive review of this theme.

Many studies pursued ways to overcome the performance gap, and the occupancy was pointed out as a significant factor that impacts on energy performance (AZAR; MENASSA, 2012). Menezes *et al.* (2012) proposed a method to reduce the performance gap by using post-occupancy data in the simulation process. Pisello *et al.* (2012) proposed a method to integrate dynamic simulation and measurements of thermal performance in houses.

Pisello *et al.* (2012a) brought the discussion about the impact of surrounding buildings on the energy performance once building simulations have used boundary conditions very different than the actual building – e.g., using weather conditions collected in airport locations that do not consider inter-buildings interactions. Pisello *et al.* (2014a) proposed a model to consider the relation among buildings in order to mitigate those differences of context. The study aimed to break down the energy consumption and analysed only primary energy for lighting because it was the end-use most affected by surrounding buildings. Results showed that considering the inter-building effect is essential to enhance energy predictions.

Case studies that bring integrations between simulation and *in-situ* experiments were found in the literature. In residential typology, Lehman *et al.* (2017) compared a very high energy performance housing with a regular dwelling in Geneva. Results showed that average values are similar in both cases, and conclusions showed that there is a vast potential of optimisation during the operational phase of a building.

In non-residential typologies, Burman *et al.* (2018) investigated the energy performance of five schools designed under the programme “schools for the future” in England. This programme defined guidelines to design energy-efficient school buildings and sustainable and high-quality environment. However, the analysis of the real operational performance showed that these schools consumed 37 to 191% more energy than the average of similar schools in the same region. The study highlights the need for post-occupancy evaluation to assess the operational performance and suggests a holistic perspective to evaluate the performance of buildings.

Regarding office buildings, Liang *et al.* (2019) surveyed LEED-certified buildings to investigate the driving factors of the performance gap. The authors grouped the reasons of the performance gap into three: (a) occupants use more energy than modelled, (b) there are more occupants than modelled, and (c) failures of energy-efficient technologies. Gunay *et al.* (2019) examined the operational parameters of HVAC that impacts the performance gap in office buildings in Canada. Results showed that habits of the occupants and default features of equipment could be improved to optimise the operation.

Zou *et al.* (2019) performed structured interviews with professionals from designing and operation of buildings in order to find causes of the performance gap. Eight leading causes were drawn from the results: "(i) Inaccurate design parameters, (ii) Failure to account for uncertainties, (iii) Lack of accountability, (iv) Poor communication, (v) Lack of knowledge and experience, (vi) Inefficient and over-complicated design, (vii) Lack of post-construction testing, and (viii) Lack of feedback". Suggestions of ways to overcome the performance gap were grouped into three categories: strategies to better regulation, strategies to enhance the design process, and strategies for training the operation workforce. The training of the operating team was addressed by Elzarka (2009). This study brought the best practices in commissioning and highlighted that timing of commissioning, independence and certification are essential skills that the commissioner must possess.

Salehi *et al.* (2015) presented a case study of a LEED-certified university building in Canada. The performance of the analysed building was about 60% higher than the predicted. The leading cause of this performance gap was due to the operation process – very different from the model. Part of the operation problems relied on the unpredicted heat exchange and wastewater treatment plant existent but not considered in the modelled loads. Besides, the actual usage with lighting and loads were also hugely discrepant than the predicted consumption.

Stoppel and Leite (2014) analysed different time resolutions of energy consumption to address the energy model accuracy. Monthly resolution can be used to describe the seasonal error in energy performance. Daily resolution can be used to confirm schedules of operation and to give patterns of usage. A 15-minute resolution provides the efficiency of the equipment and fault detections.

3.1.2. Energy Audit

Energy audit studies are related to practices and methods to characterise the building regarding energy usage and, recurrently, to assess Fault Detection and Diagnosis (FDD). The primary reference for energy auditing is the EnergyStar® building management guidelines (EPA, 2016) and the International Standard ISO 50002 (ISO, 2014). Frequently, the product of the energy audit is the rating of the performance of the building. O'Learey (2015) presents a relevant review of using metered data for rating. Geng *et al.* (2019) present a comprehensive review of the overall monitoring in green buildings.

In this sense, the quantification of energy use and end-uses assessment are relevant. A comprehensive review of the methods to assess quantitative energy performance during the operational stage is presented by Wang (2012). The author summarises the objectives of the energy performance assessment (either classification or diagnosis) as well as examples of applications. The energy quantification methods were divided into calculation-based (e.g., simulation), measurement-based (e.g., monitoring), or hybrid (e.g., calibrated simulation).

Since energy audit is a widely known and very regulated topic, we only present some studies that present highlights in technological innovation. Ham (2013) presents an integration of thermal analysis added to the simulation model using augmented reality (3D inspection), which dramatically facilitates the job of the energy auditor. Kalz *et al.* (2009) presented minute-to-minute monitoring associated to the thermal comfort evaluation in a group of mixed-mode buildings. Felix *et al.* (2016) proposed an integrated monitoring-simulation technique in order to identify failures. Petri et al. (2017) proposed an integration of monitoring with Building Information Modelling (BIM) to provide an optimised environment and Zhang (2015) proposed a similar monitoring-BIM integration. Nordström *et al.* (2013) developed a method to estimate U-values in housing using the energy signature. O'Neill *et al.* (2014) proposed a method to integrate monitoring and real-time simulation to make a continuum energy modelling improvement. Henze *et al.* (2015) combined the energy consumption of each system into a real-time dashboard based on web application. Noye *et al.* (2016) improved commissioning by using wireless sensors to measure the air conditioning use. Energy auditing also supports the study of the performance of specific systems in the buildings. For example, Fan and Ito (2012) integrated CFD (Computational Fluid Dynamics) to an energy simulation to enhance recovery ventilation model using measured data from real offices.

Non-Intrusive Load Monitoring (NILM) is a noticeable technology that uses machine learning to breakdown the aggregated energy data into end-uses. It was presented by Hart (1992). Yan *et al.* (2012) presented an alternative disaggregation method using billed data. Alzaatreh (2018) proposed a method to disaggregate gas consumption from minute-monitored data. Machlev *et al.* (2019) proposed an improvement on one type of algorithm disaggregation. Carrie Armel (2013) discussed the relevance of this technology in energy policies.

Some case studies express the importance of energy auditing and the impact of this technique in identifying energy contributors (GONÇALVES; GASPAR; SILVA, 2012), measuring post-occupancy satisfaction (GUERRA-SANTIN *et al.*, 2013; LAWRENCE; KEIME, 2016), measuring components properties (FICCO *et al.*, 2015), measuring environmental impact (DAHLAN *et al.*, 2013), improving building automation and control (AHN.; CHO, 2017; COSTA *et al.*, 2013; FERRARINI; MANTOVANI, 2013) and comparing the actual performance to predicted energy use (LIZANA *et al.*, 2018).

3.1.3. Retrofit Savings Assessment

A retrofit action is usually triggered by a motivation to improve energy efficiency (FERRARI; BECCALI, 2017; RASLAN; RUYSSEVELT, 2016) or to mitigate inefficiencies of systems (MAGOULÈS; ZHAO; ELIZONDO, 2013a). In this sense, retrofit is straightforwardly aligned with operational performance because it happens in the post-constructed stage.

Ma *et al.* (2012) presented a comprehensive state of the art of the methodologies used for retrofitting. First, the authors gathered generic retrofit problems. Then, a group of sustainable retrofit methodologies and strategies were listed, including energy audit, diagnosis, prognostic, economic analysis and risk assessment. Finally, the authors presented applications of retrofit technologies to improve performance of buildings by giving examples of technologies and case studies. Additional inspiring reviews regarding retrofitting can be found in Hong *et al.* (2015) for energy monitoring and diagnosing and in Sanhudo *et al.* (2018) for energy modelling.

The International Performance Measurement and Verification Protocol (IPMVP) proposes methods to quantify energy savings in retrofits. The IPMVP outlines methods to calculate the retrofit savings according to four options: option A is related to minor system metering (specific and isolated system); option B is related to metering the retrofit constantly; option C is related to whole-building metering, and option D is related to energy simulation. Only option D can quantify multiple energy conservation measures at the same time (IPMVP, 2002). However, energy simulation demonstrates limitations in modelling energy conservation measures (LI *et al.*, 2015). Improvements in IPMVP methods can be found in literature, such as the enhancement of the energy simulation using genetic algorithms (RAMOS; FERNÁNDEZ BANDERA, 2017), gaussian modelling (HEO; ZAVALA, 2012), consideration of uncertainties (HEO; CHOUDHARY; AUGENBROE, 2012), and integration with a real-time monitoring system that continuously inform the energy savings occasioned by a retrofit (TSENG *et al.*, 2013).

Energy conservation measures can be implemented through system upgrading (e.g., HVAC systems (PAN *et al.*, 2012), lighting system (FERNANDES *et al.*, 2014; PETCHARAT; CHUNGPAIBULPATANA; RAKKWAMSUK, 2012)); envelope improvement (e.g., for office buildings (GÜÇYETER; GÜNAYDIN, 2012), historic buildings (AKANDE *et al.*, 2016; CORNARO; PUGGIONI; STROLLO, 2016)); or a whole-building modernising (e.g., school buildings (ZINZI *et al.*, 2016), houses (CORRADO; BALLARINI, 2016; ZAHIRI; ELSHARKAWY, 2018)). Furthermore, combinations of minor actions could lead to a great intervention (NIEMELÄ; KOSONEN; JOKISALO, 2017; PETTERSEN *et al.*, 2017). New methods to assess the amount of energy saved according to the retrofit intervention and minimising uncertainty are emerging in literature (MAGRINI; MAGNANI; PERNETTI, 2012), such as artificial neural networks (BECCALI *et al.*, 2017) and multi-objective optimisation (CARLI *et al.*, 2015). Recently, the findings of the impact of occupants on energy consumption have encouraged authors to consider campaigns of changing the occupant behaviour as an energy conservation measure as well (BARTHELMES; BECCHIO; CORGNATI, 2016; DELLAVALLE; BISELLO; BALEST, 2018; RUBENS *et al.*, 2017; SUN; HONG, 2017).

The real estate sector is profoundly affected by retrofit actions. Energy performance is one of the main points of interests of new tenants in Europe, who seek for high-performance homes (DE RUGGIERO *et al.*, 2017; TADEU *et al.*, 2016). In this sense, Entrop *et al.* (2010) proposed the consideration of real estate values in the retrofit analysis. The study showed that investments in wall and roof insulation could provide payback about 40-50% shorter if the analysis considered the increase of the property value as well. Christersson *et al.* (2015) evaluated the benefits of making regular energy audits in properties in order to maintain high-quality operation. Results showed an increase of 2.5% in the value of properties that had frequent energy audits.

It is possible to find a vast number of case studies of retrofit assessments in the literature. Some relevant ones bring that energy conservation measures provide reductions up to 81% in school buildings (ZINZI *et al.*, 2016) and also increase user satisfaction in houses (ALONSO *et al.*, 2017). Furthermore, an adequate, cost-effective retrofit action provides not only indoor quality improvement but also the boosting of the occupants' productivity (VALANCIUS; JURELIONIS; DOROSEVAS, 2013). However, we highlighted the case study of Sun *et al.* (2018), which monitored a refurbished building with LEED EBOM gold certification. The retrofit was designed to provide 30% of savings, but the real performance indicated only 16%. This performance gap was credited to occupancy variability.

3.1.4. Zero Energy Buildings (ZEB) Evaluation

Zero Energy Buildings (ZEB) are the ultimate goal for a high-performance building. It integrates energy efficiency strategies with energy generation to achieve fully sustainable operation of the building. ZEB is the path to a more sustainable city according to the European Energy Performance of Buildings Directive (EPBD) which targets the building stock renovation towards Near Zero Energy (denominated project Near Zero Energy Buildings or NZEB) (FERRARI; BECCALI, 2017).

The EPBD regulates methodologies to calculate energy use in buildings as well as requirements for new and existing buildings, periodic inspection of systems and requirement of certifications. The Directive 2010/31/EU of 19 May 2010 and The Commission Recommendation (EU) 2016/1318 of 29 July 2016 address NZEB renovation targeting. A structured platform was developed to help the compliance of this target, by recording, charactering and classifying ZEBs retrofits according to a specific criteria to provide information and insights to new projects (D'AGOSTINO; CUNIBERTI; MASCHIO, 2017).

Relevant studies in different countries across Europe addressed lessons learned due to the implementation of NZEB, such as: considering the comfort model and its parameters in energy demand of ZEBs – including the difference in employing adaptive comfort model against stationary model in Spain (GUILLÉN-LAMBEA; RODRÍGUEZ-SORIA; MARÍN, 2017); quantifying the impact of the directives in the stock renovation due to technologies and constructive updates in Greece (GAGLIA *et al.*, 2017) and Spain (LÓPEZ-OCHOA *et al.*, 2019a); reviewing the requirements for NZEB renovation for heating demand in houses in Poland (FIRLAG; PIASECKI, 2018); evaluating specific retrofits and suitable energy conservation measures in school buildings using a simulation-audit integrated approach in Italy (ROSPI *et al.*, 2017; SALVALAI *et al.*, 2017) and Spain (LÓPEZ-OCHOA *et al.*, 2019b); a comprehensive review regarding local Building Energy Regulation Codes and their relation with the geographical level (SALVALAI; MASERA; SESANA, 2015); analysing the Passive Haus Standard suitability as a solution for integrating NZEB directive, considering environmental quality energy consumption and costs of heating and ventilation of social housing (COLCLOUGH *et al.*, 2018). Additionally, the experience gathered allowed the development of innovative techniques for optimization combining energy generation and energy efficiency measures (D'AGOSTINO; PARKER, 2018).

Notwithstanding, it is crucial to assess the operational performance of ZEB to assure that the building reaches its target. For example, in Portugal, Magalhães (2014) compared standardised and actual requirements for thermal performance in the residential sector, showing the difference between predicted and actual performances. In Italy, a full monitoring study performed in a residential building-lab evidenced that the photovoltaic energy generation lacks the prediction very often implying in optimization needs (ASCIONE *et al.*, 2019).

A general overview regarding NZEB in southern EU countries was presented by Attia *et al.* (2017), who highlighted the retrofit of the existent stock as a major challenge for the NZEB agenda. Further detailed information of the NZEB topic of the EU commission can be found in the Overview of Member States information on NZEBs (GRÖZINGER *et al.*, 2014; WEHRINGER, SCHERBERICH, GROEZINGER, BOERMANS, JOHN, 2014).

Nevertheless, considering studies found in the literature, it is possible to note substantial benefits from ZEB cases. For example, Colon (2010) analysed four case studies of ZEB houses by monitoring and comparing them with a simulated model. Results showed that the houses consumed about 80-100% less energy than a standard house. Zhou *et al.* (2016) examined an ZEB case in China, and conclusions showed that the energy savings were 18% lower than the simulated case. However, the energy generation presented performance gaps, i.e., variations in the expected/generated energy ratio from 13% to 65%. To reduce the performance gap in ZEB evaluations, Berggren and Wall (2017) proposed two methods that normalise ZEB measurements. The first method normalised the geothermal generation (and it reduces the gap from 12 to 5%), and the second normalised the photovoltaic systems (and it reduces the gap from 17 to 5%). Li *et al.* (2018) evaluated the real performance of six ZEB houses in Canada. The study used energy auditing to obtain specific energy demand by end-use and to compare the performances to improve the comprehension of the variations. Schimschar *et al.* (2011) estimated the greenhouse gas emissions reductions through NZEB stock upgrading in Germany. In the most optimistic scenario, it would be possible to reduce up 50% of the greenhouse gas emissions by 2020 compared to 1990 values.

In South Korea, Suh and Kim (2019) proposed a framework to turn the buildings of a community buildings into ZEBs. The study pointed out that energy efficiency strategies could reduce energy consumption by 20%. However, one strategy for energy generation alone could not supply all the remaining demand. So, the solution was to integrate energy generation strategies (e.g., photovoltaic system, geothermal heat pump and solar thermal system).

A relevant insight is presented by Robert and Kummert (2012). The authors presented a framework to assess ZEB performance evaluation using future estimated weather files in simulation modelling. In this work, the authors highlighted that ZEB has the trend to become less efficient over time due to climate change interference.

3.2. Level of Information

Different levels of information were observed in the building-level studies reviewed. The energy consumption is related to the frequency of the amount of energy that was used during a period. It is given in units of energy per time. Each study used a different time resolution according to its objective. A summary of the time resolution is presented in Table 2.4, according to each identified purpose of research.

Table 2.4 – Time resolution of energy consumption in the building-level analysis.

Purposes	Time Resolution	Sources
Performance gap	15-minute	(STOPPEL; LEITE, 2014)
	Hourly	(HEIDARINEJAD *et al.*, 2013; KALZ *et al.*, 2009; LEE; HENSEN, 2015; PISELLO *et al.*, 2012b, 2014a)
	Monthly	(GUPTA; GREGG, 2016; LIANG; QIU; HU, 2019; STOPPEL; LEITE, 2014)
	Annually	(BURMAN; KIMPIAN; MUMOVIC, 2018; PISELLO; GORETTI; COTANA, 2012)
Energy audit	1-second (Hertz)	(FERRARINI; MANTOVANI, 2013; MACHLEV *et al.*, 2019; O'NEILL *et al.*, 2014)
	1-minute	(ALZAATREH *et al.*, 2018; HAM; GOLPARVAR-FARD, 2013; KALZ *et al.*, 2009; NORDSTRÖM; JOHNSSON; LIDELÖW, 2013)
	15-minute	(KIM; HABERL, 2018; PETRI *et al.*, 2017)
	Hourly	(COSTA *et al.*, 2013; HENZE *et al.*, 2015)
	Monthly	(KIM; HABERL, 2018; LAWRENCE; KEIME, 2016; LIZANA *et al.*, 2018; O'LEARY *et al.*, 2015)
Retrofit savings assessment	1-minute	(FERNANDES *et al.*, 2014)
	15-minute	(ALONSO *et al.*, 2017)
	Hourly	(GÜÇYETER; GÜNAYDIN, 2012)
	Monthly	(AKANDE *et al.*, 2016; CORNARO; PUGGIONI; STROLLO, 2016; LOURENÇO; PINHEIRO; HEITOR, 2014; NIEMELÄ; KOSONEN; JOKISALO, 2017; SERRANO-JIMÉNEZ *et al.*, 2019)
ZEB evaluation	30-seconds	(LI *et al.*, 2018)
	Hourly	(ASCIONE *et al.*, 2019; BERGGREN; WALL, 2017; COLON, 2010; ZHOU *et al.*, 2016)
	Monthly	(COLCLOUGH *et al.*, 2018; FOKAIDES; POLYCARPOU; KALOGIROU, 2017; LÓPEZ-OCHOA *et al.*, 2019a; SUH; KIM, 2019)
	Annually	(D'AGOSTINO; CUNIBERTI; MASCHIO, 2017; FERRARI; BECCALI, 2017; FIRLAG; PIASECKI, 2018; GAGLIA *et al.*, 2017; LÓPEZ-OCHOA *et al.*, 2019b; MAGALHÃES; LEAL, 2014; ROSPI *et al.*, 2017; SALVALAI *et al.*, 2017; SCHIMSCHAR *et al.*, 2011)

Studies that addressed the performance gap have often used hourly data to compare actual with simulated performance. Commonly, retrofit savings assessment used monthly data. Otherwise, energy audit studies addressed systems performances, rating of buildings and end-use assessments, which raises the need for high-resolution data. ZEB evaluation studies follow no identified pattern.

It is noteworthy that some studies used various granularity (CARRIE ARMEL *et al.*, 2013; KIM; HABERL, 2018; MALAVAZOS, 2017). For example, Kim (KIM; HABERL, 2018) used billed data (monthly) of five years to assess performance of the whole-building as well as sub-metered data (15-minute resolution) of three years to assess end-uses.

3.3. Methods and Tools

In this section, we summarised the methods and tools used in the building-level studies reviewed. We classified the relevant methods and tools according to the main issues that they attempted to achieve: addressing energy end-uses, addressing retrofit savings (measure the potential or the effective amount of energy saved due to the retrofit); and evaluating a ZEB performance (measure the performance of an ZEB). It is essential to highlight that those issues do not correspond exactly to the identified purpose of research of section 3.1 because the same methods and tools are often used for many purposes.

Table 2.5 shows a summary of the methods and tools observed in this approach.

Table 2.5 – Summary of methods and tools used for building-level analysis.

Issue	Methods (Tools)	Sources
Addressing energy end-uses	Energy audit (metering, sub-metering)	(GUERRA-SANTIN *et al.*, 2013; GUPTA; GREGG, 2016; HENZE *et al.*, 2015; KIM; HABERL, 2018; LAWRENCE; KEIME, 2016; O'NEILL *et al.*, 2014)
	Energy disaggregation (NIALM - using specific algorithms)	(ALZAATREH *et al.*, 2018; CARRIE ARMEL *et al.*, 2013; MACHLEV *et al.*, 2019; YAN; WANG; XIAO, 2012)
	Energy simulation (EnergyPlus, CFD, DOE, TRNSYS, or others)	(AHN; CHO, 2017; FAN; ITO, 2012; FERRARINI; MANTOVANI, 2013; GONÇALVES; GASPAR; SILVA, 2012; LIZANA *et al.*, 2018; O'LEARY *et al.*, 2015)

Table 2.5 – Summary of methods and tools used for building-level analysis. (continuation).

Issue	Methods (Tools)	Sources
Addressing retrofit savings	Longitudinal analysis	(ALONSO *et al.*, 2017; FERNANDES *et al.*, 2014; SUN; HONG, 2017)
	Cross-sectional analysis	(AKANDE *et al.*, 2016; LI; HONG; YAN, 2014)
	Energy simulation (EnergyPlus, CFD, DOE, TRNSYS, or others)	(CORNARO; PUGGIONI; STROLLO, 2016; COSTA *et al.*, 2013; GÜÇYETER; GÜNAYDIN, 2012; LI *et al.*, 2015; NIEMELÄ; KOSONEN; JOKISALO, 2017; RAMOS RUIZ; FERNÁNDEZ BANDERA, 2017; SERRANO-JIMÉNEZ *et al.*, 2019)
Evaluating ZEB performance	Energy bill analysis	(D'AGOSTINO; CUNIBERTI; MASCHIO, 2017; GAGLIA *et al.*, 2017; LÓPEZ-OCHOA *et al.*, 2019a; MAGALHÃES; LEAL, 2014; SCHIMSCHAR *et al.*, 2011; SUH; KIM, 2019)
	Energy audit (metering, sub-metering)	(ASCIONE *et al.*, 2019; COLON, 2010; FOKAIDES; POLYCARPOU; KALOGIROU, 2017; LI, H. X. *et al.*, 2018)
	Energy simulation (EnergyPlus, CFD, DOE, TRNSYS, or others)	(BERGGREN; WALL, 2017; COLCLOUGH *et al.*, 2018; FERRARI; BECCALI, 2017; FIRLAG; PIASECKI, 2018; KOLOKOTSA *et al.*, 2018; LÓPEZ-OCHOA *et al.*, 2019b; ROSPI *et al.*, 2017; SALVALAI *et al.*, 2017; ZHOU *et al.*, 2016)

Addressing energy end-uses is an essential issue because the end-use could explain the energy consumption pattern, expose an energy waste or reveal a system inefficiency. Thus, end-uses identification was present in a large portion of the studies of this review. In this case: energy auditing was the act to measure the energy end-use directly; energy disaggregation means the obtention of end-uses from processing the measured data using algorithms; and sometimes it was used energy simulation to obtain the end-uses from a model of the building assuming that the actual building will consume a similar value.

As for addressing retrofit savings, longitudinal analysis refers to an approach that compared the building with itself in different periods. Cross-sectional analysis refers to the comparison of the building with its pairs (benchmarking). Energy simulation implies that the energy savings information was obtained from the simulation of the energy conservation measures in the model of the building.

In ZEB performance evaluations, energy bills analysis, energy audit and energy simulation were used.

3.4. Conceptual Model

A conceptual model of the building-level analysis was drawn from the literature review of the studies.

The conceptual model consists of a diagram elaborated using logical links to map the paths of research for displaying the topics connections. Furthermore, it was possible to recognise insights for further research. Figure 2.2 presents the conceptual model of building-level analysis.

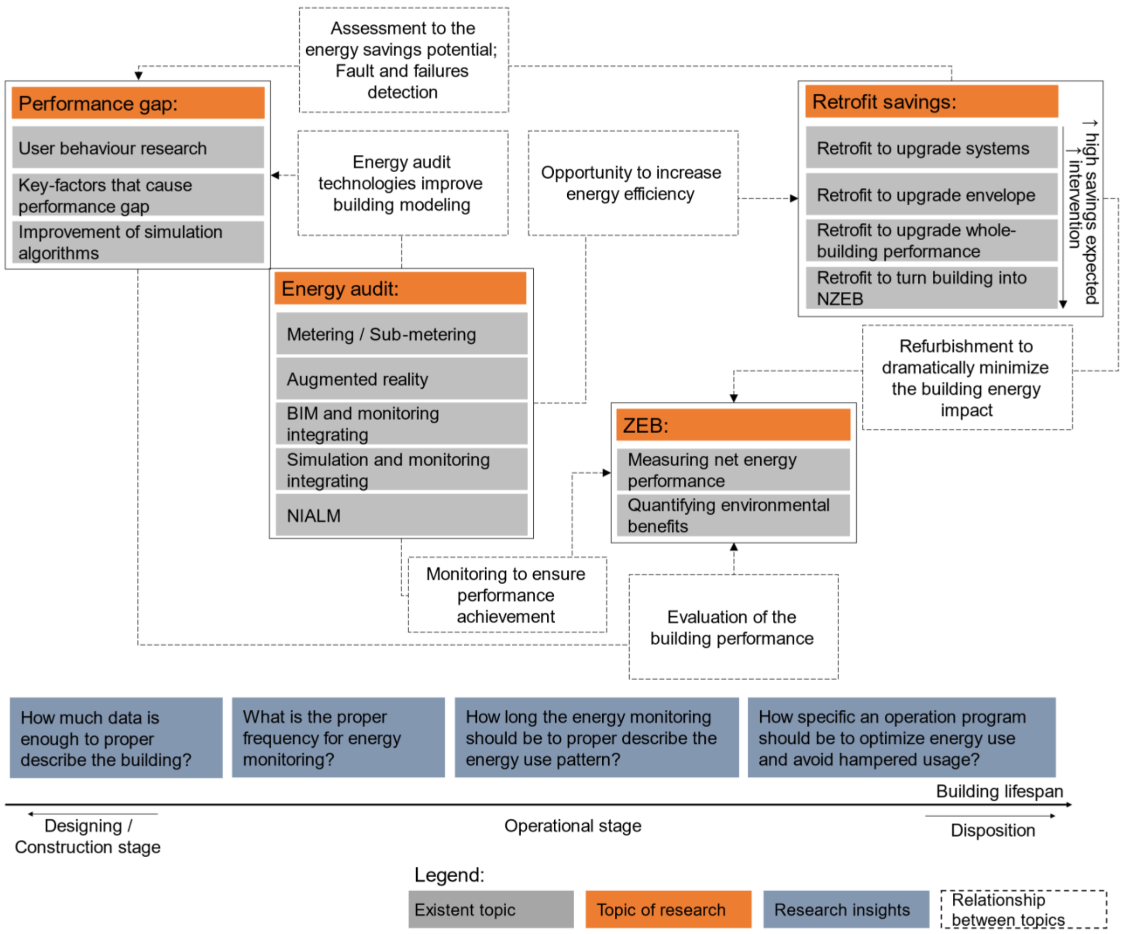


Figure 2.2 – Conceptual model of building-level analysis.

The four main purposes of research identified in the literature review were highlighted and broken down into the relevant existent topics.

Current performance gap studies have enlightened the need to consider occupant behaviour in prediction models (D'OCA; CORGNATI; HONG, 2015; D'OCA; HONG; LANGEVIN, 2018; SUN; HONG, 2017) whereas the identification of the key factors that cause the gap was also assessed (DE WILDE, 2014; GUNAY *et al.*, 2019; LIANG; QIU; HU, 2019; ZOU; WAGLE; ALAM, 2019). Therefore, the conclusions of the studies pointed to a need for modelling improvement (MENEZES *et al.*, 2012; PISELLO *et al.*, 2012b, 2014a; PISELLO; GORETTI; COTANA, 2012) by enhancing the representation of the operation (BURMAN; KIMPIAN; MUMOVIC, 2018; ELZARKA, 2009; LEHMANN; KHOURY; PATEL, 2017; LIANG; QIU; HU, 2019; SALEHI *et al.*, 2015).

Energy audit studies are remarkable for their technological innovations. New methods and tools (FELIX *et al.*, 2016; HAM; GOLPARVAR-FARD, 2013; KALZ *et al.*, 2009; NORDSTRÖM; JOHNSSON; LIDELÖW, 2013; NOYE; NORTH; FISK, 2016; PETRI *et al.*, 2017; ZHANG; CHEN, 2015) help to create a thorough description of the built environment not only in the physical but also in social dimensions (GUERRA-SANTIN *et al.*, 2013; HENZE *et al.*, 2015; LAWRENCE; KEIME, 2016). A remarkable study is the one by Gilani *et al.* (2017), which presented a review of methods to assess occupants monitoring in order to improve modelling. This full detailed description could lead to a high-resolution model and also to enhance prediction process (AHN; CHO, 2017; ALZAATREH *et al.*, 2018; COSTA *et al.*, 2013; FERRARINI; MANTOVANI, 2013; FICCO *et al.*, 2015; GONÇALVES; GASPAR; SILVA, 2012; YAN; WANG; XIAO, 2012). Ultimately, this high-resolution model and the advanced prediction approach could aid mitigating the performance gap (CARRIE ARMEL *et al.*, 2013; FAN; ITO, 2012; LIZANA *et al.*, 2018; O'NEILL *et al.*, 2014).

Systems' inefficiencies or opportunities for improvements are identified in the moment of the energy audit. Then, a retrofit is performed to improve energy efficiency (FERRARI; BECCALI, 2017; MAGOULÈS; ZHAO; ELIZONDO, 2013b; RASLAN; RUYSSEVELT, 2016). Energy simulation is widely used to predict the effect of a retrofit action, and the performance gaps are noticeable in this scenario as well (HEO; CHOUDHARY; AUGENBROE, 2012; HEO; ZAVALA, 2012; IPMVP, 2002; LI *et al.*, 2015; RAMOS RUIZ; FERNÁNDEZ BANDERA, 2017; SANHUDO *et al.*, 2018; TSENG *et al.*, 2013). Case studies present retrofits savings according to the purpose of the building and the size of the intervention (AKANDE *et al.*, 2016; CORNARO; PUGGIONI; STROLLO, 2016; CORRADO; BALLARINI, 2016; FERNANDES *et al.*,

2014; GÜÇYETER; GÜNAYDIN, 2012; NIEMELÄ; KOSONEN; JOKISALO, 2017; PAN *et al.*, 2012; PETCHARAT; CHUNG; PAIBULPATANA; RAKKWAMSUK, 2012; PETTERSEN *et al.*, 2017; ZAHIRI; ELSHARKAWY, 2018; ZINZI *et al.*, 2016). The impact of the occupants has been pointed out as a relevant factor to be considered in retrofit (ALONSO *et al.*, 2017; BARTHELMES; BECCHIO; CORGNATI, 2016; DELLAVALLE; BISELLO; BALEST, 2018; RUBENS *et al.*, 2017; SUN; HONG, 2017; SUN *et al.*, 2018; VALANCIUS; JURELIONIS; DOROSEVAS, 2013; ZINZI *et al.*, 2016).

Furthermore, remarkable studies proposed retrofits to turn buildings into ZEB (COLON, 2010; D'AGOSTINO; CUNIBERTI; MASCHIO, 2017; FERRARI; BECCALI, 2017). In this sense, the literature has several ZEB case studies that emphasize that they reduce the environmental impact of operation of buildings significantly (COLON, 2010; D'AGOSTINO; CUNIBERTI; MASCHIO, 2017; SUH; KIM, 2019; ZHOU *et al.*, 2016). However, there is a lack of standardisation to evaluate ZEB performance, which leads to a performance gap since several studies used distinct approaches (BERGGREN; WALL, 2017; LI *et al.*, 2018; ROBERT; KUMMERT, 2012).

Therefore, when the building-level is the research approach, it is vital to assess energy performance of the building precisely because, otherwise, the guidelines could lead to confused strategies that increase greenhouse gas emissions and decrease energy efficiency (KELLY; CRAWFORD-BROWN; POLLITT, 2012).

Studies about building-level analysis during the operational stage occurred in different moments throughout the lifespan of the building. Thus, the lifespan of the building was placed in the conceptual model to highlight that the performance gap is (not always, but often) adjacent to the designing stage, while retrofit is (not always, but often) closer to the building deactivation stage. Energy audit and ZEB are topics of study relevant throughout the whole building lifespan.

Thus, the current path of building-level studies shows that there are still lessons to be learned and challenges to be overcome. Integrating occupant behaviour, operation and maintenance in the building-level evaluation, and designing for the future are key accomplishments to achieve high-performance buildings.

4. Stock-Level Analysis

The stock-level analysis is an approach that considers the information from a group of buildings and considers the variations among buildings (for example, variability in size, occupation type, typology, and climate). In other words, the stock-level approach considers the subject of study as a population. Furthermore, in this section, we included a relevant discussion about the definition of the stock.

4.1. Identified Purposes of Research

We identified three main purposes that the studies at stock-level addressed: benchmarking, regulations and directives for the building stock, and strategies to overcome climate change effects.

4.1.1. Benchmarking

Benchmarking is a useful practice to be applied in building performance analysis during the operational stage. Benchmarking is widely referred to as a method to verify a single performance in contrast to other with same-typology. However, in this topic, we discussed studies that addressed methods to obtain benchmarks – how studies have clustered building stock information? How much information was used to assure representativeness? What methods were applied according to what purpose?

In summary, we considered studies that have somehow modelled the building stock to obtain reference values of real energy performance. Chung (2011) presents a comprehensive review of current methodologies for benchmarking. Li *et al.* (2014) present an informative overview of benchmarking methods and classified them according to the complexity level (white, grey or black-box approaches). In general, benchmarking methods can be categorized as:

- Simple Normalization, which is a simple calculation of the statistical measures (e.g., mean, maximum, and minimum values). Further statistical analysis can be done, such as the determination of quantiles and histograms (BOEMI *et al.*, 2011; LI, 2008; SCOFIELD, 2013; SCOFIELD; DOANE, 2018; TAYLOR *et al.*, 2018);

- Ordinary Least Square (OLS, or simple regression), which uses a cause-effect function to determine an Energy Use Intensity (EUI) equation (BORGSTEIN; LAMBERTS; HENSEN, 2016; HONG *et al.*, 2014; PAPADOPOULOS; KONTOKOSTA, 2019; SABAPATHY *et al.*, 2010).
- Stochastic Frontier Analysis (SFA), which is also a regression method but the calculation of the benchmarks includes the determination of a geometric element (frontier of performance) using data of high-performance buildings (BUCK; YOUNG, 2007; YANG; ROTH; JAIN, 2018).
- Data Envelopment Analysis (DEA), which is a regression method as well, but the benchmarks are determined by a boundary calculated using all dataset (CHUNG, 2011; LEE 2008, 2009a).
- Other advanced methods, such as geostatistical approaches (KOO; HONG, 2015; ÖSTERBRING *et al.*, 2018), and machine learning techniques (CHUNG; YEUNG, 2017; PARK *et al.*, 2016; RUZZELLI *et al.*, 2010; SEYEDZADEH *et al.*, 2018), are found to enhance building stock modelling.

In the review of Borgstein, Lamberts and Hensen (2016), an enriching explanation of the benchmarking methods is presented. Specifically, the authors highlighted the algorithms used, the variables involved, and the level of accuracy according to each method. Inaccuracies of benchmarking approaches were raised in the literature, especially regarding the static nature of benchmarks that can lead to a never-ending chasing of the performance gap (HEESEN; MADLENER, 2018). The development of tailored benchmarking and the use of correction factors (weather, occupancy and end-uses) are strategies to adjust benchmarking tools. A calibrated simulation of archetypes is usually employed to consider end-uses in benchmarking (BORGSTEIN; LAMBERTS, 2014). However, measured end-uses data is widely more reliable (HAMILTON *et al.*, 2017; HAMILTON *et al.*, 2013).

Benchmarking is supported by the amount of data obtained from policies of energy disclosure in buildings. Those policies have drastically grown in the past few years. Hsu (2014) discussed the power of benchmarking as a predictor in New York city using Bayesian Regression. In this study, the author used data from monthly billing and energy audit. The author highlighted that the improvement of the operation could bring more results rather than the upgrade of systems. Furthermore, by obtaining information about operation, occupancy, and existing conservation measures, it could be possible to improve the comprehension of heterogeneity in buildings.

The advance of digital technologies (e.g., Internet of Things – IoT, and Artificial Intelligence – AI) increases the presence of technological devices into the built environment. Controlling devices not always include monitoring purposes (GUERRA-SANTIN; TWEED, 2015a). However, big data are often formed by sensors and meters that exist in buildings (especially non-residential) (ZHOU; FU; YANG, 2016). The analysis of these databases can be productive in order to draw user profiles to enhance simulation models (D'OCA; CORGNATI; HONG, 2015) or to classify building performances in relation to its pairs (MATHEW *et al.*, 2015).

All the data provided by sensors and Building Energy Management Systems result in a Big Data issue (MATHEW *et al.*, 2015; ZHOU; FU; YANG, 2016). Thus, the quantity of information is an issue to be addressed. Corry *et al.* (2015) proposed an ontology to address the information from various buildings. Buildings are heterogeneous, and building data can be as well. The paper proposed a framework to transform building data into semantically enriched information. A similar framework was proposed for the residential building stock (CSOKNYAI *et al.*, 2016).

The study of Mata *et al.* (2014) associated stock characteristics among countries in a statistically perspective. Clustering methods can be used to group buildings into a stock model (COTTAFAVA *et al.*, 2018). The age of the building was pointed as a relevant but undervalued factor for the building performance (AKSOEZEN *et al.*, 2015).

As a final remark on this topic, the methods to model the building stock according to its relevant characteristics is a crucial step to achieve reliable benchmarks. The EUI indicator is an issue to be addressed as well. Since benchmarking models commonly use yearly EUI rated by floor-plan area (kWh/m^2.year), the precision of the indicator is low. Rating benchmarks by cooling/heating demand and using a monthly-based time resolution could improve benchmarking application (KIM; KIM; LEE, 2019). Likewise, rating benchmarks according to the building occupancy could be better suitable to specific typologies (HONG *et al.*, 2014; PEREIRA *et al.*, 2014).

4.1.2. Regulations and directives for the building stock

In the past few years, a significant number of new regulations, directives and public policies related to the energy performance of buildings has been arising. In this topic, we bring some interesting applications of stock-level analysis to evaluate this guidance.

Regarding regulations for evaluating the performance of buildings during the operational stage, energy transparency policies play a prominent role. Those policies included Energy Performance Certificates (EPCs) and the Display Energy Certificates (DECs), and they continually contribute to increasing the empirical data about performance of buildings. These policies are especially relevant in Europe, where the EPC policies are not compulsory, but most countries involved have a system to gather data voluntarily. The EPC registers compound a key source of information for the use of energy and characteristics of buildings. A comprehensive overview of the EPC schemes hitherto and a discussion of future improvements towards next generations of EPCs can the found in (LI *et al.*, 2019). Although the share of buildings records in the database varies across Europe, some studies have shown the benefits of EPC application in their countries. For example:

- In France, Florio and Teissier (2015) analysed the stock information of the *Enquête Nationale Logements* (ENL) and developed an algorithm to determine reference models in the ENL database in order to analyse the energy performance of the building stock. An actual overview of the energy usage according to the typologies analysed is presented.
- In Spain, Las-Heras-Casas *et al.* (2018) proposed an algorithm to correct information in EPC databases especially in climate zoning, using the region of Aragón as case study. A similar case was applied for energy planning in a different region (LÓPEZ-GONZÁLEZ *et al.*, 2016).
- In Ireland, Ahern *et al.* (2016) discussed the effect of using default values of U-values in obtaining EPC for houses. Despite the difficulty of obtaining U-values in practice, default values could lead to significant bias in assessing the real energy performance rate. Analysing the stock of EPCs, the authors concluded that most U-values are underestimated, contributing to rating the dwellings wrongly which increases the prebound effect.

- In Greece, Droutsa *et al.* (2016) used more than 650,000 EPCs to present an overview of the energy performance of the Hellenic residential building stock. A summary of the most common building characteristics, average energy performance and common retrofit strategies are presented and discussed.
- In Sweden, residential buildings obtained the first EPC in 2008 and the second in 2018. The study of von Platten *et al.* (2019) compared those pairwise EPCs in order to analyse changes in performance pioneeringly considering building-specific evaluations.
- Other studies in the Netherlands (FILIPPIDOU; NIEBOER; VISSCHER, 2017) and Denmark (CHRISTENSEN *et al.*, 2014) used EPC data to analyse the stock refurbishment and the applicability of regulation requirements to enhance the quality of retrofits.

Pasichnyi *et al.* (2019) reviewed 79 studies regarding EPC across Europe and proposed a method to assess the quality of information gathered by the EPC policies. By comparing the current data that have been collected among countries − the most common errors (such as spelling and typo errors) − the authors suggested that the EPC features could be reviewed to guaranteed compatibility among datasets.

In the United States, Ye *et al.* (2019) reviewed the data sources for energy usage in commercial buildings from energy transparency policies. Benefits from those policies can be outlined, such as making the energy usage visible and exhibiting the energy performance of a building to a potential user. A relevant overview of those certificates is presented by Cohen and Bordass (2015).

Innovations have been continually developed to aid the evaluation of regulations and directives in the building stock. For example:

- To map, visualise and analyse the building stock interactively (MHALAS *et al.*, 2013; ZOU; ZHAO; ZHONG, 2017); and to interact with the building energy performances using a geographic dashboard (GIOVANNINI *et al.*, 2014);
- To enhance the simulation modelling by considering inter-building effect (PISELLO *et al.*, 2014b);

- To uptake the transition of building stock into ZEB considering cost-optimal criterion (FERREIRA; ALMEIDA; RODRIGUES, 2016);
- To assess Net-Positive Energy Buildings (COLE; FEDORUK, 2015);
- To estimate the building energy usage using high-resolution data (BALLARINI; CORRADO, 2017);
- To test the accuracy of energy performance certificates through Artificial Neural Networks (ANN) (BURATTI; BARBANERA; PALLADINO, 2014), statistical analysis (STREICHER *et al.*, 2018), comparative testing using simulation software (ABELA *et al.*, 2016) and structural equation modelling (MAFIMISEBI *et al.*, 2018);
- To integrate technologies to support decisions towards low-carbon cities (MOGHADAM; LOMBARDI; MUTANI, 2017).

Pritchard and Kelly (2014) reviewed the impact of three notorious initiatives – Energy Performance of Buildings Directive (EPBD), BREEAM and Cambridge Work – on the operational performance of buildings at the University of Cambridge. The study highlighted the importance of considering the actual performance. Moreover, evidence-based studies stated that operational performance is considerably higher than standardised and theoretical performance. Goldstein and Eley (2014) proposed the Operation and Maintenance (O&M) index, which is "the ratio of the measured energy consumption and the simulated energy performance, calibrated for the actual operating conditions of the building". This O&M index was proposed to complement the Asset ratio (modelled energy use) and the operation ratio (measured energy use) in order to represent a more realistic metric.

Although certifications usually rate buildings using specific methods, likewise the performance gap there is the prebound effect. The prebound effect is the difference between the energy performance rated and the actual consumption. This effect is noticeable, and it is not random (SUNIKKA-BLANK; GALVIN, 2012).

Public Policies are strong in the residential sector. While the overall potential energy savings of the residential sector is high (FAZELI; DAVIDSDOTTIR, 2018), the user behaviour plays a decisive role in determining the energy performance of buildings (LOWE; CHIU; ORESZCZYN, 2018). Even with the existence of public policies to stimulate the owners to improve their buildings, further refinement is required to highlight the benefits of implanting energy-efficient strategies (WATTS; JENTSCH; JAMES, 2011).

Nevertheless, the improvement of residential buildings with retrofits and energy conservation measures can lead to both energy and cost savings (DWAIKAT; ALI, 2016). Additional economic benefits include high rent taxes of efficient building when compared to ordinary ones (MARCELO, 2013). To the landlord, the additional profit on renting and selling is more than enough to justify a retrofit investment for improving buildings (CHEGUT; EICHHOLTZ; HOLTERMANS, 2016). However, people have strong apprehension about losing their autonomy in homes. Thus, a clear and well-informed framework is crucial to guarantee the programme effectiveness (VAN MIDDELKOOP; VRINGER; VISSER, 2017). This statement is supported by the study of Rubens *et al.* (2017), which highlights the need for educating occupants to enhance the performance of the building. For this effort, educational tools and technologies can be taken into consideration (HAWAS; AL-HABAIBEH, 2017). Furthermore, the relationship between energy performance and social equity is discussed (CHEN; TAN; BERARDI, 2018). A recent conclusion is that efficient buildings are more present in wealthy locations (GOLUBCHIKOV; DEDA, 2012; ZOU; ZHAO; ZHONG, 2017).

Finally, we highlight that the efforts towards a sustainable and efficient society must begin on a small scale (from neighbourhoods or apartment complexes) (HACHEM, 2015).

4.1.3. Strategies to Overcome Climate Change Effects

The energy performance of buildings is closely related to the thermal performance and, as climate changes the thermal performance of buildings, they will have a different performance from what was designed. Climate change affects the weather making extreme events more frequent (BATES *et al.*, 2008). In this panorama, high-insulated buildings might not provide the best performance (ROBERT; KUMMERT, 2012). Overcoming climate change interference in building performance is a significant challenge. A comprehensive overview of the impact of climate change on building performance is presented by Yau and Hasbi (2013).

Studies that addressed this issue proposed strategies of isolation and assessed it using future-estimated weather files (BERGER *et al.*, 2014; DIRKS *et al.*, 2015; JENTSCH *et al.*, 2013; NIK, 2016; SHEN, 2017; WANG; CHEN, 2014). Usually, a simulation-based approach was employed on archetypes modelled from stock information. For example, Nik *et al.* (2013) used information from 153 existing buildings and simulated the energy performance to assess the impact of climate change considering uncertainties.

A relevant study presented by Nik *et al.* (2015) proposed a method to improve performance resilience of buildings due to climate change. The study evaluated scenarios of the energy performance of housing that receive five ECM: (a) lighting system improvement; improvement of U-values of basement (b); façade (c); ceiling (d); and fenestration (e) replacement. Results showed the averages and standard deviations of the building performance according to each strategy in different time scales for each scenario. A similar study was conducted in Argentina by Filippin *et al.* (2018). A group of ten buildings was clustered and similar retrofits strategies proposed according to their impact on energy consumption.

The "post-carbon cities" is a new term towards reducing energy demand to avoid the impact on the environment caused by energy usage in buildings. The concept of "post-carbon cities" is to turn most of the buildings of a city into ZEB employing the energy and cost-effective retrofits. This concept relies on minimising the influence of occupants (BECCHIO *et al.*, 2016). However, in the review of Groove-Smith *et al.* (2018), it is presented that passive buildings and low energy buildings have more efficient economic and energy performance (rather than ordinary and self-sufficient buildings). A worthy example is the stock analysis for ZEB evaluation presented by Fokaides, Polycarpou and Kalogirou (2017), who analysed the social housing building stock in regard to the EPBD in Cyprus. The study showed the possibility of decreasing energy consumption due to the social housing stock renovation towards ZEB. Yet, it also highlighted the importance of considering aspects such as energy end-use and lifestyle of the users to provide reliable outcomes.

Therefore, from a broader perspective, the stock-level analysis is a suitable approach to assess the impact of climate change during the operational performance of buildings. Using a population analysis is useful for either identifying strategies to mitigate climate change effects and assessing the energy demand associated with geographic attributes.

4.2. Level of Information

As observed in building-level analysis, stock-level studies used different levels of information regarding measured energy consumption. Table 2.6 presents a summary of the different time resolution of energy consumption according to each identified purpose of the study.

Table 2.6 – Time resolution of energy consumption in the stock-level analysis.

Purposes	Time Resolution	Sources
Benchmarking	Hourly	(SABAPATHY *et al.*, 2010)
	Monthly	(ALFARIS; ABU-HIJLEH; ABDUL-AMEER, 2016; BOEMI *et al.*, 2011; KIM; KIM; LEE, 2019; LI, 2008; MATA; SASIC KALAGASIDIS; JOHNSSON, 2014; SCOFIELD, 2013; SCOFIELD; DOANE, 2018)
	Annually	(AKSOEZEN *et al.*, 2015; ALFARIS; ABU-HIJLEH; ABDUL-AMEER, 2016; BHATNAGAR; MATHUR; GARG, 2019; BRAULIO-GONZALO *et al.*, 2016; BURMAN; MUMOVIC; KIMPIAN, 2014; COTTAFAVA *et al.*, 2018; CSOKNYAI *et al.*, 2016; HONG *et al.*, 2014; HSU, 2014; KOO; HONG, 2015; NÄGELI *et al.*, 2018; ÖSTERBRING *et al.*, 2016, 2018; PAPADOPOULOS; BONCZAK; KONTOKOSTA, 2018; PAPADOPOULOS; KONTOKOSTA, 2019; PARK *et al.*, 2016; PITTAM; O'SULLIVAN; O'SULLIVAN, 2014; TAYLOR *et al.*, 2018; YANG; ROTH; JAIN, 2016, 2018)
Regulations, directives and guidance for the building stock	Weekly	(RUBENS *et al.*, 2017)
	Monthly	(ABELA *et al.*, 2016; GIANNIOU *et al.*, 2015; GIOVANNINI *et al.*, 2014; GOLDSTEIN; ELEY, 2014; HACHEM, 2015; PISELLO *et al.*, 2014b; PRITCHARD; KELLY, 2017)
	Annually	(BURATTI; BARBANERA; PALLADINO, 2014; CHEGUT; EICHHOLTZ; HOLTERMANS, 2016; DWAIKAT; ALI, 2016; FAZELI; DAVIDSDOTTIR, 2018; FERREIRA; ALMEIDA; RODRIGUES, 2016; GOLUBCHIKOV; DEDA, 2012; MHALAS *et al.*, 2013)
Strategies to Overcome Climate Change Effects	Annually	(BECCHIO *et al.*, 2016; FILIPPÍN; FLORES LARSEN; RICARD, 2018; GROVE-SMITH *et al.*, 2018)
	Monthly	(FOKAIDES; POLYCARPOU; KALOGIROU, 2017)
	20-year	(NIK; MATA; SASIC KALAGASIDIS, 2015; NIK; SASIC KALAGASIDIS, 2013)

Tabula and Episcope projects support stock-level analysis because they provide a large dataset of annual energy consumption in Europe. Furthermore, building physical characteristics such as transmittance and building age were provided.

In this topic, a remarkable study by Papadopoulos *et al.* (2018) assessed the energy performance of a sample of buildings over time. Although the study utilised yearly data, the authors pointed out that the granularity of the measured data can be a target to be studied. A high granularity of energy end-uses could help to explain factors that drive energy usage.

We observed a low resolution of the measured data in benchmarking studies. This limitation demonstrates the need for high granularity (both spatial and temporal) of energy end-use data (TAYLOR *et al.*, 2018). The low-resolution data in stock-level studies are associated with the definition of EUI (kWh/m².year). Nevertheless, with the advance of technologies in building automation and building performance analysis, a new indicator for EUI is crucial (KIM; KIM; LEE, 2019).

4.3. Methods and Tools

We summarised the methods and tools used by stock-level studies in two main issues. The first issue is the development of benchmarks, which is related to the methods used to represent the typical values of energy use intensity of the stock. The second issue is the stock modelling, which describes methods used to summarise all the stock heterogeneity into representative groups. The main difference between those two issues is that the development of the benchmarks implies in quantifying energy usage while stock modelling entails classifying according to the qualitative features of the buildings.

Table 2.7 shows a summary of the methods and tools observed in this approach.

Table 2.7 – Summary of methods and tools used for the stock-level analysis.

Issue	Methods (Tools)	Sources
Development of benchmarks	Simple normalization (Statistical analysis)	(SCOFIELD, 2013; SCOFIELD; DOANE, 2018; TAYLOR *et al.*, 2018)
	Statistical analysis (Regression analysis)	(AKSOEZEN *et al.*, 2015; ALFARIS; ABU-HIJLEH; ABDUL-AMEER, 2016; BURMAN; MUMOVIC; KIMPIAN, 2014; HONG *et al.*, 2014; KIM.; KIM; LEE, 2019; LI, 2008; PAPADOPOULOS; KONTOKOSTA, 2019; YANG; ROTH; JAIN, 2018)
	Machine Learning (Artificial Neural Network, Genetic Algorithm, Bayesian Network, other)	(BURATTI; BARBANERA; PALLADINO, 2014; KOO; HONG, 2015; PARK *et al.*, 2016)
Stock modelling	Cluster analysis from characteristics (K-means or machine learning)	(BEN; STEEMERS, 2018; BHATNAGAR; MATHUR; GARG, 2019; COTTAFAVA *et al.*, 2018; FOKAIDES; POLYCARPOU; KALOGIROU, 2017; MATA; SASIC KALAGASIDIS; JOHNSSON, 2014; PAPADOPOULOS; BONCZAK; KONTOKOSTA, 2018; STREICHER *et al.*, 2018)
	Synthetic generation (iterative proportional fitting)	(NÄGELI *et al.*, 2018)
	Geographical aggregation (GIS, Google Street-view, Google Maps)	(AKSOEZEN *et al.*, 2015; BRAULIO-GONZALO *et al.*, 2016; KOO; HONG, 2015; ÖSTERBRING *et al.*, 2016; PITTAM; O'SULLIVAN; O'SULLIVAN, 2014; YANG; ROTH; JAIN, 2016)

In the stock-level analysis, the buildings are treated as a population. Thus, summary metrics are needed to express both the overall stock performance and a single performance of the building when compared with pairs. Benchmarks are reference values to establish those summarised metrics. Although benchmarking is a quantitative approach, stock modelling (through archetypes) is often adopted to obtain benchmarks because surveying all building stock is expensive and time-consuming. In stock modelling, we identified two main approaches to group buildings: clustering by characteristics and aggregating by geographical location.

4.4. Defining Building Stock: Geo-Stock versus Type-Stock

Some studies have defined the building stock as a geographic delimitated group of buildings (e.g., neighbourhood, city) (BRAULIO-GONZALO *et al.*, 2016;

CSOKNYAI *et al.*, 2016; GIANNIOU *et al.*, 2015; GIOVANNINI *et al.*, 2014; ÖSTERBRING *et al.*, 2016, 2018; PAMPURI *et al.*, 2017; YANG; ROTH; JAIN, 2016, 2018). This definition implies in heterogeneous typologies compounding the stock. Other studies have defined the building stock as the group of same-type buildings (e.g., schools, bank branches, office buildings, residential buildings) (BEN; STEEMERS, 2018; BORGSTEIN; LAMBERTS, 2014; BURMAN *et al.*, 2014; COTTAFAVA *et al.*, 2018; HONG *et al.*, 2014; LI, 2008; MARRONE; GORI, 2018; SCOFIELD; DOANE, 2018; STREICHER *et al.*, 2018), which implies in different location of each building.

Therefore, there is an overlapping of definition of "building stock" that needs clarification. By specifying the terminology, one makes clear what the boundary condition of the study is.

We propose a distinction in "building stock" definition into:

- Geo-building stock, which is the group of buildings composed of geographic delimitation. For example, this terminology is suitable for addressing urbanisation-level and inter-building effects, the interface between the built environment and urban environment, land use and occupation, and others;
- Type-building stock, which is the group of buildings comprised of buildings that share a purpose. It is adequate for benchmarking, performance comparison among pairs, establishing guidelines for construction, operational scheme guidelines, and others.

4.5. Conceptual Model

In the stock-level analysis, the time resolution of the energy use intensity data is different according to each purpose of research. Therefore, we used this time resolution as a reference to organise the research purposes and to outline the conceptual model of the stock-level analysis (Figure 2.3).

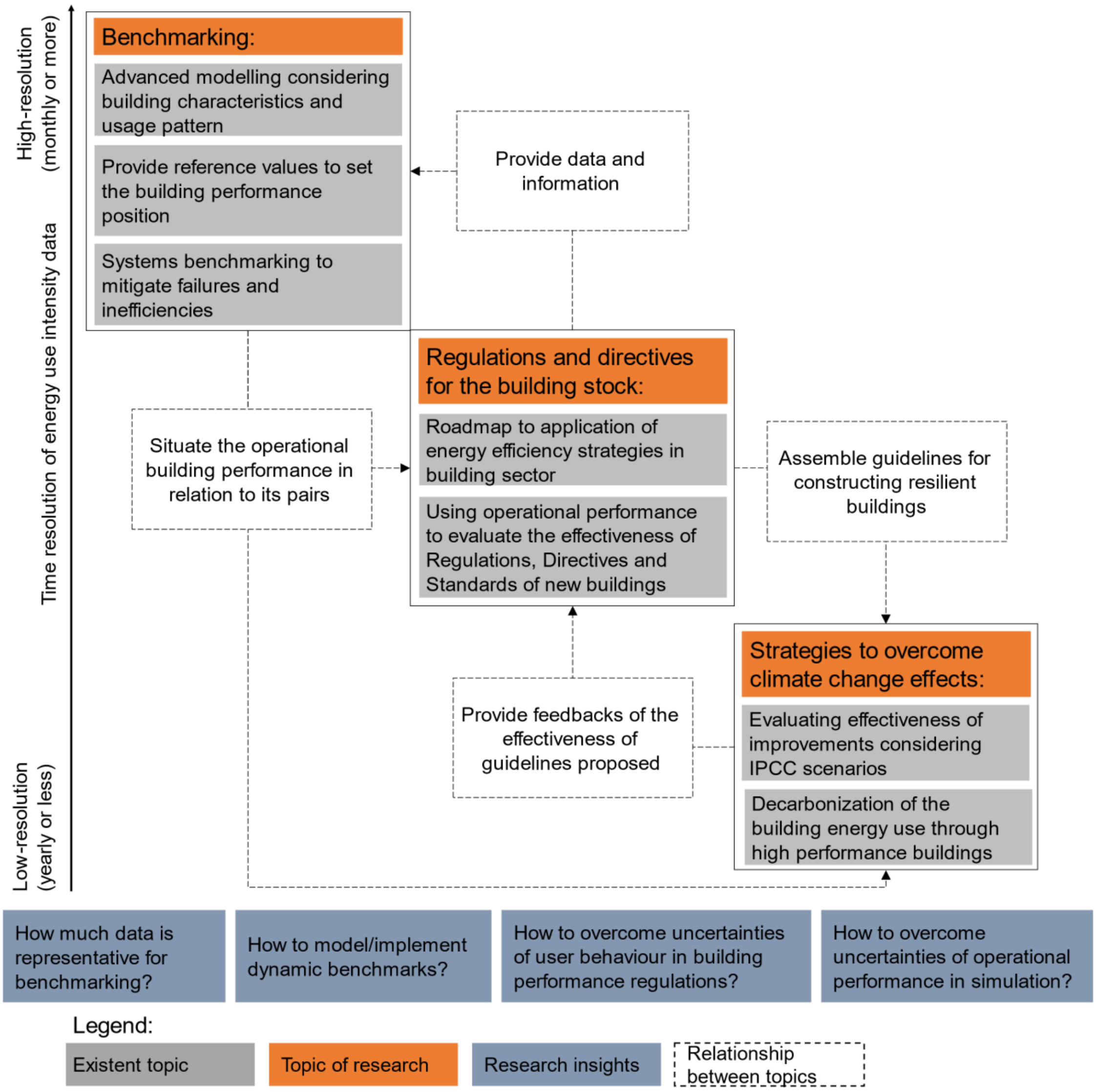


Figure 2.3 – Conceptual model of the stock-level analysis.

The literature review about operational energy performance addressed in the stock-level analysis reveals three primary purposes of research: benchmarking, regulation and directives for the building stock; and strategies to overcome climate change effects. Nowadays, there are widely known benchmarking methods (BOEMI *et al.*, 2011; BORGSTEIN; LAMBERTS; HENSEN, 2016; BUCK; YOUNG, 2007; CHUNG, 2011; CHUNG; YEUNG, 2017; KOO; HONG, 2015; LEE, 2008, 2009b; LI, 2008; LI; HAN; XU, 2014; ÖSTERBRING *et al.*, 2018; PAPADOPOULOS; KONTOKOSTA, 2019; RUZZELLI *et al.*, 2010; SABAPATHY *et al.*, 2010; SCOFIELD, 2013; SCOFIELD; DOANE, 2018; SEYEDZADEH *et al.*, 2018; TAYLOR *et al.*, 2018; YANG; ROTH; JAIN, 2018) that use-different complexity levels for obtaining benchmarks. However, there is a lack in finding an adequate indicator of the energy use intensity, since kWh/m^2.year is not always suitable for all typologies (BORGSTEIN; LAMBERTS; HENSEN, 2016; HONG *et al.*, 2014; MATA; SASIC KALAGASIDIS; JOHNSSON, 2014; MATHEW *et al.*, 2015) or end-uses (BORGSTEIN, LAMBERTS, 2014; GUERRA-SANTIN; TWEED, 2015b; HSU, 2014). Additionally, the time reference is questionable (KIM; KIM; LEE, 2019): what is an adequate time resolution to benchmark a building (monthly, yearly, or even weekly)? The development and implementation of dynamic benchmarks become an interesting trend of research. Some studies already proposed dynamic rating schemes (FAZELI; DAVIDSDOTTIR, 2018; KOO; HONG, 2015). However, the proper investigation of a reliable framework integrating building, government and energy companies is required.

Benchmarking is supported by the information provided by regulations and directives that obligate the declaration of energy performance using specific protocols (YE; ZUO; WANG, 2019). In the design stage (for new buildings), regulations and directives guide through guidelines for construction. The effectiveness of those guidelines is often tested by some studies (BURMAN; MUMOVIC; KIMPIAN, 2014; CHEGUT; EICHHOLTZ; HOLTERMANS, 2016; FAZELI; DAVIDSDOTTIR, 2018; LOWE; CHIU; ORESZCZYN, 2018; MARCELO, 2013; SUNIKKA-BLANK; GALVIN, 2012; WATTS; JENTSCH; JAMES, 2011), and enhancements of the guidelines are proposed (ABELA *et al.*, 2016; BALLARINI; CORRADO, 2017; BURATTI; BARBANERA; PALLADINO, 2014; COLE; FEDORUK, 2015; FERREIRA; ALMEIDA; RODRIGUES, 2016; MAFIMISEBI *et al.*, 2018; MOGHADAM; LOMBARDI; MUTANI, 2017; PISELLO *et al.*, 2014b; STREICHER *et al.*, 2018). A remarkable insight of research regarding incentives to upgrade buildings is to study the consideration of the human dimension (HAWAS; AL-HABAIBEH, 2017; RUBENS *et al.*, 2017; VAN MIDDELKOOP; VRINGER; VISSER, 2017). In existing buildings, regulations and directives establish a certain level of performance, require transparency in performance of buildings to society, and specify guidance to improvement in buildings and systems. Additionally, stock-level analysis opens the opportunity to utilise Geographic Information Systems (GIS) to develop innovative ways to address the stock for benefiting both the government and the society (GIOVANNINI *et al.*, 2014; MHALAS *et al.*, 2013; ZOU; ZHAO; ZHONG, 2017).

Overcoming Climate Change effects in buildings, initiatives around the world (especially in Europe and the United States) established directives to turn buildings more resilient and assess those directives using future scenario analysis. Improvements in building insulation and fenestration technologies were tested under future weather conditions (BERGER *et al.*, 2014; DIRKS *et al.*, 2015; FILIPPÍN; FLORES LARSEN; RICARD, 2018; JENTSCH *et al.*, 2013; NIK, 2016; NIK; MATA; SASIC KALAGASIDIS, 2015; NIK; SASIC KALAGASIDIS, 2013; SHEN, 2017; WANG; CHEN, 2014). However, most of those studies are based on future scenario estimations – which make sense since climate change implies in trends on the weather. This condition favours the use of computer simulation and exposes opportunities to enhance simulation engines by considering operational routines more realistically. Thus, one can ask: how the uncertainties in operational schemes can be overcome in simulation modelling? Also, strategies and programmes to decarbonise building operational energy usage are tested – including transitions of the stock towards ZEB (BECCHIO *et al.*, 2016; GROVE-SMITH *et al.*, 2018).

Therefore, considering buildings as a population brings both solutions and challenges. It is noteworthy that the visualisation of energy performance in scale extremally facilitates energy management and supports public policies definitions. Furthermore, by providing reference values, the benchmarking not only instigates competitivity but also allows to set new targets of high performance for the building sector and to clarify the energy consumption (turning the consumption visible).

5. Discussions

5.1. Interfacing Building-Level and Stock-Level Analyses

By considering the operational performance, the building-level analysis differs from stock-level analysis, especially due to the energy data resolution. We observed that building-level analysis usually employed high-resolution data because it aimed to examine specific buildings issues. Otherwise, stock-level approaches generally employed data from energy bills and EPCs once aimed to explore large scale solutions.

We understood that there is no fixed rule to delimit boundaries between stock and building-level. Where stock-level scale begins and building-level ends depend on the analysis performed, available data, and expected results. Thus, the boundaries conditions are defined in each study. Furthermore, it is important to highlight that those definitions are not mutually exclusive – in fact, it is the opposite: the stock contains buildings. In this study, we proposed this differentiation of terminologies to promote distinct perspectives to the building performance analysis in order to understand the energy usage phenomenon.

The interface of those scales could be the key to consider elements hitherto hard to consider in building energy modelling. For example, using large vegetation as shading elements were considered only in building scale (MANGONE; VAN DER LINDEN, 2014); however, this is a clear case to use urban building energy modelling (UBEM) which means to consider the stock-level approach as well.

The modelling of the weather is a significant issue in building performance analysis. This problem extends to the data resolution (CRAWLEY; LAWRIE, 2015), availability (JENTSCH *et al.*, 2013; JENTSCH; EAMES; LEVERMORE, 2015), variability (HUBBARD *et al.*, 2005) and, currently, to the climate change consideration (BELCHER; HACKER; POWELL, 2005; DICKINSON; BRANNON, 2016; HACKER; CAPON; MYLONA, 2009; KIKUMOTO *et al.*, 2015) in building performance analysis. There are advanced studies on the representativeness of weather data to improve simulations. However, the integration of building-level and stock-level analyses (in this case, specific to urban-level) is applicable. In fact, in real-world the buildings are not isolated – they are inserted into social and environmental contexts. Thus, adjustments in building modelling must be implemented to consider microclimate effects, inter-building interactions, and building-urban interaction (REINHART; CEREZO DAVILA, 2016).

Top-down and bottom-up approaches are strategies of information processing that were adopted in some studies to create benchmarking by adequately considering the building context according to the level of information. Top-down is described as a method that uses a comparison of a building against its pairs (HONG, 2014). Otherwise, bottom-up methods use specific building context and theoretical analysis (BURMAN *et al.*, 2014). Those terminologies are somehow similar to stock-level and building-level analyses (respectively) that we identified in this literature review.

Along these lines, Annex 70 (Building Energy Epidemiology: Analysis of real building energy use at scale) played an important role to establish a proper framework in studying the stock-level approach. The concept of Energy Epidemiology (HAMILTON *et al.*, 2013) is an essential step towards comprehending energy usage in building stock (HAMILTON *et al.*, 2017). Additionally, this approach can be used not only to promote insights to improve the building stock (HAMILTON *et al.*, 2014) but also to encourage progress in energy usage understanding (HAMILTON *et al.*, 2016;

HUEBNER *et al.*, 2016; HUEBNER *et al.*, 2015). Ultimately, considering each building as an individual subject and the building stock as a population, it can be the key to achieve healthy and environmental-friendly built environments (RYDIN *et al.*, 2012).

5.2. Research opportunities

Along with the two conceptual models for both building-level and stock-level approaches, we raised questions that might be explored in further research opportunities.

The evaluation of energy performance of buildings at the operational stage relies on quantitative assessment of energy consumption through measurements. Despite the innovations in collecting energy data due to smart meters, IoT innovations and building automation techs, the representativeness of the time resolution is still an open question. Therefore, time series analysis in building performance analysis is a relevant topic that deserves exploration in both building-level and stock-level analyses. Going forward, specific questions regarding time resolution can be outlined, such as: What is the proper frequency for energy monitoring? How long should be the energy monitoring to describe the energy use pattern accurately? How specific the data should be to assure representativeness in benchmarking? Therefore, all the data available due to the increasing automation in buildings opens the opportunity to high-resolution benchmarking.

Meanwhile, the heterogeneity among buildings is a challenging issue to be considered in building performance analysis. We inferred that such heterogeneity affects energy usage because of the variations in usage patterns and operations schemes. In fact, buildings are recently described as a cyber-physical-social system (BAVARESCO *et al.*, 2019). Therefore, some topics of study can be drawn, such as: How to consider uncertainties due to user behaviour in building performance analysis? How to overcome uncertainties due to operational performance in the simulation? Going through the optimisation of the building operation: How specific should be an operation programme to optimise energy use and avoid hampered usage?

Therefore, this literature review is expected to contribute to the efforts of the ongoing pieces of research by providing disruptive perspectives regarding managing and improving energy performance of buildings during the operational stage.

6. Conclusions

In this paper, we presented a review of energy performance of buildings during the operational stage. A survey in web directories was performed using systematic research and adequate terms. An up-to-date (of the past ten years) literature survey was applied to determine the trends of research in this field. Using a meta-analysis approach, we identified two main research approaches: one considering the building-level and other the stock-level. Then, we used this differentiation to carry out the structure of this paper. Regarding each approach, it was possible to identify the leading purposes that the studies addressed. A general aspect of this review was the contemplation of the empirical assessment in all studies reviewed, by surveying the level of information (granularity of the measured energy data) and methods and tools employed in the analysis.

The building-level analysis was defined as a perspective that assumes the building as the subject of study. From this perspective, we identified four principal purposes of research: performance gap, energy audit, retrofit savings assessment and ZEB evaluation. Since the prediction of energy consumption has been the main objective of energy building performance from several studies hitherto (WEI, 2013), the performance gap became a critical issue to be mitigated (SCOFIELD, 2009). The proposition to improve existent buildings using retrofits and the concept of ZEB has raised to decarbonise the existent building stock. Hence, the consideration of the occupant behaviour on buildings energy performance assessment as well as the operation and maintenance of systems are the leading issues to be overcome to achieve high-performance buildings. We defined as a stock-level approach the studies that considered a group of buildings as the system of study. Benchmarking, regulation and directives for buildings and evaluation of strategies due to climate change were the main purposes of research explored in this approach. Abstracting the relevant features of the stock is essential to proceed with the large-scale analysis. For instance, the establishment of referenced values allows performance comparison among pairs. The statistical analysis provides inferences regarding improvements opportunities in a particular typology, and it aids evaluating the effectiveness of policies and regulation to enhance energy efficiency. Thus, we concluded that stock-level analysis is a field with extensive potential to improve building performance analysis.

The interface between both approaches was discussed. A remarkable benefit from the assumption of each approach is the consideration of the climate, urban, and social context in building performance analysis. In this sense, we encourage researchers to specify the boundary condition adopted in the study. For both approaches, building and stock-level, we summarised the level of information and the methods and tools applied in the studies. By analysing the level of information, we concluded that building-level analysis employed higher time resolution than stock-level analysis. However, with the increasing use of technologies in the built environment, it is possible to bring high-resolution levels to stock-level approach as well.

Furthermore, this action could improve stock detailing and promote solutions for energy efficiency. The summary of methods and tools underlined the connections between appropriated methods and specific purposes. Moreover, we could identify a need for clarification on the stock definition. Then, a specification was proposed: geo-stock for grouping buildings according to a geographic delimitation; and type-stock for grouping buildings according to characteristics in common (such as usage or purpose).

Finally, conceptual models were drawn to both building-level and stock-level analyses. In these conceptual models, we mapped the actual situation in the field and established relationships between the purposes identified. By sketching the conceptual model, we could recognise insights for opportunities for further research. A remarkable prospect for investigation is the study of representativeness of time resolution regarding energy measurement. Since energy monitoring is a challenging and time-and-money consuming task – especially in measuring end-uses consumption – optimising energy monitoring could benefit the building energy managing sector. Automated and smart buildings can take advantage of sensors and energy meters, but a large portion of buildings do not have such technologies implemented yet.

Therefore, the study of energy performance of buildings during the operation stage is a promising path to achieve the comprehension of energy usage. Studying the management of empirical data, structuring adequate frameworks to improve construction and building renovation, and applying real-world information in prediction models are duties that certainly will drive our society to more efficient buildings.

3. Overview of the school building stock in Brazil

This Chapter is the transcription of the following paper:

Mapping the energy usage in Brazilian public schools
Authored by Matheus Soares Geraldi and Enedir Ghisi.
Published in Energy and Buildings (ISSN: 0378-7788), volume 224, in 2020, and catalogued through the DOI: https://doi.org/10.1016/j.enbuild.2020.110209

Abstract:
Understanding the actual conditions in school buildings regarding energy usage and environmental satisfaction gives way to the development of consistent building stock modelling. In the Brazilian context, a deep-rooted inefficient structure of energy management implies a lack of mapping the actual conditions of the public schools. Therefore, this paper aimed to assess the actual energy performance of school buildings in Brazil. This paper innovates by integrating questionnaire responses and billed energy data to allow the construction of an evidence-based stock model through a statistical approach, which was never per- formed for the Brazilian building stock. Moreover, the association of energy use intensity (EUI) with the core aspects of building characteristics, occupancy, environmental satisfaction and necessary improvements mapped the relevance of such aspects in energy usage patterns. Additionally, a discussion of the EUI indicators was addressed. Results showed an unprecedented broad panorama of the school building stock in Brazil and its main features. In terms of statistical analysis, the Weibull distribution was appropriate for representing the continuous variables of the stock. The EUI as a function of the number of students was more suitable than the floor-plan area to achieve a reliable energy performance analysis. Several tests were performed to assess if the energy management, environmental satisfaction and maintenance practices impacted the EUI or not. Finally, the main conclusion was that the stock model obtained was simple and fit the energy management structure in the Brazilian scenario.

1. Introduction

School buildings have a fundamental role in society, acting as a vector of information for several different groups. The activities taken in school buildings may not only benefit the school environment itself but also reach the social and family circles of students and employees (MALDONADO, 2016). Understanding the energy consumption in those buildings can lead to both effective actions of upgrading the energy performance and promoting the construction of a conscious energy usage culture in society.

Analysing the energy performance in buildings is important to both compare the performance among technologies and identify patterns of consumption (WILDE, 2018). At stock-level, the energy performance analysis provides information to estimate future consumption and also to develop public policies regarding energy efficiency, which improves resources management (GERALDI; GHISI, 2020a).

The International Energy Agency (IEA) carried out the annexe 15 (Energy Efficiency in Schools) between 1988 and 1990 dedicating efforts specifically to study school buildings. The main outcome was a set of guidelines for the construction of school buildings in order to achieve a certain level of energy efficiency considering mainly Heating, Ventilation and Air-Conditioning (HVAC) and water heating (IEA, 1996). Aspects such as insulation of the envelope and window-to-wall ratio were also addressed.

Since then, Schools have been the target of many studies on building energy performance. In the building-level, some studies focused on identifying key indicators (LOURENÇO; PINHEIRO; HEITOR, 2014), lessons learned from retrofits (BURMAN; KIMPIAN; MUMOVIC, 2018; ZINZI *et al.*, 2016) and assessing low carbon performance (KOLOKOTSA *et al.*, 2018; LIZANA *et al.*, 2018; VIVIAN *et al.*, 2018). Meanwhile, at the stock-level, other studies addressed issues such as the overall energy performance evaluation (MONCADA LO GIUDICE *et al.*, 2013), the characterisation of the stock (BURMAN; KIMPIAN; MUMOVIC, 2018; KIM *et al.*, 2019; WANG, 2019; WILLIS *et al.*, 2011), stock modelling using cluster analysis (MARRONE; GORI, 2018), and the experiences from LEED certification (SCOFIELD; DOANE, 2018).

Table 3.1 summarizes a literature review of the previous works regarding energy performance assessment in school buildings. A non-exhaustive list is presented with major contributions important for this study. Table A.1 shows the authors, their contributions, the location of the study and the year of publication.

The energy performance of school buildings is very related to the context where the building is constructed, as shown by Pereira (2014), who established a functional statistic benchmarking by comparing the energy usage in several countries. The authors proposed indicators, such as total energy consumption, energy use intensity for heating, electricity use, and energy use intensity in relation to the number of students and floor plan area. The authors underlined that internal environmental quality (IEQ) must be considered in the stock analysis and comparative evaluations might help to achieve energy savings. Besides, the authors highlighted that many studies available in the literature analysed the energy performance based on estimations, simulations or primary energy. However, it is important to address the energy performance considering the real-world information, such as the billed energy consumption, especially due to the performance gap (the lack between simulated and measured energy consumption (BURMAN; MUMOVIC; KIMPIAN, 2014; JONES; FUERTES; DE WILDE, 2015; VAN DEN BROM; MEIJER; VISSCHER, 2018). For example, in Spain, Herrando *et al.* (2016) found a difference up to 30% between the actual and predicted energy consumption of school buildings. The authors pointed out that the main factor that caused this gap was the unrealistic consideration of the user behaviour in the simulation model and the hardship in modelling unusual loads. This outcome highlighted the need to know the building stock properly in order to achieve high reliability in energy performance analysis.

The energy performance is usually analysed through the energy use intensity (EUI) in terms of energy consumption per unit of floor-plan area or useful area (kWh/m².year) no matter the type of building. However, some studies discussed the unit of EUI for school buildings by calculating it in terms of energy consumption per number of students (kWh/student.year). Hong *et al.* (2014) compared the EUI indicator in relation to both number of students and floor-plan area using a regression analysis for schools in the United Kingdom for electric and heating demand. All coefficients of determination (R^2) were low (lower than 0.8), and the EUI that took into account the floor-plan area was considered suitable to represent the total energy demand. However, considering only the electric demand, the EUI that considered the number of students was the most suitable indicator.

Butala (2002) presented an energy audit analysis of 24 school buildings in Slovenia and compared their consumption for space heating, water heating and lighting with the minimum standard parameters of the energy code. Results were presented in terms of kWh/m², kWh/m³ and kWh/student. The suitability of each indicator was pointed out as a niche of study because any indicator can be used depending on the purpose of the analysis.

School buildings differ considerably in use, occupation, facilities, and user behaviour. Those differences make it difficult to summarise all features into a reliable statistical stock representation. For example, the level of education impacts energy performance (PEREIRA *et al.*, 2014). According to the dataset of the Displayed Energy Certification (DEC) of schools in the UK, buildings with high school have higher average consumption than primary schools due to the expressive differences in patterns of consumption (HONG *et al.*, 2014). Additionally, the age of the building is a significant aspect that impacts energy performance as well. In Canada, newer school buildings, which were built with more technologies and consciousness about energy conservation, presented a consumption lower than the average (OUF; ISSA, 2017).

The stock modelling – which consists in modelling all relevant characteristics of the group of the buildings – can be used to reveal improvements. For example, Marone (2018) used the k-means method to cluster a group of 80 schools into two well-defined representative elements. Those two reference buildings were used to select scenarios for retrofitting using simulation models. After the retrofits, the previous simulation results were compared to the actual operational performance. However, the study considered only energy demand for space heating ($kWh_{heating}/m^3$). Another example proposed a set of improvements in school buildings in a similar way in Rome (DE SANTOLI *et al.*, 2014). The main intervention was the enhancement of the thermal transmittance, resulting in energy savings up to 20% of the energy for heating when combined with some small modifications in the architecture.

Therefore, the understanding of the actual conditions in school buildings and their energy usage combined with a consistent stock modelling process might contribute for both improving the energy performance of this typology and enhancing the internal environmental quality (GERALDI; GHISI, 2020a). Furthermore, the correct use of energy contributes for preventing energy loss, providing affordable and large-scale access to energy, mitigating negative impacts on the environment, and, in the long run, achieving sustainable development (ARMIN RAZMJOO; SUMPER; DAVARPANAH, 2019).

In this sense, a combination of both top-down and bottom-up approaches was used in two complementary studies performed based on EPC (Energy Performance Certificate) and DEC (Display Energy Certificate) dataset in the UK. In the first evaluation, Hong (2014) applied a more general approach (top-down) by using a broad perspective and low detailed data (low granularity). A benchmarking process was developed using Artificial Neural Networks (ANN) and the building characteristics as inputs. The output was the benchmarks of electric energy performance and heating energy demand. Conclusions pointed out that this approach is useful to compare building among pairs. In the second study (bottom-up), Burman (2014) proposed an intrinsic method to evaluate a building by comparing it with itself, using past performance as a baseline. A post-occupancy evaluation was applied in four school buildings for two years. The authors identified specific building characteristics by considering the social context, mapping operations issues and establishing the baseline. A very detailed simulation model was developed to analyse the energy performance and to propose energy conservation measures. In both studies the level of detail was different – and complementary –, although school buildings were used as protagonist of a disruptive framework to assess energy performance. Thus, an integrative approach was indicated as a requirement to achieve high potential for energy performance in large-scale school buildings.

Nevertheless, the school building is inherently dependent on the context where it is inserted. Most of the studies in the literature discussed energy performance focusing mainly on space heating – which is a high end-use in terms of energy consumption. However, space heating is not a significant end-use in the Brazilian context (BORGSTEIN; LAMBERTS, 2014) due to the predominant hot weather, which requires space cooling or simply natural ventilation strategies. In addition, some recent studies detailed and analysed their national school building stock in terms of energy consumption, such as Taiwan (WANG, 2019) and Korea (KIM *et al.*, 2019). Due to the lack of studies which addressed the energy performance of school buildings in Brazil, considering the specificities of this country, this work seeks to map the actual conditions of the Brazilian school buildings.

The aim of this study is to assess the actual energy performance of the school buildings in Brazil and to analyse the main building characteristics and conditions that affect it. It was presented an integrated approach to analyse the school buildings at stock-level using the combination of self-reported information and billed energy data, establishing a panorama regarding energy usage of this typology in Brazil. A quantitative cross-sectional analysis was performed using correlation tests between annual energy consumption and the building characteristics such as occupation, appliances and size features. An indicator to better represent the energy performance was discussed. In addition, a descriptive analysis was presented by associating such a performance indicator with a perception of the key person about consumption, satisfaction with the built environment and the need for improvements. This study is the first part of a broader research. It is meant as source of information for the development of a suitable benchmarking methodology for Brazilian school buildings, by providing a comprehensive analysis and valuable data regarding energy performance.

2. Method

2.1. Data collecting

The data was prospected on energy consumption at the State Education Department of each of the 27 states of Brazil. Fifteen states joined in the survey and provided information of 5,321 schools which composed the population of this study. An interview was performed on the State Education Department Infrastructure sector and asked questions regarding the dynamics of energy management. Each State Education Department showed a singular process to manage the energy bills. There is no integrated system, and the energy bills are mostly dealt with by the finance department – i.e., in almost all State Education Departments, there is no analysis of the energy performance of the schools. Basically, the State Education Departments receive the energy bills and automatically pay them. They analyse the energy bill only when it is too expensive.

The dataset of 5,321 schools is composed of: monthly energy consumption over 2018; the number of students registered in that year; and the contact information (telephone, address and e-mail) for each school. From this dataset, only 2,315 schools had information about the floor-plan area (two out of the 15 Education Departments). Additionally, the datasets were sorted by names of the schools, which causes errors in matching information from different databases. Some information was lost due to the process of correlating information on energy bills with other information about the schools. This is due to the lack of building management that most State Education Departments struggle within Brazil. Since the dataset provided by the State Education Departments was too general, a questionnaire was applied to a sample of schools to raise specific information.

The sample size was calculated considering the 5,321 schools as the population of the study. Additional parameters were considered as recommended by the Brazilian National Electric Energy Agency (ANEEL, 2008) and Montgomery (2003), such as the level of confidence (95%) and the margin of error (5%). The sample size resulted in 359 schools to be surveyed. The sample size was similar to the one used for other studies in Brazilian schools for different purposes (359 schools by (INEP, 2018)). We applied the questionnaires via e-mail and considered a valid response when the questionnaire was fully completed.

It is remarkable to state that the voluntary aspect of the responses implies in supporting the aleatory nature required by the statistical data collecting. However, it also limited the survey to acquire data in a stratified sample mode – with the sample calculated for each state – which would be more suitable for this research. After the application, 419 valid responses were received, referring to schools all over the 15 states that joined the research.

2.2. Questionnaires

The aim of the questionnaire application was to obtain a comprehensive characterization of each school. This questionnaire was developed based on the EnergyStar ® Portfolio Manager (EPA, 2016) and on questionnaires of post occupant evaluation (LEAMAN; BORDASS, 2001). The platform Google Forms was used for the application. The target audience was the school headmaster (the Principal). The questionnaire was structured to obtain information regarding the building (as floor-plan area, building age, school facilities, etc.) as well as to qualify the energy use, environment satisfaction, and the necessary improvements in the building, according to the opinion of the Principal. The questionnaire response is related to the perception of the Principal – and not to a technical evaluation. For example, it was questioned about the perception of the Principal regarding retrofit needs, and it was not evaluate the real need, because it would require a technical inspection. In the same way, one questioned about the perception of the Principal regarding the satisfaction of the users in relation to the built environment. A comfort analysis was no performed because it is time and resource consuming. However, this assumption is justified by the approach of "questionnaire applied to a key person" (LEAMAN; BORDASS, 2001). This approach supposes that the Principal has a broad and representative perception of the built environment and the occupants of the school. Figure 3.1 represents the structure of the questionnaire and how the contents are connected.

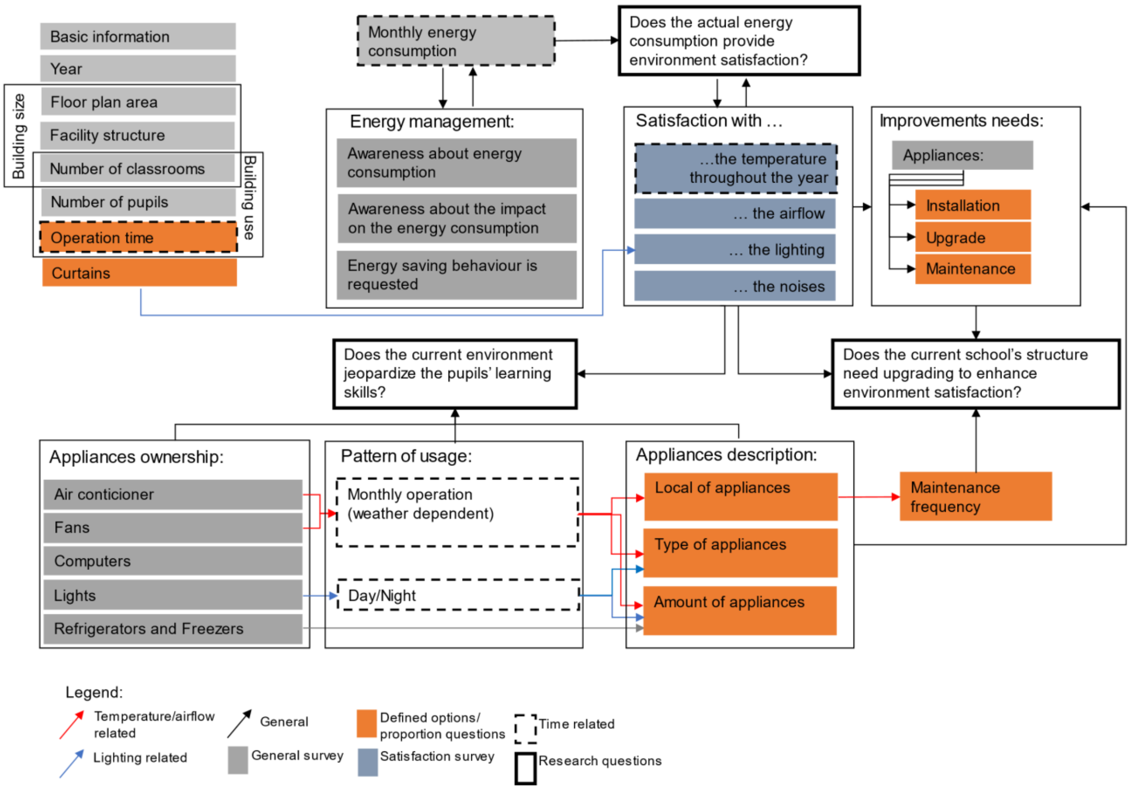


Figure 3.1 – Questionnaire framework: contents covered and research questions.

The questionnaire application was meant to characterise the stock of school buildings by taking advantage of the Principal as a pathway of dialogue and using the questionnaire to reach many schools. It is important to emphasize that Brazil does not have a database such as the one available on DECs in countries with a consolidated energy consumption declaration policy. The questionnaire is available in Appendix B.

2.3. Data analysis

The questionnaires responses were merged with the energy consumption information compounding an integrated dataset. This type of integrated dataset is a pioneer in the context of the Brazilian public schools, once it assembled information of the building stock in terms of energy performance and satisfaction with the built environment.

Firstly, all the dataset variables were recoded into their types: continuous, categoric and string variables (text-based). Then, an exploratory analysis was performed to check for outlier values and identify the statistical measures of the continuous variables, such as the quantiles, the average, the maximum and minimum values. A specific analysis of the energy bills of big consumers is presented, as well.

Thenceforth, the energy performance was analysed at a stock-level to discuss the EUI unit and define an adequate indicator to represent the stock reality regarding the energy performance of buildings.

Finally, correlations between the energy performance indicator and the questionnaire responses were performed. Statistical tests were used to assess the impact of energy management, the satisfaction with the built environment, and the necessary improvements on energy usage.

2.3.1. Overview

In this step, it was presented the statistical summary (quantiles, the average, the maximum and minimum values) of the continuous variables, i.e., energy consumption, floor-plan area and the number of students. It was shown the magnitude of those variables and discussed the statistic distribution that defined them. Tests of fitting were applied to identify the statistical parameters that represent the data distribution.

Furthermore, it was presented a summary of the proportion of relevant information that the schools have. The number of air-conditioning units, classrooms and refrigerators were informed through histograms. The building age, the shifts of operation and school facilities were presented in proportion graphs. The ownership of fans and curtains, and the type of lighting system and air-conditioning units were presented as well.

Additionally, it was performed a comprehensive analysis of the detailed energy bills of schools supplied in high voltage. Data from state schools of Santa Catarina was used to perform this analysis. Analysing the detailed energy bills is important to address the consumption and demand patterns throughout the year. According to their power demand, the power distribution company classifies schools in either group A or group B.

Group A is composed of big consumers (supplied in high voltage), and the energy bill is detailed with the amount of energy consumed during peak and off-peak hours. Also, the energy contract for schools in group A is on-demand, which means that the State Education Department informs a fixed value of power demand per month that must be available for the school.

Meanwhile, group B is measured in monthly resolution, and only consumption is informed. Despite the building stock is mainly composed of schools in group B (95%), it was performed the analysis for schools in group A because there is no power demand or peak/off-peak information in group B. Additionally, as the stock is renovated, the schools tend to receive air-conditioning systems and upgrading in electrical infrastructure, moving to group A.

Thus, it is important to analyse the schools that are already in group A to understand patterns and relevant information.

2.3.2. Discussing the EUI indicator

Defining an appropriate performance indicator is relevant to represent the building stock correctly. It is important to have a simple and effective indicator that can represent the magnitude of the building energy consumption in relation to its most essential characteristics. A parallel is drawn with the Body Mass Index (BMI), which is a widely known indicator for measuring whether a person is at his or her ideal weight. It is a simple but effective measure because it uses information that is easy to obtain, and it provides a general notion of health. In addition, when compared to milestones, it serves for benchmarking performance (WANG; YAN; XIAO, 2012).

Usually, the EUI adopted is based on the floor-plan area (kWh/m^2.year) buildings in general. However, there are different units in the literature, depending on the archetype analysed. For example, the Chartered Institution of Building Services Engineers (CIBSE) presents the calculation of the EUI based on the number of people to analyse prisons (kWh/prisoner.year) and number of served meals to analyse restaurants (kWh/meal) (CIBSE, 2008); the DOE suggests EUI based on number of employees to analyse office spaces (Btu/employee.year) and based on number of beds to analyse hotels and hospitals (Btu/bed.year) (DOE, 2013).

Some studies examined the EUI unit for schools in other regions (HONG *et al.*, 2014; PEREIRA *et al.*, 2014). However, it is important to emphasise that the energy consumption in those studies contemplated environmental conditioning (mostly for heating), which makes the consumption very related to the size of the building. In Brazil, most of the public schools do not have air-conditioning systems, and information about the built environment is surprisingly difficult to obtain, unlike the number of students. Consequently, an indicator based on the number of students would be advantageous to express a representative stock model and to achieve a reliable energy performance analysis.

Hence, both indicators were tested using data of the 419 schools, i.e., EUI in relation to the floor-plan area and to the number of students. First, a matrix of correlation indicates the strength of correlations among the energy consumption, the number of students and the floor-plan area. In the sequence, a regression analysis using the general linear model was performed to fit the relation between energy consumption and both variables tested. The regression analysis calculates the equation of the model (angular and linear parameters) and its coefficient of determination (R^2) measured the correlation of the variables point to point (adjust of the observed data to the model). Conclusively the p-value indicates if the model was appropriate or not. A model was considered appropriate when the p-value was less than 0.05 (i.e., significance level equal to 5%).

2.3.3. Analysing the impact of the building energy management on EUI

In this step, the EUI was associated with the responses of the questionnaire regarding the building energy management adopted by the building administration. The aim was to verify if there are preliminary values of energy conservation that influence energy usage. A hypothesis test was applied to infer if the awareness of how much energy the school consumes and the incentive to save energy impacted energy performance. The hypotheses were H0 (there is no statistical difference between the groups) and H1 (there is a statistical difference between the groups). The analysis of responses with two or more factors was performed applying the Kruskal-Wallis test for non-parametric distributions. In these cases, when the Kruskal-Wallis rejected H0, and a post hoc evaluation was also applied using Wilcoxon pairwise test for matching samples comparison. This post hoc test addressed the interactions among groups. P-values less than 0.05 indicated a rejection of H0 at 5% of significance level, which means that there is statistical evidence that the EUI was different between the groups analysed.

2.3.4. Analysing the impact of the satisfaction with the built environment on EUI

The satisfaction with temperature, lighting and airflow were registered on a Likert-like scale in the questionnaire. The correlation between environmental satisfaction and the EUI was performed in order to verify the hypothesis that schools with high energy consumption provided good environmental satisfaction. To help the reader to understand this analysis, a Likert-like horizontal bar was plotted for each question showing the frequencies of the responses (from very unsatisfied to very satisfied) and above it, the average EUI of the schools of each category was plotted. Such graph elucidates the difference of the energy performance among the schools where people were very unsatisfied, unsatisfied, neutral, satisfied and very satisfied with the built environment.

2.3.5. Analysing the impact of the necessary improvement on the EUI

A similar analysis using Kruskal-Wallis and Wilcoxon pairwise test was performed to infer the influence of the necessary improvements on EUI. Responses regarding the frequency of maintenance and which system (HVAC, curtains, fans and lighting) should be improved, replaced or installed were correlated with the EUI.

Finally, the questionnaire had an open-ended question so that the Principal could complement the data collection with information that was not pre-established. This question was analysed through text mining technique in the R environment, applying a tidy approach (packages: tidyr, tm, stringr, tidytext, purr, dplyr) (SILGE; ROBINSON, 2017). This technique quantifies the frequencies of significant words (and synonymous) to illustrate the most frequent terms graphically. In the result of text mining, it was possible to recognise insights about the context of the schools.

3. Results

3.1. Overview

An overview of the most relevant variables expresses a first concept about the buildings that compound the stock in the study. Table 3.1 shows the summary statistics of the floor-plan area, which gives an outlook of the sizes of the schools; the number of students, which gives a notion of occupancy; and the annual energy consumption which informs the energy usage.

Table 3.1 – Summary statistics of the continuous variables.

Measure	Floor-plan area (m^2)	Number of students (students)	Annual energy consumption (kWh)
Minimum value	100.00	49.00	426.00
Lower Quantile (25%)	900.00	322.25	10,796.00
Average (50%)	1,501.69	534.50	23,667.00
Upper Quantile (75%)	3,065.50	817.75	42,190.00
Standard deviation	1,785.34	342.16	22,543.57
Maximum value	7,326.37	1,569.00	98,720.00

The total annual energy consumption, the floor-plan area and the number of students, were plotted in histograms (Figure 3.2) to show the behaviour of each variable according to the stock characterisation. It is important to emphasise that in this step, it was considered the total energy consumption (from the energy bills), and no treatment to relativize the energy usage was performed. The histograms were built with 20 bins, and a curve of the Weibull distribution based on the data was plotted in red.

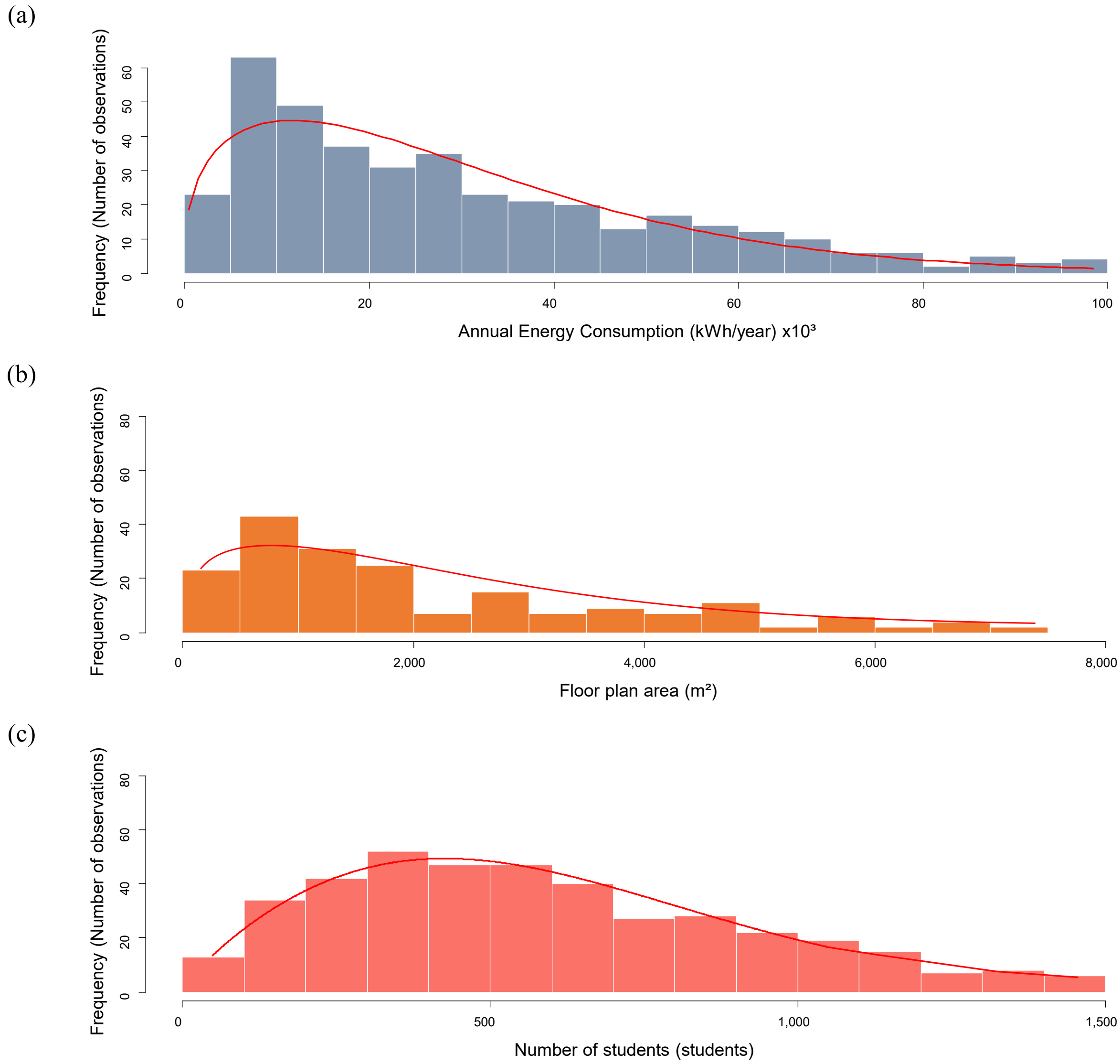


Figure 3.2 – Histograms of the continuous variables: annual energy consumption (a), floor-plan area (b), and the number of students (c).

The Anderson-Darling hypothesis test rejected the assumption that the data followed a normal distribution. It is possible to see through the histograms that the data followed an exponential distribution. A non-parametric test was applied to confirm which distribution best described those data and the Weibull distribution was the most appropriated (coefficient of determination R^2 equal to 0.997) in comparison with other distributions tested (gamma distribution R^2 equal to 0.970 and exponential R^2 equal to 0.91).

The Weibull distribution is a particular type of exponential distribution. It is commonly used for testing the lifespan of products and for representing the wind speed frequency. A dataset follows the Weibull distribution if its frequency distribution can be represented through Equation 1:

$$f(\alpha,\beta,x) = \frac{\alpha}{\beta} \times (\frac{x}{\beta})^{(\alpha-1)} \times exp^{-(x/\beta)^{\alpha}} \qquad (1)$$

Where:

α is the shape parameter of the distribution {α Є |R | 0 < α < ∞}

β is the scale parameters of the distribution {β Є |R | 0 < β < ∞}

x is the independent variable

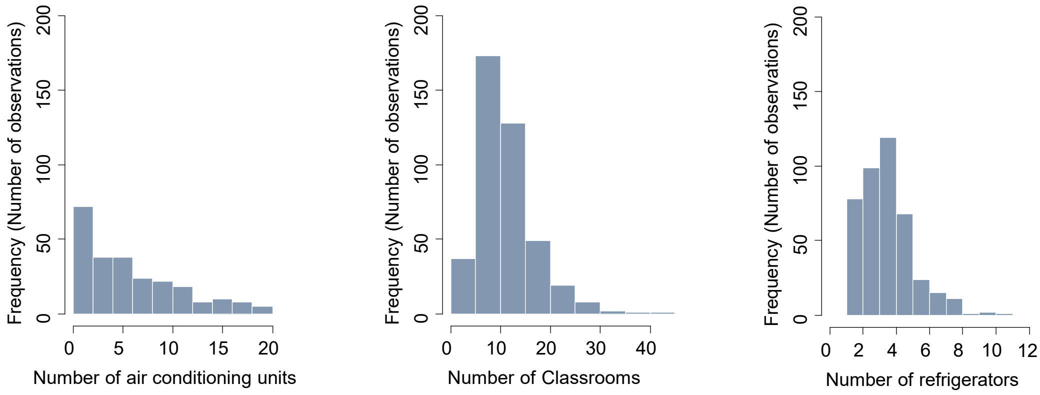
It is important to know the distribution that these continuous variables follow, as they may indicate appropriate statistical models for analysis. The distributions shown in Figure 3.2 are similar to those obtained with data from the Building Performance Database for the same typology in the US (LBNL, 2021). For the continuous variables of this study, the Weibull distribution parameters are shown in Table 3.2.

Table 3.2 – Parameters of the Weibull distribution of the continuous variables.

Parameter	**Variable (x)**		
	Floor-plan area (m²)	**Number of students (students)**	**Annual consumption (kWh)**
α (shape parameter)	2.01	1.61	1.21
β (scale parameter)	1,971.00	632.06	2,348.00
Expected value [E(x)]	1,740.53	565.95	22,114.50
Standard deviation [Sd(x)]	905.16	359.56	18,343.90
Anderson-Darling statistic (adjustment quality)	3.09	2.37	29.76
p-value	0.00	0.00	0.00

The parameters α and β define a Weibull distribution in the same way that the average and the standard deviation define a Normal distribution. The expected value is the equivalent to the average of the normal distribution, and the standard deviation has a similar function of indicating the dispersion. It is possible to notice that the hypothesis of those three variables following the Weibull distribution was accepted at the significant level of 99% (p-value less than 0.01 in all three cases) according to the Anderson-Darling test.

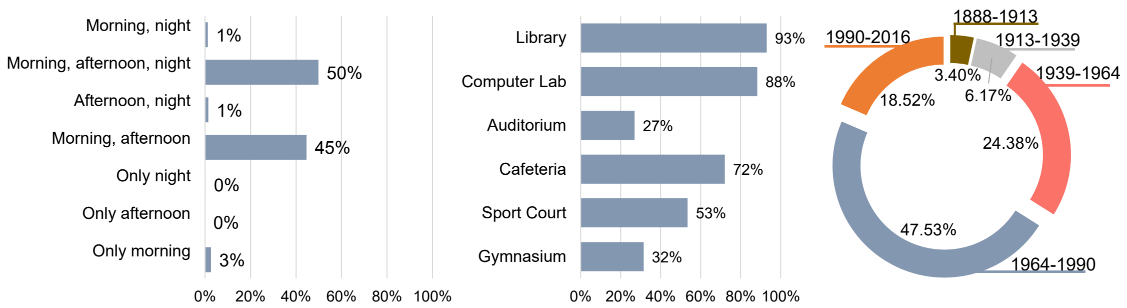
In order to address the relevant end uses in the school buildings, the number of air-conditioning units and refrigerators and freezers in each school were surveyed. It was raised the number of classrooms, which is related to the size of the school and lighting needs. Those three pieces of information are described in Figure 3.3.



(a) (b) (c)

Figure 3.3 – Histograms of the number of air-conditioning units (a), number of classrooms (b) and number of refrigerators (including freezers) (c).

Figure 3.3 shows a significant number of schools with no air-conditioning. Regarding the number of classrooms, most schools have between 5 and 15 classrooms. Additionally, most schools have between 1 and 5 refrigerators or freezers. Figure 3.4 shows the frequencies of shifts of operation, facilities and the proportion of the year of construction of the school buildings.



(a) (b) (c)

Figure 3.4 – School building characterisation due to shifts of operation (a), facilities (b) and year of construction (c).

Many of the schools operate during the morning and afternoon and night or only in the morning and afternoon. Regarding the school facilities, libraries, computer labs and cafeterias are the most frequent. Many of the schools were built between 1939 and 1990, which means that they probably were built with poor guidance concerning energy performance because they are outdated buildings.

Figure 3.5 presents the proportion of the schools with fans, curtains and the predominate types of lighting and air-conditioning systems.

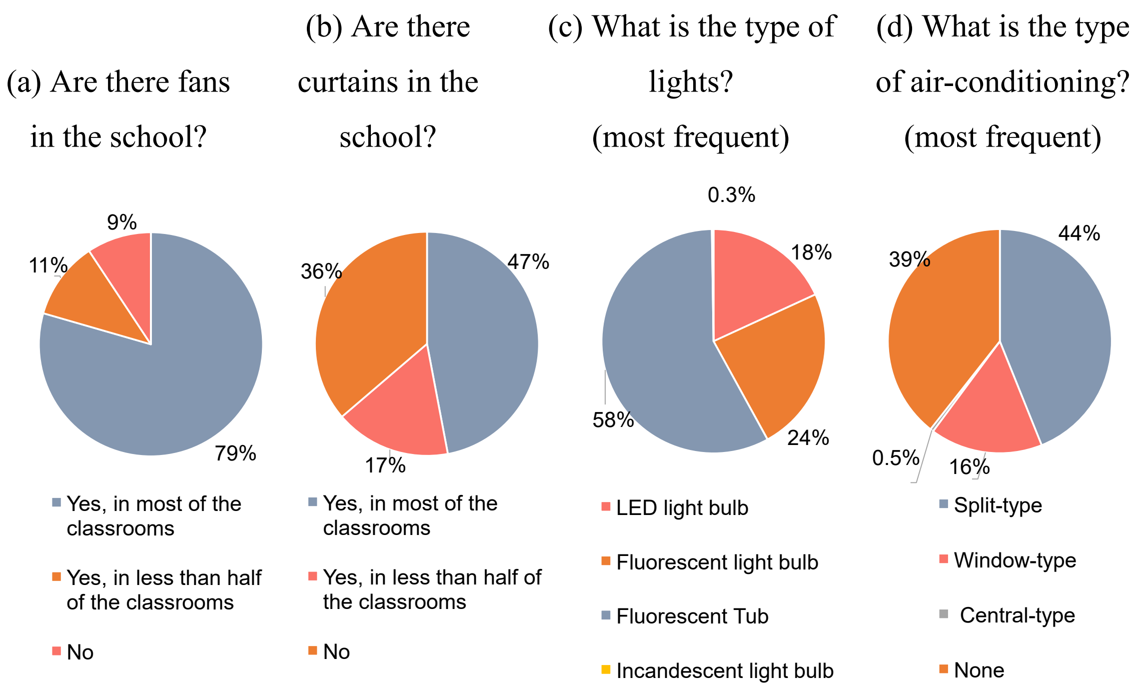
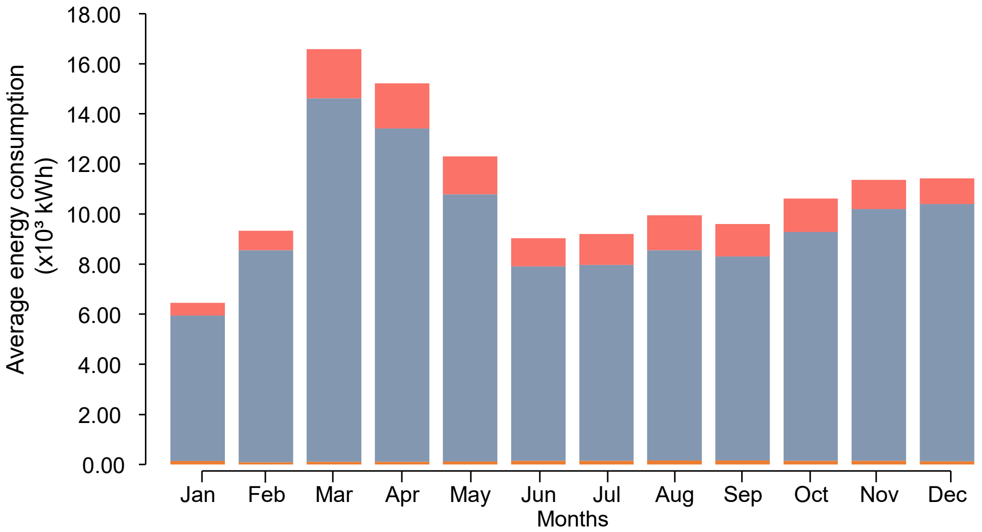


Figure 3.5 – Proportion of schools that have fans (a), curtains (b) and types of light bulbs (c) and air-conditioning (d).

Despite a significant number of schools with no air-conditioning (39%, Figure 3.5.d), the majority of schools have fans in almost all classrooms (79%, Figure 3.5.a) which expresses some concern related to the thermal comfort of students. However, although curtains are considered a basic item to improve thermal and visual comfort, there are no curtains an expressive number of schools (36%, Figure 3.5.b). Otherwise, the lighting systems are more apparently efficient, once most of the lights are fluorescent tubes or LEDs. The predominant types of air-conditioning are split type, while the central type is almost not present.

3.2. Analysing the energy bills

The energy bills can provide relevant information regarding the patterns of energy usage. Data of all high voltage consumer schools were used to perform a comprehensive analysis of the energy bills of schools in Group A, totalizing 20 schools. Those schools are in Florianópolis (State of Santa Catarina). It is important to highlight that the schools fully equipped with air-conditioning systems are in group A due to the power demand that the cooling appliances require. Figure 3.6 presents the monthly energy consumption detailed by peak, off-peak hours and reactive energy throughout the year of 2018.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Consumption (peak)	0.52	0.78	1.95	1.80	1.52	1.13	1.23	1.40	1.29	1.33	1.16	1.03
Consumption (off-peak)	5.80	8.46	14.51	13.29	10.66	7.75	7.82	8.39	8.14	9.13	10.05	10.27
Reactive consumption	0.14	0.10	0.11	0.12	0.12	0.15	0.15	0.16	0.16	0.15	0.15	0.13

Figure 3.6 – Average monthly consumption categorised according to the type of consumption of the schools supplied in high voltage (group A).

Figure 3.6 shows that the most expressive consumption occurred during off-peak hours. Peak hours are considered between 6pm and 9pm. This is expected since the activity in schools occurs mainly during the day. Summer holidays often occur between December and February in the public education system in Brazil. The months with higher consumption are those following the summer holidays, but still with high temperatures (March, April and May).

It is possible to see that the reactive energy consumption is existent but not expressive. Reactive energy is the fraction of the total energy that does not produce work. Thus, the lower the reactive energy consumption, the more efficient the building appliances. The lowest power factor calculated for the stock analysed was 0.96, which indicates that the schools are a typology with good power quality. However, it is important to keep up with this trend because reactive energy consumption has been increasing in the past few years (AHMAD *et al.*, 2019). According to Ahmad *et al.* (2019), the end uses that are leading the increase of reactive energy consumption are the use of laptops, mobile chargers and LED technologies. Since these technologies will be more and more present in schools as well, reactive energy consumption could be a potential issue in the future.

The energy contract of the schools in group A is on-demand: the State Education Department informs and pays a fixed value of energy demand per month. If the school demanded more energy than this fixed value, an overpriced fee is charged on the exceeding energy demand. If the school demanded less energy than the contract value, the contract demand is charged. Thus, the difference between contracted and measured power demand could show if energy contracting is well defined or not. Figure 3.7 presents the maximum, minimum and average values of these differences between contracted and measured power demand throughout the year. The standard deviation is presented by means of error bars. The ideal case will be if the difference between contracted and measured power demand reaches zero in every month.

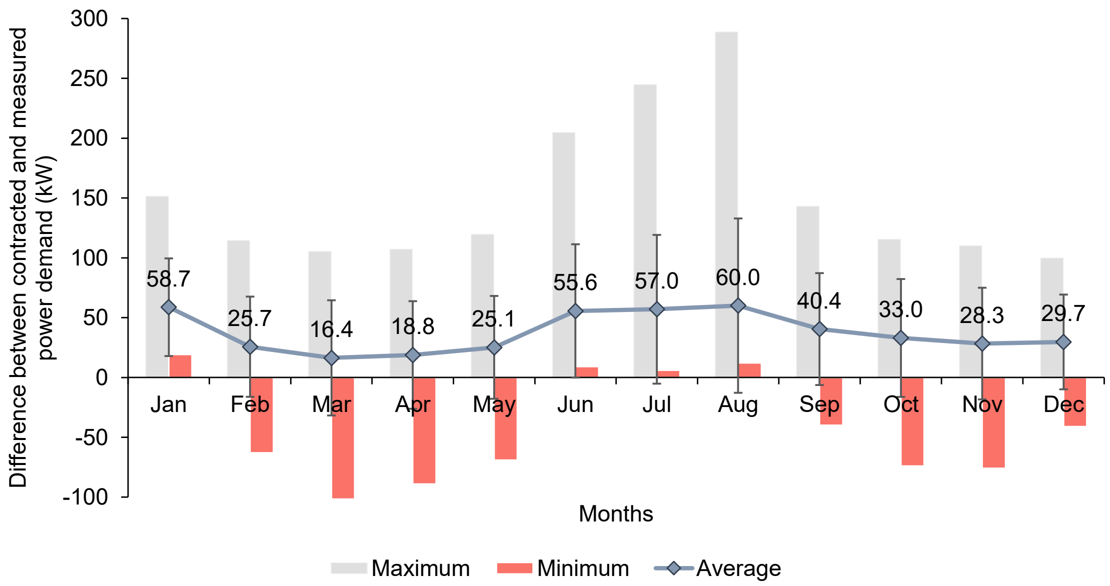


Figure 3.7 – Averages and standard deviations of the difference between contracted and measured power demand of the schools supplied in high voltage (group A).

Figure 3.7 shows that the contracting of power demand is overestimated since the average of differences is positive in every month. In 2018, the total remaining power demand was 7,834.94 kW. Meanwhile, the excessive power demand was 724.05 kW. A simple adjustment on the energy purchasing terms could save about R$ 122,000.00 considering the whole year of 2018, resulting in savings of about 10% of the total amount paid (sum of all energy bills of group A).

Also, as the building stock is renovated and full air-conditioning structures are installed, many schools probably receive electrical infrastructure renovation as well, shifting from Group B to Group A. This is propelled, at some level, by the impact of the climate change that increases global temperatures. Thus, it is important to keep in mind that climate change will impact future trends of the energy consumption of the Brazilian school stock. Concurrently, the energy consumption increases to provide indoor thermal comfort since the cooling demand increases due to global warming. This makes the greenhouse gas emissions escalate, resulting in a contribution to climate change.

An alternative to mitigate this vicious cycle is the use of integrated Hybrid Power Systems. As discussed by Razmjooa *et al.* (2020) in Iran, the use of those systems is a reliable way to achieve energy sustainability in developing countries, in alignment with the Sustainable Development Goals from the United Nations. However, a concise framework is required from leaderships including adequate policies, planning and strategy, and enough investment on clear energy production.

In the light of the above, two topics to be explored in further studies are the calculation of the impact of climate change in future trends on the school building stock and the effectiveness of alternatives to mitigate those impacts, such as to optimise the stock renovation considering Hybrid Power systems.

3.3. Discussing the EUI indicator

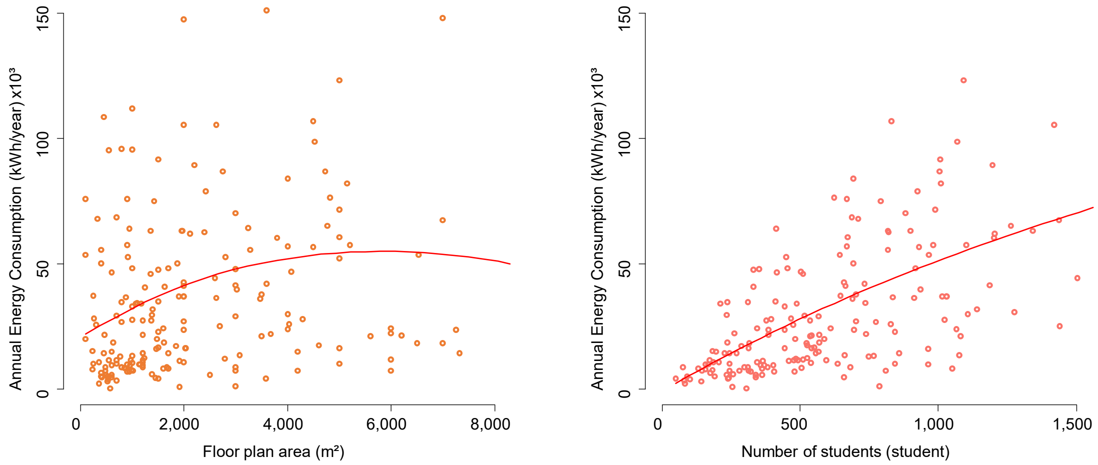
The Energy Use Intensity (EUI) is a necessary indicator to relativize the energy performance according to a notable characteristic of the building, once the energy consumption itself is too general. Usually, the EUI is presented in terms of the floor-plan area (kWh/m².year). However, what is the adequate unit to represent the energy performance of a specific typology? This answer can be found in the statistical representation of the data. Table 3.3 presents the Spearman correlation matrix of continuous variables of the building stock.

Table 3.3 – Correlation matrix of continuous variables.

	Floor-plan area (m²)	**Number of students**	**Number of classrooms**	**Number of refrigerators**	**Number of air-conditioning units**	**Annual energy consumption (kWh)**
Floor-plan area (m²)	1.00					
Number of students	0.18	1.00				
Number of classrooms	0.29	**0.58**	1.00			
Number of refrigerators	0.23	0.14	0.26	1.00		
Number of air-conditioning units	0.08	0.09	0.08	0.23	1.00	
Annual energy consumption (kWh)	0.13	**0.33**	0.28	0.24	**0.61**	1.00

The number of students presented a stronger correlation with the annual energy consumption than the floor-plan area (0.33). However, it is remarkable that the number of air-conditioning units plays an important role in energy performance once the correlation with the consumption was strong (0.61). It is important to highlight that the number of classrooms units had a slight correlation with the number of students (0.58), which makes sense once the school capacity (number of students enrolled) is planned according to the school size.

The principal variables (floor plan area, number of students and annual energy consumption) were used to perform a stronger analysis employing linear regression to identify an adequate EUI indicator. The difference of using a correlation and a regression analysis is that the correlation associates two variables according to their variances while the regression expresses the association by ordered pairs. In this sense, regression analysis is a concept of association stronger than correlation. The regression analysis was developed using the general linear model (Figure 3.8).



Model fitting:

Equation: Y = 32,912.25 + 1.944*X

R^2: 0.0115

F-statistic: 3,341.9 (p-value: 0.06906)

(a)

Model fitting:

Equation: Y = 4,061.64 + 43.278*X

R^2: 0.4005

F-statistic: 121.6 (p-value: < 2.2e-16)

(b)

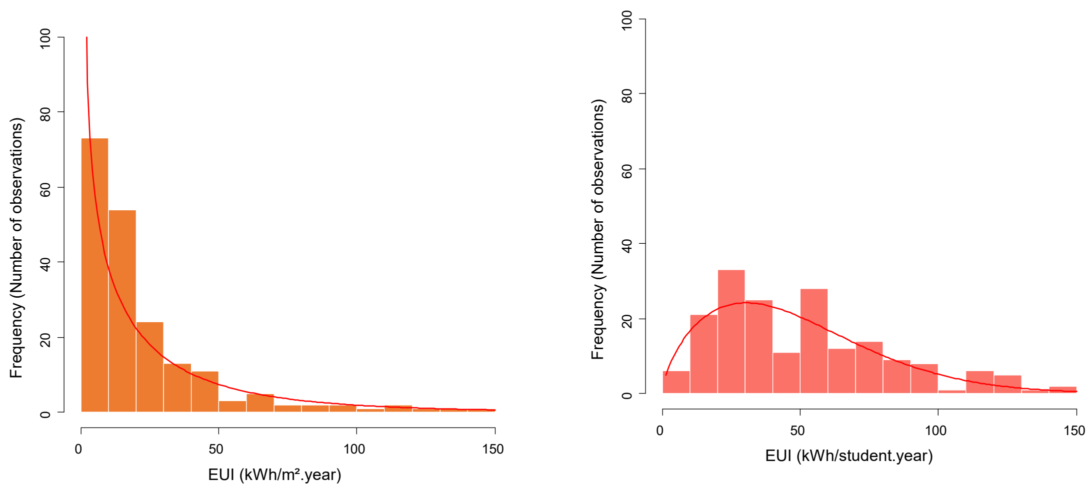
Figure 3.8 – Regression models in relation to the floor-plan area (a) and the number of students (b).

Figure 3.8 shows a higher coefficient of determination (R^2) for the regression model per number of students (0.4005) than per floor-plan area (0.0115). Both coefficients of determination were low. However, it is important to emphasize that, in this case, we did not attempt to prove a cause-effect model as such proposed by the general linear model. Instead, we took advantage of the coefficient of determination to measure the association point to point between the variables. In fact, a cause-effect model to predict the energy performance of buildings using only one variable as predictor will rarely be reliable because buildings are complex systems (WILDE, 2018).

This result is supported by Song *et al.* (2014), who investigated the correlation of energy consumption, the number of students and floor-plan area using regression analysis for schools in the UK. The authors found that the kWh/m²year was a more suitable indicator for schools in the UK when the space conditioning is considered. While only electric energy is considered, kWh/student showed higher suitability. In regions with a significant presence of cold climate (such as in the northern hemisphere), a significant amount of energy is used for space heating. Thus, adopting the EUI in relation to the area or the volume of the building in those cases makes sense once the environment is conditioned and it is closely related to the dimension of the building. In

Brazilian schools, the space conditioning is present predominately in the non-classroom environments (49% in office rooms, such as secretariat, or the principal office, and 50% in libraries or laboratories), as observed in the questionnaire responses (question 18). There are only a few schools with air-conditioning in classrooms (8%). If the schools presented space heating, the correlation between the number of students and the energy use would not be adequate. The number of students influences electricity loads but reduces the heating demand due to metabolic heat gain. However, none of the schools presented heating systems, and the energy supply was exclusively electricity.

Figure 3.9 shows the histograms of both EUI calculated in relation to the floor-plan area and number of students.



(a) (b)

Figure 3.9 – Histograms of EUI in relation to kWh/m².year (a) and kWh/student.year (b).

Figure 3.9 elucidated the behaviour of both EUI per floor-plan area and the number of students. It is possible to see that both variables have different trends and shapes. The EUI per floor-plan area follows an exponential distribution (red line) and have a high number of frequencies ranging from 0 to 10, which means many schools with low consumption and a big area. In contrast, the EUI in relation to the number of students follows a Weibull distribution (red line) and present a smoother shape. This is also a similar distribution of energy consumption itself. One can identify an expected value (peak of the red line in Figure 3.9.b) ranging from 30 to 40 kWh/student.year.

Thus, in light of the above, we understood that EUI in terms of the number of students is more reasonable and reliable to express the energy use intensity for the

Brazilian stock. From here on, we adopted the unit for EUI as kWh/student.year for all analysis.

An interesting analysis using EUI is to check the EUI behaviour throughout the year. Figure 3.10 presents this evaluation for schools with air-conditioning in most of the classrooms or at least in half of them (blue bars), and schools without air-conditioning in classrooms (orange bars).

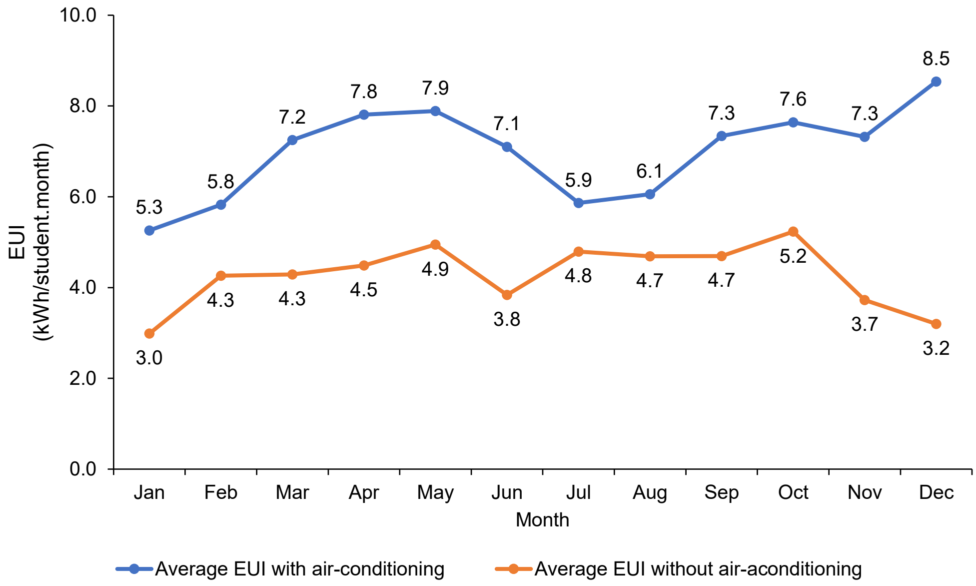


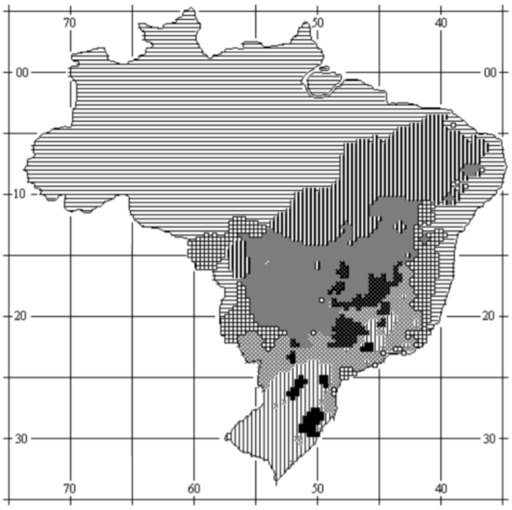
Figure 3.10 – Average EUI of the schools with and without air-conditioning throughout the year.

Schools with air-conditioning have an average annual EUI up to 60% higher than schools without air-conditioning. The standard deviation is higher as well, indicating that schools with air-conditioning are very heterogeneous. An exception is the EUI in December for schools with air-conditioning, which had a standard deviation of 19.1 kWh/student.year. This higher variability in December could be due to the beginning of the summer when the air-conditioning started to operate depending on the will of the teachers and Principal.

Despite a smooth variation throughout the year, it is possible to verify the constancy of the EUI in both groups of schools. As expected, the EUI of schools with air- conditioning is impacted by temperature variation. However, it was noticed a major influence of the summer (January) and winter (July) breaks on the EUI. A relative higher EUI during the breaks is observed, probably due to the occupancy of the employees (even with reduced working time) or continuous loads such as server rooms.

Nevertheless, in this case, energy audits are necessary to understand the energy end-uses and establish the baseline. A suggestion for further works is to perform energy audits based on sub-monitoring and TM22 sheet to breakdown the energy consumption information in case studies.

In addition, the EUIs of the schools were analysed according to each bioclimatic zone of Brazil (Figure 3.11). The Brazilian Standard NBR 15220 (2003) (NBR 15220, 2005) determines and delimitates eight bioclimatic zones in Brazil. Briefly, the zones are characterised by the predominant monthly average maximum temperature, monthly average minimum temperature and monthly average relative air humidity. Those zones serve to define building guidelines for comfort directives. Zone 1 predominantly needs heating strategies during winter and passive cooling strategies during summer (temperate climate), while zone 8 needs cooling strategies during all year (tropical climate). Zones 2 to 7 refer to intermediate climate conditions.



Zone	Symbology	Proportion of the territory (%)	Number of schools included in this research	Average EUI (kWh/students. year)
Zone 1		0.8	1	90.57
Zone 2		6.4	35	58.75
Zone 3		6.5	161	57.70
Zone 4		2.0	28	58.98
Zone 5		5.6	25	74.05
Zone 6		12.6	60	47.86
Zone 7		12.6	28	139.30
Zone 8		53.7	81	108.89

Figure 3.11 – EUI of the schools according to each bioclimatic zone in Brazil. Source: Based on (NBR 15220, 2005).

Figure 3.11 shows how many observations (schools' responses) were obtained for each zone. Although the zoning covers all Brazilian territory, it is important to mention that the proportion of schools in the sample will not match the proportion of the zones in the territory. For example, Zone 8 represents 53.7% of the territory, but most of it represents no-urban areas, such as the Amazon Forest. Likewise, São Paulo state (the most populated state and probably with more schools) is covered part by Zone 3 and part by Zone 5.

Figure 3.11 shows a higher average EUI for Zones 1, 7 and 8. As Zone 1 only has one observation, it might not represent the stock; thus, no analysis can be made. Zones 7 and 8 represent tropical climates, then, the use of the air-conditioning all year and a higher proportion of schools with air-conditioning can be possible explanations for the higher EUI.

It is important to clarify that none of the schools had heating systems. Hence, all appliances are supplied with electricity. There is an exception for cooking food, which is performed using liquefied petroleum gas (LPG). However, this activity is outsourced by the public administration and fully controlled by the contracted companies. Thus, we do not have access to this information and the cooking of food was disregarded in this study.

The work of Saraiva *et al.* (2019) compared the comfort indicators for one school in zone 8 (Amapá State) and one school in zone 3 (Minas Gerais State) in Brazil. Differences were found in the indicators for thermal comfort. The school in zone 3 showed higher levels of comfort than zone 8. Both schools had HVAC systems; however, in the school in zone 8, the air-conditioning was damaged in several classrooms, which gives the school in zone 3 a more stable comfort condition (but as a consequence, higher energy consumption).

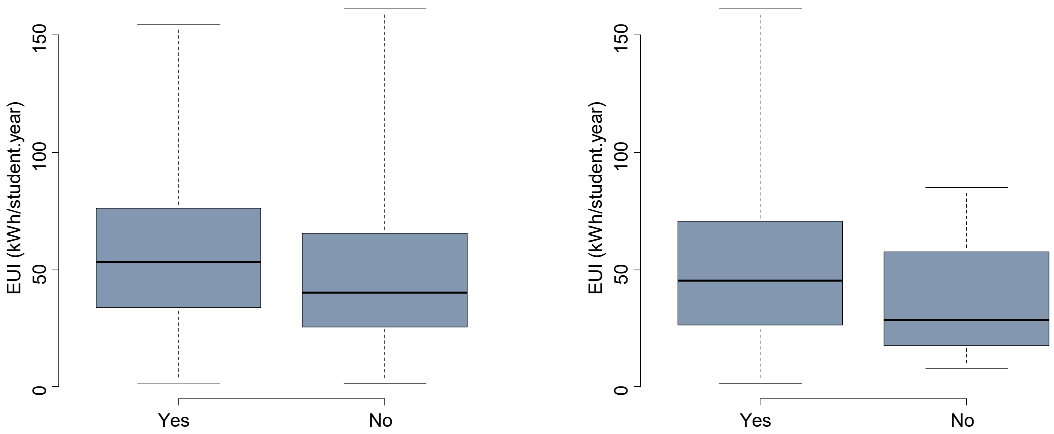
Nevertheless, both data presented by Saraiva *et al.* (2019) and by this study elucidated that a framework considering bioclimatic zoning could explain specificities regarding energy performance and comfort indicators in Brazilian schools. However, it requires a suitable sample, stratified by zones (or states). Thus, this analysis is indicated for further studies. From now on, all analyses were performed considering no stratification.

3.4. Impact of the building energy management on EUI

The whole building management in Brazilian school buildings is fully performed by the Principal. Examples of such activities are hiring systems maintenance, appliances replacements, and awareness of energy savings. However, the energy bills are not delivered at the school – they are forwarded directly to the State Education Department due to a standard process in Brazil. The energy performance is closely related to the awareness of energy usage (NGUYEN; AIELLO, 2013). So, it was attempted to verify if the energy awareness had an impact on the EUI in the school building stock under study (Figure 3.12).

(a) Do you (as the Principal) know the monthly energy consumption of this school?

(b) Does the school motivate the employees to save energy?



Kruskal-Wallis test
Chi-Square = 2.4871
degree of freedom = 1
p-value = 0.1148 (accept H0)

Kruskal-Wallis test
Chi-Square = 0.9009
degree of freedom = 1
p-value = 0.3425 (accept H0)

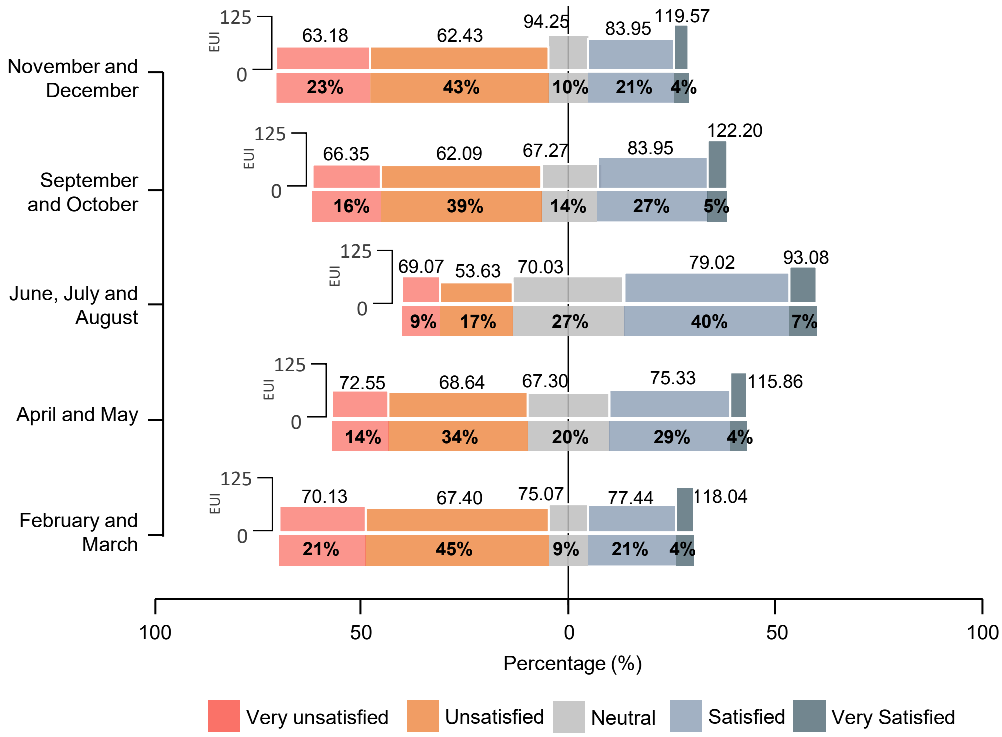
Figure 3.12 – EUI versus building energy consumption information.

Both tests showed that there is no statistical difference of EUI between schools whose Principal knows how much the energy consumption is or not. The same inference was obtained regarding the awareness about energy savings or not. Yet, it is possible to verify in Figure 3.12.b a higher variation in “Yes” responses. In fact, there were much more responses as “Yes” for this question, and it was considered a bias due to the social desirability. It is more socially acceptable for the Principal to answer that he/she does motivation work in his/her school, even though his/her awareness is not real or effective.

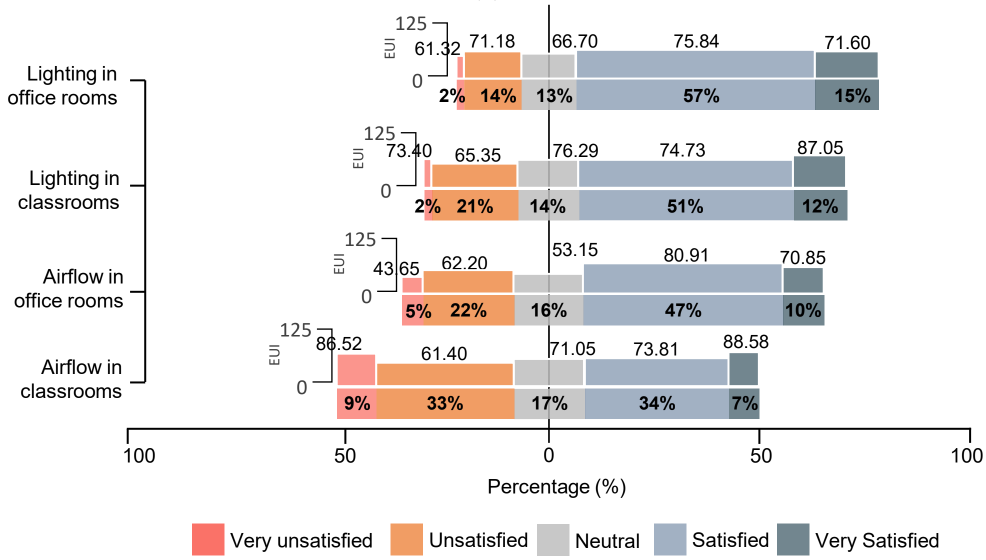
Thus, it was identified a missing link between the energy consumption place (school) and who pays the energy bill. The energy is consumed at the schools, but who receives the information about how much energy was used is the sector of payments of the State Education Department. There is no analysis of the energy bills to understand school building performance. In fact, the team that receives the energy bills is composed of employees of the financial area, with no expertise in energy performance. We found that this gap of information is the explanation of why knowing or not the energy performance of the school does not affect the performance of the school: there is no penalty or consequence for the schools that are inefficient in terms of energy consumption.

3.5. Impact of the environmental satisfaction on EUI

Analysing the satisfaction with the built environment is important to assure that the building is achieving its purpose. For school buildings, providing adequate environmental satisfaction delivers a fertile space the teaching-learning processes. Figure 3.13 presents the environmental satisfaction perception as well as the average values of the EUI for each category in a Likert-like scale graph. As it was explained in Section 2.3.4, the frequencies of the Likert-like scale were plotted (values in percentage) and the average EUI. The size of the bars is proportional to their value, and a simple y-axis was plotted in order to enable visual comparison among values. For example, in Figure 3.13.a, 23% of the schools responded to be very unsatisfied with the temperature in November and December, and the average EUI of those schools is 63.18 kWh/student/year.



(a)



(b)

Note: EUI expressed in kWh/student/year.

Figure 3.13 – EUI versus environmental satisfaction with the temperature throughout the year in classrooms (a), and the lighting and airflow in office rooms and classrooms (b).

Figure 3.13.a shows an overall dissatisfaction with the temperature. It is possible to notice that the hottest months (February to April and October to December) showed higher levels of “Very unsatisfied” and “unsatisfied” responses, while the coolest

months (June, July and August) presented higher levels of “Very satisfied” and “satisfied” responses.

It is possible to see that schools with higher levels of satisfaction with the temperature presented an expressive higher average EUI. The average EUI of “very satisfied” responses ranged from 93.08 to 122.20 kWh/student.year, while the average EUI of “very unsatisfied” responses ranged from 63.18 to 72.55 kWh/student.year. Although variations throughout the year were observed, it is possible to infer that schools with higher levels of satisfaction with the temperature achieved this comfort condition due to air-conditioning. In fact, as shown in Figure 3.10, schools with air-conditioning had an expressive higher EUI than schools without air-conditioning. It is important to mention that only increasing the energy consumption will not necessarily provide environmental satisfaction, once the energy might be wasted with non-efficient loads such as non-operational hours, or inefficient HVAC systems. Further analysis can be conducted to elucidate the possibility of determining how much energy one can employ in the building to provide adequate environmental satisfaction, considering the efficient use of energy.

Due to the expressive observation of negative satisfaction with the temperature in all periods of the year, this outcome enlightened that the thermal performance is an issue to be greatly improved in the schools. High temperatures not only influence the quality of the built environment but also jeopardize the learning skills of the students — the built environment works as a key factor for productivity (VALANCIUS; JURELIONIS; DOROSEVAS, 2013) and health (HAMILTON *et al.*, 2013). Therefore, improvements are needed to enhance the conditions of the built environment in schools.

Figure 3.13.b showed overall satisfaction with the lighting in classrooms and office rooms. In general, schools presented a high level of positive satisfaction with lighting in both environments, with more than 70% of “neutral” to “very satisfied” results. However, regarding airflow satisfaction, the quality of airflow in classrooms presented an expressive negative satisfaction. About 41% of the responses are negative. This result is somehow related to the satisfaction with the temperature presented in Figure 3.12.a. Low levels of airflow satisfaction in the classrooms might cause low levels of satisfaction with the temperature, once the speed of the air is determinant to provide thermal comfort in mixed-mode buildings in hot climates (RUPP; GHISI, 2017). Moreover, the indoor environmental quality (IEQ) is a determinant issue to be addressed. A high density of occupants, as observed in classrooms, might result in high

CO_2 concentrations and low levels of IEQ. An integration between energy and indoor air quality performance is explored by Heibati *et al.* (2019), who raised the importance to consider such aspect on energy simulation models in order to predict a more realistic scenario.

Analysing the correlation of the satisfaction with the lighting in classrooms and office rooms with the EUI, it is possible to verify that the lower the satisfaction level, the lower the EUI. This is explained by the lack of lighting systems to provide adequate environmental satisfaction with the lighting in some schools, which causes negative satisfaction perception. In fact, when HVAC is not considered, the lighting is often the end-use with a major impact on the whole-building energy consumption in schools (PEREIRA *et al.*, 2014). Therefore, the inadequate lighting system (often undersized lighting systems) might cause an expressive difference in energy performance.

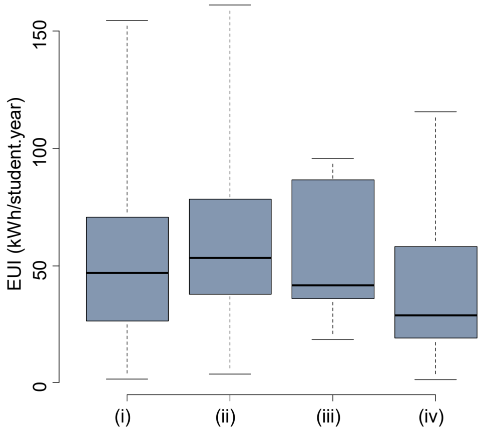
3.6. Impact of the necessary improvements on EUI

A priori, we knew that the schools have an important bound with the community where they are inserted. The association of parents and teachers are the leading actor for changing the structural conditions in some schools. Occasionally, the association of parents and teachers or a personal effort from the school crew are responsible for acquiring and installing air-conditioning units or fans.

Maintenance actions are delegated from the Education Department to the Principal by means of a specific budget for this purpose. The Principal is responsible not only for the educational leadership at the school but also for infrastructure management. Thus, he/she is the person to recognise the maintenance and improvements needed in the school.

Figure 3.14 presents the perspective of the Principal regarding necessary improvements according to each system (air-conditioning, fans, curtains and lighting) in function of the EUI of the school.

(a) Does the air-conditioning system need improvements?

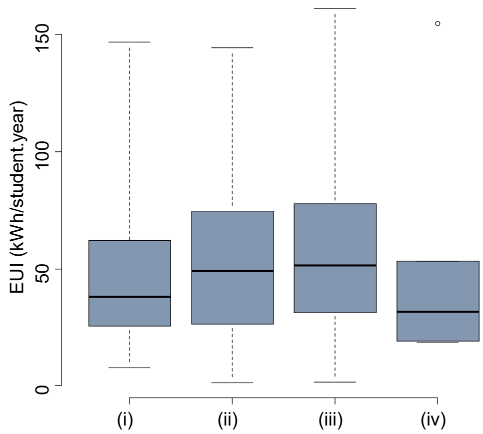


Pairwise Wilcoxon test

p-value matrix:

	(i)	(ii)	(iii)
(ii)	1.000	-	-
(iii)	1.000	1.000	-
(iv)	0.275	0.086	0.522

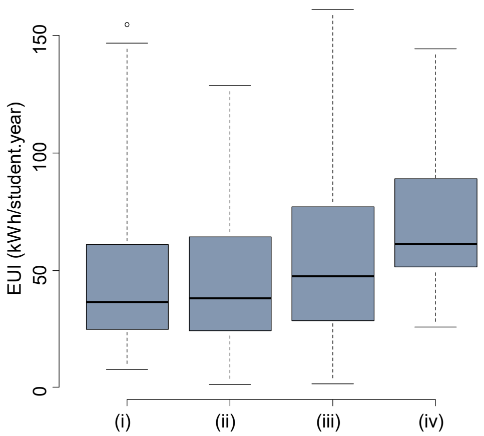
(b) Do the fans need improvements?



Kruskal-Wallis test:

Chi-Square = 1.6721
degrees of freedom = 3
p-value = 0.6432 (accept H0. A post hoc test is not applicable).

(c) Do the curtains need improvements?

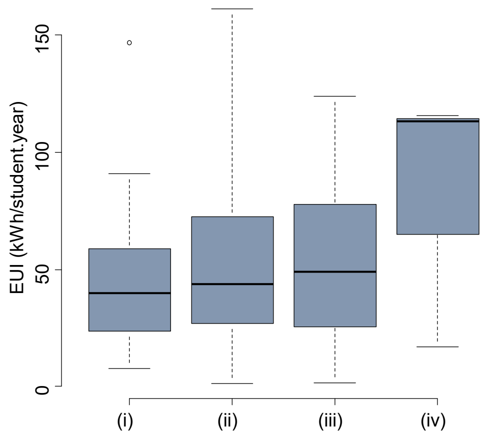


Pairwise Wilcoxon test

p-value matrix:

	(i)	(ii)	(iii)
(ii)	1.000	-	-
(iii)	1.000	1.000	-
(iv)	0.013	0.035	0.457

(d) Does the lighting system need improvements?



Kruskal-Wallis test:

Chi-Square = 2.1858
degrees of freedom = 3
p-value = 0.5347 (accept H0. A post hoc test is not applicable).

Note: (i) = Needs Installation, (ii) = Needs Maintenance, (iii) = Already have enough and works well, (iv) = There is no need.

Figure 3.14 – EUI versus necessary improvements, according to air-conditioning (a), fans (b), curtains (c) and lighting (d) in the function of the EUI of the schools.

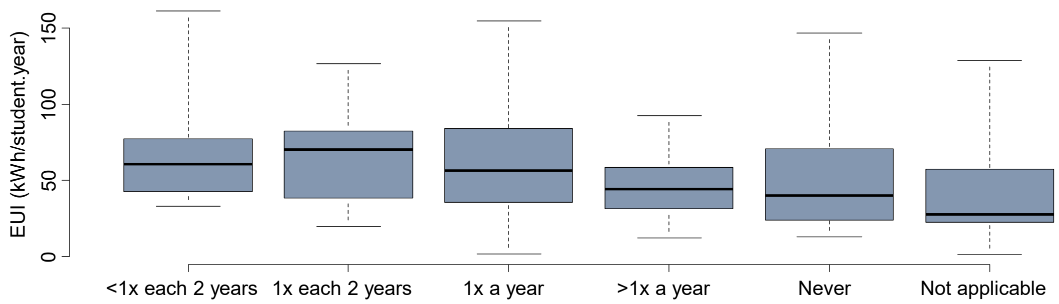
Figure 3.14.a shows that the statistical test rejected the hypothesis H0, indicating that there is a difference of EUI among the treatments of the variables analysed. The post hoc pairwise Wilcoxon test indicated that the average EUI between the school

where air-conditioning is not needed is statistically lower than the schools that need maintenance, at 10% of the significance level. Observing the patterns of the boxplots, it is possible to assume that schools which need installation and maintenance presented a higher average EUI than others.

Regarding the need for improvements in fans. Figure 3.14.c shows that the EUI of schools where there is no need for fans are statistically higher than the schools which need installation and need maintenance, at 5% of the significance level. This could be explained because the schools with air-conditioning probably might have responded that there is no need for fans.

Figure 3.14.b and d show that there is no difference of EUI in schools that need installation, maintenance, or already have lights and fans once the statistical test accepted the hypothesis H0. However, it is possible to note an expressive variation of EUI in the observations of Figure 3.14.d, category (ii), indicating an expressive need for maintenance in the lighting system.

Regarding the air-conditioning, the maintenance might be determinant for energy performance. Figure 3.15 presents the analysis of different periods of maintenance of the air-conditioning system as a function of the EUI.



Pair wise Wilcoxon test

p-value matrix:

	< 1x each 2 year	1 x each 2 years	1 x a year	> 1 x a year	Never
1 x each 2 years	1.000	-	-	-	-
1 x a year	1.000	1.000	-	-	-
> 1 x a year	1.000	1.000	1.000	-	-
Never	0.8682	1.000	1.000	1.000	-
Not applicable	0.0302	0.0327	0.0019	1.000	1.000

Figure 3.15 – EUI versus frequency of maintenance of the air-conditioning

Figure 3.15 shows that the schools without air-conditioning (not applicable) have a EUI statistically lower than the schools with air-conditioning, which received at least 1 maintenance a year, at 5% of the significance level. This result is expected, as observed in Figure 3.10. Nevertheless, there was no statistical difference between schools without air-conditioning and schools that frequently receive maintenance in the air-conditioning systems (more than one time a year). Since schools without air-conditioning had a low EUI, this result shows that a good routine of maintenance causes a positive effect on the energy performance of the schools.

Moreover, the statistical analysis could not identify a trend on the frequency of maintenance that affected the EUI. It is possible to see that the average EUI and the variation on the responses decreased as the frequency of maintenance increased. Yet, further investigations are required once many variables that are beyond the contribution of the Principal need to be taken into account for this analysis, e.g., the coefficient of performance (COP) of the air-conditioning and the cooling capacity.

Additionally, an open-ended question asked about the main conditions and need for improvements in the school. The Principals wrote a small text about the general characteristics of the school and what needs to be improved. The objective of this analysis was to make room for discussion of aspects that were not considered before. After the reading of all responses, a text mining technique was applied to account the more frequent terms in the responses. Figure 3.16 presents the twenty terms mostly used. Those terms were cited more than 10 times in the responses.

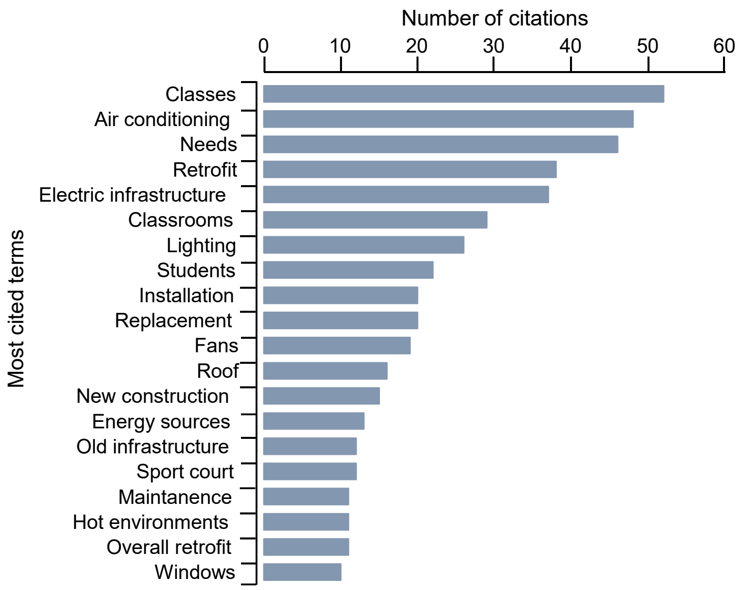


Figure 3.16 – Most cited terms in the open-ended responses about the need for improvements obtained from the text mining.

The open-ended question gives way to discuss the perception of improvements needed in the school from the perspective of the Principal directly. It is possible to verify a strong concerning regarding the quality of the classes, which indicates that the actual environments might jeopardise the learning process of the students.

A need for air-conditioning and retrofit are the lead terms regarding energy efficiency. Additionally, the emerging term “electric infrastructure” indicated that not only simple installations of air-conditioning would be enough, but rather an overall upgrade of the electric systems. In addition, the terms “old infrastructure” informed that many schools operate in outdated buildings. “Classroom” is a frequent term that indicates these spaces as the main target for improvements.

4. Conclusions

This study aimed to assess the actual conditions of the school buildings in Brazil by establishing a comprehensive panorama regarding energy usage in those buildings. An integrated approach combined billed energy data and pieces of evidence from questionnaires responded by the school principals. The study was carried out considering the modelling of the stock by means of statistical inferences of a sample of school buildings.

First, a broad overview provided the big picture of the main features of the school buildings, such as the floor-plan area, number of students, annual energy consumption, number of classrooms, ownership of air-conditioning, refrigerators and freezers, fans, curtains and type of air-conditioning and lighting. In this assessment, it was found that the Weibull distribution was the most suitable statistical distribution to represent the main features of the building stock under study.

Likewise, an analysis of the energy consumption during peak and off-peak hours, reactive energy, and power demand were carried out for school buildings supplied in high voltage. It was noteworthy that the contracted power demand was oversized, and the most expressive portion of the consumption occurred during off-peak hours. Conclusively, as the stock renovation occurs and more school buildings begin to be supplied in high voltage, it must be considered careful management of the power demand contracting.

Furthermore, a discussion regarding the EUI indicator to represent the energy performance of the stock was presented. The statistical analysis determined that the EUI as a function of the number of students (kWh/student.year) was more suitable than the EUI as a function of floor-plan area (kWh/m².year) to represent the building stock.

Moreover, the impact of the building energy management, environmental satisfaction and the need for improvements were addressed through the association between questionnaire responses and the EUI. It was possible to conclude that there is a lack of communication between building and energy management – they were not only functioning in distinct sectors but also had defective communication. Regarding environmental satisfaction, there is an expressive dissatisfaction with the temperature throughout the year. Therefore, the thermal performance of the school buildings stock is an issue to be significantly improved. As a final remark on this topic, we found that schools with higher levels of thermal satisfaction presented higher EUIs, and this is due to the use of HVAC systems.

Additionally, by associating the EUI with the maintenance practice, we concluded that schools with maintenance in the air-conditioning at least once a year have a better performance than schools with no maintenance at all.

This assessment can be applied for different typologies, such as industrial buildings or health facilities by adjusting the questionnaire. However, a set of previous in-situ visits should be carried out before organizing the questionnaire in order to guarantee coherent questions. It is important to mind the approach outcome: an overview of the stock actual condition with non-technical information.

The limitations of this research and suggestions for further investigations are described as follows:

- The data collection and compilation implied in some loss of data due to the inoperability and lack of integration of databases. The information of the school features was sorted by the code of the schools, but the information on the energy bills was sorted by the name of the schools (filled manually). Thus, these pieces of information often did not match.
- The voluntary nature of the research implied in the disregarding of some states of the country. Thus, the results of this research are applicable only to the population of this study. For further works, we suggest an expansion of this research, including missing states.
- It was used an approach of questionnaires applied in key person due to the budget and time limitations to address the environment satisfaction of the users inside the school. However, we suggest a broad investigation of the actual environmental comfort conditions of the students and employees of the school – considering thermal, acoustic and visual measurements

according to the ASHRAE 90.1 requirements. A suggestion is to use well-established building user questionnaires, such as Building Use Studies (BUS Methodology) or Occupant Survey Toolkit (Berkeley), in order to obtain systematic responses from occupants.

In summary, the outcomes of this study enable the development of politics of real energy performance analysis at stock-level according to the Brazilian scenario. For example, benchmarking school buildings in Brazil in terms of number of students can be more reliable than in terms of floor plan area, such as adopted by other countries.

Finally, it was possible to conclude that the school buildings stock could be modelled considering the statistical attributes acquired from the billed data and the questionnaires. Although the stock model needs improvement, it was possible to achieve an overall perspective of how the school buildings are in Brazil, how the energy is used, what the levels of satisfaction are, and how the aspects that need improvements are.

4. Top-down building stock model

This Chapter is the transcription of the following paper:

> **Integrating evidence-based thermal satisfaction in energy benchmarking: a data-driven approach for a whole-building evaluation**
> Authored by Matheus Soares Geraldi and Enedir Ghisi.
> Submitted to Energy (ISSN: 0360-5442), in May 2021. Under Review.

Abstract:
Energy benchmarking methods compare the operational performance of buildings with the corresponding stock. Multi-criteria methods emerged to consider different factors in benchmarking assessment. However, there is a lack in considering clear proxies for occupants' thermal satisfaction in those methods based on actual data. The study aimed to propose a method to integrate thermal satisfaction data into energy benchmarking. The main innovation is to propose a single metric that takes into account energy consumption, construction aspects, climate conditions, system type and thermal satisfaction level to benchmark a building. The method consists of a statistical analysis to select relevant variables in the building stock, the process of discretization of such variables, and the developing and validation of a Bayesian Network to serve as an instrument for the benchmarking method. A detailed, evidence-based dataset of 426 schools in Brazil was used. Results showed associated with occupants' low thermal satisfaction were benchmarked as less efficient than those with high thermal satisfaction and similar energy consumption. Regarding the validation step, the benchmarking model achieved an error rate ranging from 17.78% to 29.17%. The main conclusion is that machine learning techniques can adequately integrate subjective aspects such as occupant satisfaction in data-driven energy benchmarking methods.

1. Introduction

Energy benchmarking is a beneficial practice used in building performance analysis during the operational stage. Benchmarking the energy performance of buildings is widely described as a method to evaluate the building performance in comparison to other same-typology ones. This comparison allows building owners or stakeholders to recognise the actual performance of their building, identify inefficiencies and prospect improvements (WILDE, 2018).

Since the energy performance of a building relies on several aspects, the benchmarking method must be carefully developed. The use of a simplified metric (for example, using only the traditional energy use intensity – EUI) might lead to an inaccurate result (WANG; YAN; XIAO, 2012). Thus, diverse characteristics are employed in the benchmarking model to make the process fair, including climate conditions or building systems. Literature supports that the development of a benchmarking method requires a comprehensive database from the building stock (HAMILTON, 2017). Additionally, benchmarking policies are implemented through actions of the public administration or instruments from organisations that promote energy efficiency in buildings (BORGSTEIN.; LAMBERTS; HENSEN, 2016). Therefore, it is important to select an adequate benchmarking method to ensure a trustworthy representation of the building stock.

A comprehensive review of methods for building benchmarking was presented by Chung (2011) according to their properties and types of calculation. Li *et al.* (2014) presented an informative overview of benchmarking methods according to their complexity level (white, grey or black-box approaches) and discussed the requirements for selecting an adequate benchmarking model. Geraldi and Ghisi (2020a) reviewed methods to evaluate operational building performance and classified benchmarking methods by using different approaches, such as: Simple Normalisation (SCOFIELD, 2013; SCOFIELD; DOANE, 2018; TAYLOR *et al.*, 2018); Ordinary Least Square (OLS, or simple regression) (BORGSTEIN.; LAMBERTS, 2014; HONG *et al.*, 2014; PAPADOPOULOS; KONTOKOSTA, 2019); Stochastic Frontier Analysis (SFA) (YANG; ROTH; JAIN, 2018); Data Envelopment Analysis (DEA) (CHUNG, 2011; LEE, 2009a); or other advanced methods, such as geostatistical approaches (ÖSTERBRING *et al.*, 2018), and machine learning techniques (CHUNG; YEUNG, 2017; PARK *et al.*, 2016; SEYEDZADEH *et al.*, 2018).

The benchmarking method must be tailored according to each typology (PAPADOPOULOS; BONCZAK; KONTOKOSTA, 2018). Borgstein and Lamberts (2014) proposed a benchmarking method for Brazilian bank branches using a bottom-up approach by employing the regression analysis in simulation of archetypes, based on Energy Star approach (EPA, 2016). Veloso *et al.* (2020) introduced a statistical evidence-based benchmarking for office buildings in Brazil. Different assessments were performed for fully air-conditioned and mixed-mode operation buildings. The benchmark method proposed presented an 81% degree of reliability, leading to conclusions that an evidence-based benchmark is highly reliable, but it is restricted to its region. The studies of Hong *et al.* (2014) and Burman *et al.* (2014) structured both top-down and bottom-up approaches, respectively, for benchmarking schools in the United Kingdom. In both studies, the aspects of analysis were different – mainly by the magnitude of the details. Therefore, an integrative method of both approaches was proposed as a condition to achieve high-quality energy performance benchmarking in large-scale for school buildings. Along these lines, the necessity for a comprehensive framework in benchmarking to consider building specificities is clear.

Other examples of energy benchmarking applications can be found in the literature, such as focusing on identifying key characteristics (LOURENÇO; PINHEIRO; HEITOR, 2014), recognising retrofits improvements (ZINZI *et al.*, 2016), evaluating low carbon performances (LIZANA *et al.*, 2018), assessing the global performance (MONCADA LO GIUDICE *et al.*, 2013), characterising (TAYLOR *et al.*, 2018) and modelling the building stock (MARRONE; GORI, 2018). Further studies assessed building stock response of energy efficiency measures. Such as the study of Gui *et al.* (2021), who evaluated green building performance relationship under the optic of real estate; and Kubule *et al.* (2020), who reported the efficiency of energy audits programme installed in Latvia, showing through a comprehensive benchmarking analysis that the programme could accomplish better results by mitigating some inefficiencies in the implementation. A comprehensive cross-country energy benchmarking was presented by Pereira *et al.* (2014), who compared the energy performance of schools in different countries, establishing a statistical benchmarking. The authors discussed that the indoor environmental quality (IEQ) should be considered as an important factor to enhance the comparison precision.

Thenceforward, the consideration of IEQ and occupant behaviour has been increasingly studied in benchmarking policies. Although benchmarking is capable of placing the energy performance of a building in the stock performance range, the energy performance is related to environmental satisfaction and operation schedule. As noticed by Hsu (2014), who studied benchmarking efforts of New York City, the improvement of the operation could bring more effective results rather than the upgrade of systems. Ashouri *et al.* (2020) agree with this result, by showing that using a framework to provide feedback on lighting and HVAC to occupants, an energy reduction of around 20% is achievable. Additionally, the study of Guillén *et al.* (2019) compared types of benchmarking methods and indicators (simple energy benchmarking, regression, and comfort) and concluded that the benchmark outcome could be significantly different according to the technique or indicator used – i.e., the same building can present a good rate in terms of energy performance and poor quality in terms of comfort aspects.

Consequently, environmental benchmarking methods of buildings were proposed to fill this gap, especially by CEN Standard EN 15203 (CEN, 2006) in Europe. Even though there are methods for benchmarking the energy performance of buildings, and there are different methods to assess environmental quality of buildings, the integration of both aspects is not considered. Multicriteria evaluations emerged in the literature to fill this gap. For example, the study of Wang *et al.* (2017) proposed a benchmarking evaluation through a TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) approach to assess the energy performance fairly. However, this data-driven approach was performed for dwellings, remaining a gap for non-domestic buildings since benchmarking is essentially dependent on the evidence-based data. Other integration of IEQ criterion with energy efficiency can be found for office buildings (KONG *et al.*, 2012).

The study of Burman *et al.* (2014) assessed the benchmarking of school buildings based on simulation results – using cooling or heating degree days as the metric. Thus, when the integration is considered, environmental quality is not based on measured data. The mere integration of standard comfort metrics (such as, heating or cooling degree days) in benchmarking model does not assure that the building achieves such performance in practice.

Therefore, a building that consumes less energy than the benchmark and provides poor environmental quality cannot be considered efficient. Developing countries generally have warmer climates, mixed-mode operation, energy poverty issues (lack of air-conditioning), and lack of regulations regarding thermal performance. Thus, regular benchmarking models based on building construction aspects and energy performance are not suitable to mitigate such problems.

This issue was noticed in our previous work (GERALDI; GHISI, 2020b), in which we mapped the energy performance of school buildings in Brazil, using a combined approach of billed data and survey evidence. It was found that 71.1% of the sample schools have no air-conditioning systems in the classrooms, and 46.0% have no air-conditioning at all. A simple classification of energy performance, based on energy use intensity (EUI), led to the classification of buildings with poorer indoor conditions as more efficient. This classification informed stakeholders that those buildings were not a priority to receive an intervention. At the same time, what was really happening was an energy poverty problem – because those buildings actually needed air-conditioning. This can also be the problem of any country or region with the same issues as identified.

Performing such evaluation requires a method that merges building characteristics and thermal satisfaction reported by occupants. Simulation-based thermal satisfaction metrics are already considered in benchmarking methods, but they are not necessarily representing the reality due to the performance gap (MAHDAVI *et al.*, 2021). There was evidence in the literature about the performance gap regarding thermal aspects as well (PALMA; GOUVEIA; SIMOES, 2019) – i.e., only because the room achieved a certain comfort temperature does not mean that there is comfort condition for the occupants. Because it is a qualitative metric, evidence-based thermal satisfaction is hard to integrate into regular numeric models. Therefore, there is a lack of benchmarking methods that integrate thermal satisfaction reported by the users and evidence-based energy performance of buildings to obtain a final classification.

Along these lines, this paper aims to introduce a new top-down benchmarking method to evaluate whole-building energy performance by integrating building features, energy consumption, climate conditions and occupant thermal satisfaction. The output of the method is a single indicator that incorporates all those factors through a statistical approach. A database of school buildings in Brazil was used to develop the method. Specifically, this paper aims to select the relevant variables from the existing dataset and use those variables to model a useful and practical tool to help stakeholders to decide the physical and energy conditions of their buildings.

The main innovation of this study is the contribution to the literature of an energy benchmarking method that integrates occupant-reported thermal satisfaction and building features to provide a final classification of the building performance using a single metric instead of using several different metrics or evaluations. Also, there is a novelty regarding the use of a Bayesian Network for benchmarking energy performance of buildings in probabilistic approach, which is able to integrate subjective aspects of the building performance such as thermal satisfaction, with technical aspects to provide a whole-building evaluation.

2. Method

A summary of the method proposed is shown in Figure 4.1. The dataset of the school building stock was collected, treated and presented in our previous work (GERALDI; GHISI, 2020b). From the dataset, it was possible to apply a statistical analysis to identify the relevant stock characteristics in energy performance. Discrete variables were ready to be inserted in the network, but continuous variables needed to be discretised. Then, a Bayesian Network was created by arranging the variables into connected nodes and trained using part of the evidence-based dataset (50%). A cross-validation step was performed by testing the model using the remaining dataset.

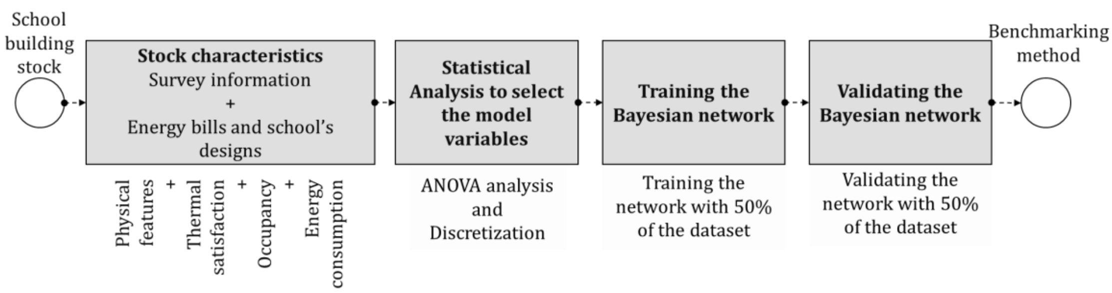


Figure 4.1 – Flowchart of the method.

2.1. Selecting a machine learning solution

To tackle the problem addressed, we used computational intelligence by means of expert systems. Expert systems are a type of computational intelligence focused on replicating the knowledge or actions of an expert human being in a determined case, such as to diagnose a disease (VAN DER GAAG, 1996), to understand faults in systems

(CHEN *et al.*, 2018), or to interpret images (MAGOULÈS; ZHAO, 2016). From a given problem, this type of system is composed of: a framework of the main aspects involving the problem obtained from human expertise, a dataset of cases already solved by humans, and a module to interface the framework with the user.

In other words, expert systems use previous experience from human activity in a structured model to help solve future cases of the same problem. Thus, expert systems must have some features: the capacity to deal with uncertainties, offer explanations to the user, and capacity of continuous learning from the data (PEARL, 1988). In human decisions, uncertainties are always present; therefore, expert systems present their results in terms of probability values.

Many computational intelligence techniques were reviewed during the development of this study (such as Artificial Neural Networks, Bayesian Networks (BN), Decision Tree, and Support Vector Machines). We selected Bayesian Networks to address the problem because they work as an excellent classifier approach (MAGOULÈS; ZHAO, 2016), and they are an evidence-based model supported by probabilities. The output is also provided in probabilities, which offers the user a degree of truth and not an absolute result.

A BN is an artificial intelligence technique that proposes heuristic modelling. BNs are graphical acyclic models that take advantage of the conditional probability to correlate nodes and establish a cause-effect relation in terms of probability (PEARL, 1988). This tool is useful for classifying purposes; it has been widely used in the health sector to aid the diagnosis of diseases, among other objectives. Recently, some initiatives have started to use BN to deal with the energy performance of buildings. For example: predicting monthly energy consumption (GERALDI; BAVARESCO; GHISI, 2019); improving renewable energy systems (BORUNDA *et al.*, 2016); diagnosing faults in building energy management systems (TAAL; ITARD; WIM, 2019); sizing rainwater harvesting systems (GERALDI; GHISI, 2019); modelling user behaviour patterns (BARTHELMES *et al.*, 2017); and predicting post-retrofit energy performance of heating systems (O'NEILL; O'NEILL, 2016). However, there is still room for the exploration of BN for benchmarking the energy performance of buildings.

2.2. Analysing the building stock

A comprehensive data survey regarding the energy performance of schools in Brazil was carried out by Geraldi and Ghisi (2020b). That study mapped the most relevant features of the school buildings through questionnaire application and correlated them to the billed energy consumption. The dataset provided information regarding energy consumption, building size, facilities, building systems, occupation, maintenance routine, and occupant satisfaction with temperature, lighting and airflow compiled in 69 variables from 426 schools (outliers, null values and incomplete responses already disregarded). In addition, the study compared the yearly EUI unit (kWh/m² or kWh/student) using statistical inference and concluded that kWh/student is more suitable for energy performance analysis considering the information available. Thus, we adopted EUI in terms of kWh/student.year to perform this model, using data from 2018.

The dataset provided information of the Brazilian school building stock. However, it was important to select adequate variables to develop the model to provide an adequate fitting. From the literature review, we found fundamental aspects of the building performance represented by some variables.

Furthermore, we employed a statistical analysis for each variable of the dataset to identify their impact on energy performance. We used the ANOVA test for the qualitative variables, considering the variable tested as the factor, its options as the treatments, and the dependent variable as the EUI. The hypothesis H0 was that there is no statistical difference between the treatments. P-values less than 0.05 indicated a rejection of H0 at 5% significance level, which means that there is statistical evidence that the EUI was different between the treatments analysed. Thus, the variable was considered in the model.

We used the Pearson correlation analysis for the quantitative variables, considering the variable tested as one group and the EUI as the other group. The Pearson correlation determined how strong the association between two groups is, ranging from -1 to 1, while 0 means no correlation, and values above 0.5 or below -0.5 indicate a strong correlation. When a strong correlation was identified, we considered the variable in the model.

Table 4.1 summarises the key variables pointed in other studies, which were adopted in this study (X1 to X4), and the variables adopted due to the statistical analysis of the dataset (X5 to X8) with their statistical test results. Other variables were suppressed to maintain the conciseness of this article since 69 variables were tested.

Table 4.1 – Input variables considered in the model.

Aspect	**Variable**	**Type**	**Unit**	**Variable id**	**Source**
Energy use	EUI	Continuous	kWh/student	X1	-
Physical	Floor-plan area	Continuous	m²	X2	(HONG *et al.*, 2014; PEREIRA *et al.*, 2014)
Occupation	Occupation	Continuous	Student	X3	(BURMAN; KIMPIAN; MUMOVIC, 2018; BURMAN *et al.*, 2014; HONG *et al.*, 2014; PEREIRA *et al.*, 2014)
Climate	Bioclimatic zone	Categorical	Zones 1 to 8	X4	(HONG *et al.*, 2014; OUF; ISSA, 2017)
Satisfaction with temperature	Thermal satisfaction*	Discrete (Likert-like scale)	- Very unsatisfied - Unsatisfied - Neutral - Satisfied - Very satisfied	X5	ANOVA: F = 2.98; p-value = 0.01
Systems	Cooling capacity per floor-plan area	Continuous	- BTU/h/m²	X6	Pearson Correlation: 0.68
	Type of air-conditioning in classrooms	Discrete	- Single split - Single window - Central - None	X7	ANOVA: F = 5.554; p-value = 0.01
Operation	Operation time	Discrete	- Full day - Day and night	X8	ANOVA: F = 8.95; p-value = 0.03

* Considering average perception throughout warmer months.

According to the dataset used, many other variables that we thought would be relevant for the consumption did not have statistical relevance. For instance, presence of curtains (p-value = 0.10), presence of fans (p-value = 0.21), and satisfaction with airflow (p-value = 0.08). Literature also supports that the type of education influenced the benchmarking result; however, the ANOVA test showed that this variable was not significant for such a population (p-value = 0.15). This can be attributed to the study's population being composed of public state schools, which have primary and high school in the same buildings. It is important to highlight that the variables might change according to the dataset, once this is a data-driven method.

2.3. Developing the Bayesian Network

A Bayesian Network is a visual graphic tool built to support the decision-making process. The network uses the frequencies of variables in the dataset as evidence (input) to evaluate a hypothesis's probabilities (output).

The Bayesian networks are composed of two complementary aspects: a qualitative and a quantitative assessment. The qualitative aspect is an acyclic graphical model where each variable is a node, and the nodes are connected by directed arcs, which express the dependency among variables. Then, a variable "A" is connected to a variable "B" in the way B → A, indicating that "B" (effect) is dependent on "A" (cause). In other words, this is the approach of cause and effect 'if "A", then "B"'. If there is no arc between variables, it is assumed that those variables are independent.

The quantitative aspect is composed of three probability classes (Equations refer to (VAN DER GAAG, 1996)):

a) The probabilities of each node, which are obtained from the dataset. For each node B conditioned to a node A, a table of probabilities is calculated considering the proportion of class of B related to each class of A (Equation 1).

$$P(A)_{i,j} = \frac{N(A)_{i,j}}{N(B)_j} \quad (1)$$

where: $P(A)_{i,j}$ is the probability that node A presents class i, once A is conditioned by B, $N(A)_{i,j}$ is the number of cases in A that presented class $_j$ in node B, and $N(B)_j$ is the total number of cases in B with $_j$ class.

b) The conditional probabilities are used to calculate the probabilities of instances (events) inserted in the network after each node's probabilities and the probabilities *a priori* are inserted. The conditional probabilities express the relationship between events calculated using the Bayesian Theory of conditional probability (Equation 2).

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (2)$$

where: P(A|B) is the probability *a posteriori* of the event A, conditioned by the event B; P(B|A) is the probability *a posteriori* of the event B that condition an event A; P(A) is the probability a priori of event A; P(B) is the probability a priori of event B.

c) The probabilities *a priori*: the probabilities of the output node obtained from the diagnosis of the problem. They can be calculated or assumed according to the experience of the developer.

The Bayesian network is constructed by arranging and connecting the nodes (variables) and applying the probabilities of each node. After that, the user can consult the network by setting instances on each input node, and then the conditional probability adjusts the other nodes probabilities according to the event set. Examples of application, mathematical deductions and explanations of the Bayesian Theory and Bayesian Network proposition can be found in Heckerman (1996). We follow the good practices guidelines of Chen and Pollino (2012).

In this study, the input nodes are the variables shown in Table 4.1 (variables X1 to X8), and the output variable (identified as X0) was the benchmark. An initial naïve-Bayes structure was set and continually adjusted according to the developer and BN performance experience. Figure 4.2 shows the final arrangement of the nodes of the BN proposed. The arrows indicate the conditioned arcs (connections) between nodes.

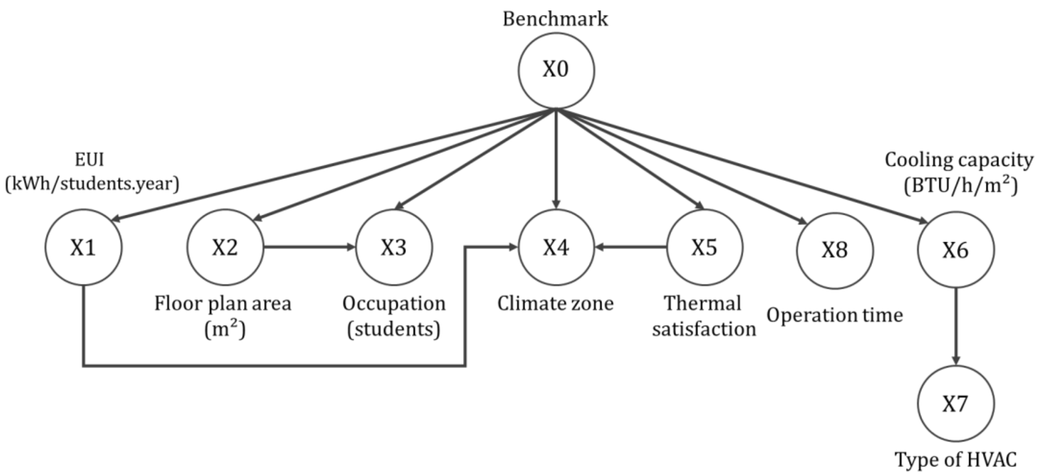


Figure 4.2 – Bayesian Network structure.

2.4. Discretisation of the variables

Variables were discretised to be inserted in the BN. All continuous variables were discretised using the Equal Depth Binning (EDB) method, which considers the variable range in N intervals, each with the same number of observations. Hence, for each interval it was calculated an upper and a lower limit by splitting the sorted dataset into N intervals according to the frequency. This method of unsupervised binning was adopted according to a previous work (GERALDI; BAVARESCO; GHISI, 2019), which concluded that this method leads to better BN performance for predicting the energy performance of school buildings.

For the EUI (node X1), a log transformation was applied in the distribution to transform the observed distribution into a normal distribution, as suggested by Veloso *et al.* (2020). Then, a five-class scale was adopted for binning, considering equal frequency for each class (20% of the dataset each). This scale was based on the literature consensus for rating energy efficiency in buildings (scales A to E) and adopted by the Brazilian Energy Performance Certificate for commercial buildings (INMETRO, 2013). According to good practices (CHEN; POLLINO, 2012), other continuous variables were discretised into four classes (25% of data each). Table 4.2 presents the criteria for the discretisation processes for the continuous variables.

Table 4.2 – Discretisation criteria for the continuous variables.

Node / Variable / Unit	Classes	Upper limit	Lower limit	Average value
X1 Log of EUI (log of kWh/student/year)	Very low EUI	0.00	1.39	1.17
	Low EUI	1.39	1.61	1.50
	Average EUI	1.61	1.77	1.70
	High EUI	1.77	1.93	1.85
	Very high EUI	1.93	2.89	2.18
X2 Floor-plan area (m²)	Small size	125.02	1228.42	734.31
	Average size	1228.42	1972.62	1554.35
	Large size	1972.62	2941.06	2377.69
	Super large size	2941.06	6623.00	3705.96
X3 Occupation (Students)	Small student size	49	504	298
	Average student size	504	744	617
	Large student size	744	994	858
	Super large student size	994	1569	1211
X6 Cooling capacity (BTU/h/m²)	Poorly air-conditioned	-	248.6	56.93
	Average air-conditioned	248.6	450.0	330.62
	Highly air-conditioned	450.0	956.8	597.91
	Fully air-conditioned	956.8	1,456.8	1,246.39

Qualitative variables are already discrete variables and are considered in the BN through their frequency. Discrete variables and their classes are described as follows:

- X4 (Climate zone): There are eight bioclimatic zones in Brazil, so each category of this variable was defined as each zone. Delimitations and characterisation of climate zoning can be found in the national standard (NBR 15220, 2005). In summary, zone 1 has predominant mild temperatures and well-defined seasons throughout the year (subtropical climate), and zone 8 has warmer temperatures and varies within wet and dry seasons throughout the year (tropical climate). Zones 2 to 7 are intermediate climates. Each school of the dataset was classified according to the city (location) where the school is located.
- X5 (Thermal Satisfaction): This is a discrete variable with five classes formed in a Likert-like scale, and it was obtained from the questionnaire applied in our previous work. The variable is correspondent to a question about the “satisfaction of users with the temperature in the classrooms” and had a 5-range response (“Very Low”; “Low”; “Neutral”; “High”; “Very High”). It is important to highlight that this information was a perspective of the school principal since a “questionnaire applied to a key person” approach was adopted, relying on the fact that a representative leadership in the building can provide a general perspective of the actual conditions throughout the year (LEAMAN; BORDASS, 2001). A survey from a representative sample of occupants would benefit the study; however, this type of survey performed on a national scale (as we performed) must be on-line, and we were not allowed to have contact information of the students due to disclosure issues. The responses were validated and explored in our previous work. Also, we acknowledge that as a limitation of our data – but not of our model, and can be solved with the prospect of data from occupants.
- X7 (Type of HVAC system): This variable was discretised into four classes according to the responses found in the data collecting step. Each class corresponds to the predominant type of air-conditioning system in the school. Once the purchase of systems in public schools is made in large quantities, schools often present the same air-conditioning type.

The classification was done according to the features of each school: Single unit Split; Single unit Window; Central, None.

- X8 (Operation time): This variable corresponds to the turns that the schools operate. Some schools offer classes during the morning and the afternoon (all day), while some schools also offer night shifts (usually for young and adult education). The classification was done into those two classes.

After the discretisation process, the network was trained using 50% of the dataset (213 observations), while 50% remaining was used for validation. This percentage was adopted as suggested by good practices in BN development for split datasets (CHEN; POLLINO, 2012). The data subset was performed using random sampling. The training process was done using Equation 1, and the result of this process is the probability of each class for each node. R environment was used to process, organise and discretise the data. Netica (from Norsys (2017) was used to build the BN and perform the network analysis.

The output variable is the benchmark result (X0). There are several ways to qualify a benchmarking result: good-practices, typical, non-efficient (EPA, 2015); classes A to E of efficiency (VELOSO *et al.*, 2020); efficient or non-efficient. For this variable, a five-scale was adopted for discretisation purposes, considering the classes of the actual performance of the building as: "A" to very good performance, until "E" to very poor performance. Since this is the output node, this node assumed the probabilities *a priori*. Since there is no *a priori* information that allowed us to determine which classification each school would have, we assumed the principle of maximum entropy, considering the same probability of occurrence for each class. Since we had five classes, each class of the output node has a 20% *a priori* probability.

It is important to highlight that the output variable is not the numerical prediction of energy consumption (kWh) or energy performance (kWh/m².year or kWh/student.year). Unlike other types of energy benchmarking methods, which usually predict a quantitative difference between the benchmarked building and a given benchmark, the result of the method proposed here is a qualitative variable that indicates the energy performance considering information from all nodes. In other words, it translates the behaviour of an expert person in determining the energy performance of a school, considering aspects of its location, systems, occupation, area and thermal satisfaction of users.

2.5. Validating the Bayesian Network

After the network training process, a validation step tested the power of the tool in providing reliable results in practice. The validation process consists of submitting already-known instances into the network and verifying if the outcome predicted by the network was equal to the actual result. This analysis is expressed through a matrix of confusion in which the lines are the actual results, and the columns are the predicted results. Metrics can be obtained from the matrix of confusion. One of the most important metrics is the error rate (Equation 3, according to Koller and Friedman, 2009).

$$\mathrm{E} = W/\mathrm{C} \tag{3}$$

where: E is the error rate; W is the number of cases wrongly classified by the BN; C is the number of cases in the validation dataset.

The lower the error rate, the strongest the capacity of the BN in predicting new cases correctly. Another validation metric is the accuracy, which is one minus the error rate (1 - E). A similar metric considered is the sensitivity, shown in Equation 4 (KOLLER, FRIEDMAN, 2009), which analyses the network's capacity to predict a correct result, i.e. evaluating if the prediction of a case in one class actually belongs to that class.

$$\mathrm{S} = P_i/C_i \tag{4}$$

where: S is the sensitivity; P_i is the number of cases predicted correctly as a class *i*; C_i is the number of cases actually classified as a class *i*; n is the number of instances of the output node.

Finally, since our process is based on a sample from the population, it is necessary to amplify the error rate by considering a confidence interval (Equation 5 according to Montgomery, Douglas and Runger, 2003).

$$\mathrm{IC} = \mathrm{E} \pm \mathrm{z} \times \sqrt{E \times \frac{1-E}{n}} \tag{5}$$

where: IC is the interval of confidence for the error rate; E is the error rate; z is the statistic score of the Gaussian distribution given a level of confidence. In this study, the level of confidence is 95%, resulting in a z score equal to 1.96; n is the size of the sample.

The interval of confidence expands the error rate into a range. This is a way to deal with the sampling error, which is a type of error inherent to the processes that use samples. The use of an interval of confidence allows the generalisation of the sample results to the population. Thresholds to define the good performance of a BN are not a consensus in the literature. In fact, it depends on each case analysed. A good reference is that values of sensitivity and accuracy higher than 80% are desirable, and the range of an interval of confidence should be less than 10% (CHEN; POLLINO, 2012).

Finally, actual cases of four schools were tested in the BN to provide examples of extreme cases. This analysis shows how the benchmarking process can be conducted and how the method presented in this study combines the impact of both energy consumption and thermal satisfaction adequately.

3. Results and Discussion

3.1. Discretised Variables

The discretisation process outlined a first overview of the results. Figure 4.3 shows the result of the discretisation by plotting the ranges of the variables in each one of their classes. In addition, the graphs show the average EUI of the schools according to their classes.

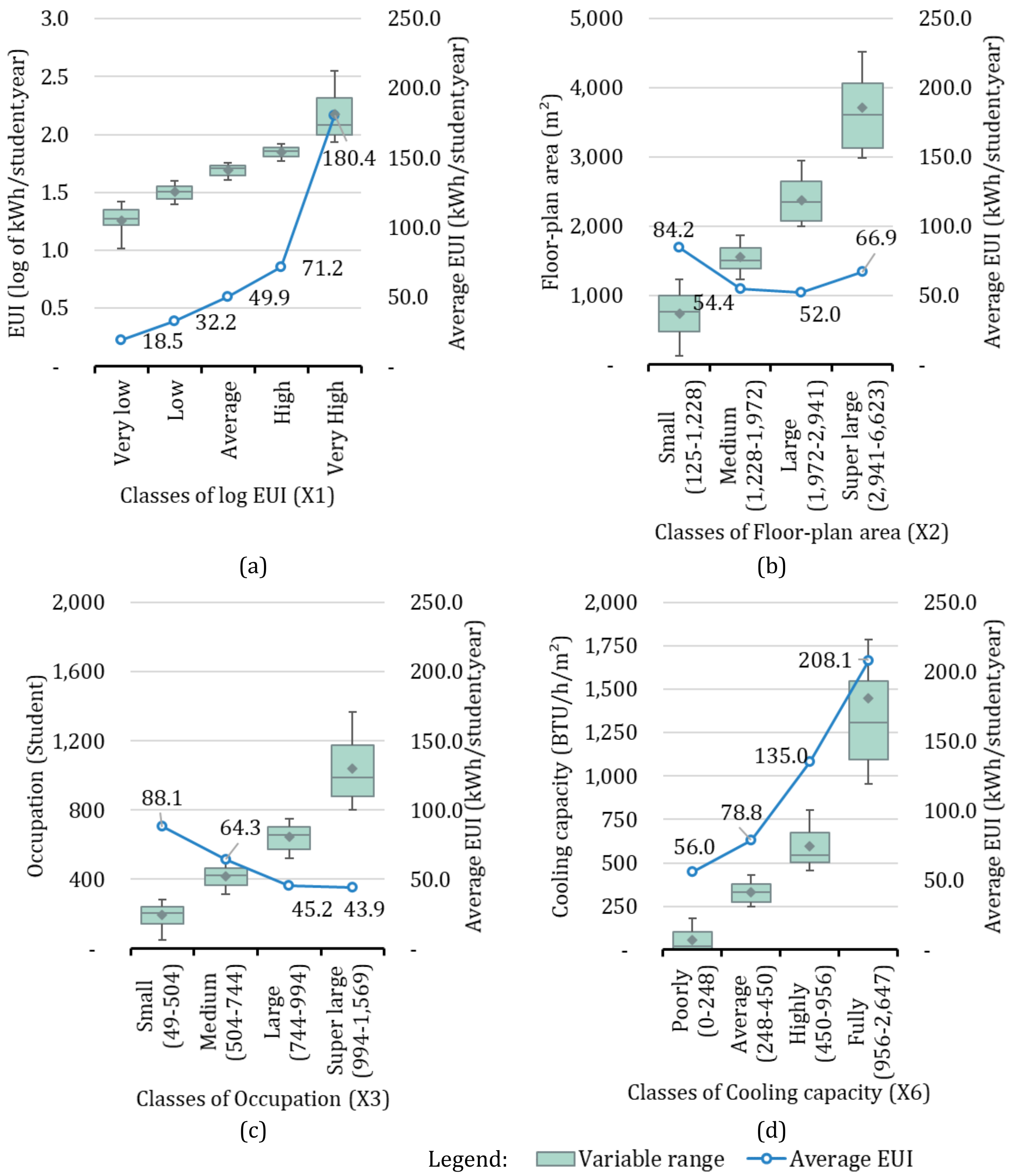


Figure 4.3 – Discretisation and average EUI of (a) Log EUI, (b) Floor-plan area, (c) Occupation and (d) Cooling capacity.

It is possible to note that the discretisation process was adequate once the classes had similar ranges. Importantly, each range had the same number of observations since EDB was employed, which implies that all classes have the same probability of being chosen in the BN.

Figure 4.3.a shows the logarithm of EUI classes and their average EUI (not log). Obviously, as the classes go from very low to very high, their average EUI increases. Interestingly, this variable provides a partial statistic benchmark, i.e. it shows expected

EUIs as references for rating (Very Low to Very High) when other factors are not considered. In other words, an EUI less than 18.5 kWh/student.year is a low EUI for schools in Brazil (or efficient school), not taking other factors into account. Figure 4.3.b shows that in small and super larger schools, the EUI is slightly higher than the intermediate school sizes (medium size and large ones).

Figure 4.3.c shows that the greater the number of students, the lower the EUI. Since those variables are connected. In this context, it is possible to infer the existence of some residual energy loads. Those residual energy loads probably are due to office loads and refrigerators and do not depend on the school's size or the number of students. Also, residual loads were evidenced in literature as Basal Energy Consumption (GERALDI *et al.*, 2021). Figure 4.3.d shows, as expected, that the EUI increases with the increasing of the cooling capacity installed in the school.

Regarding the qualitative variables, Figure 4.4 shows their classes and the average EUI for each variable.

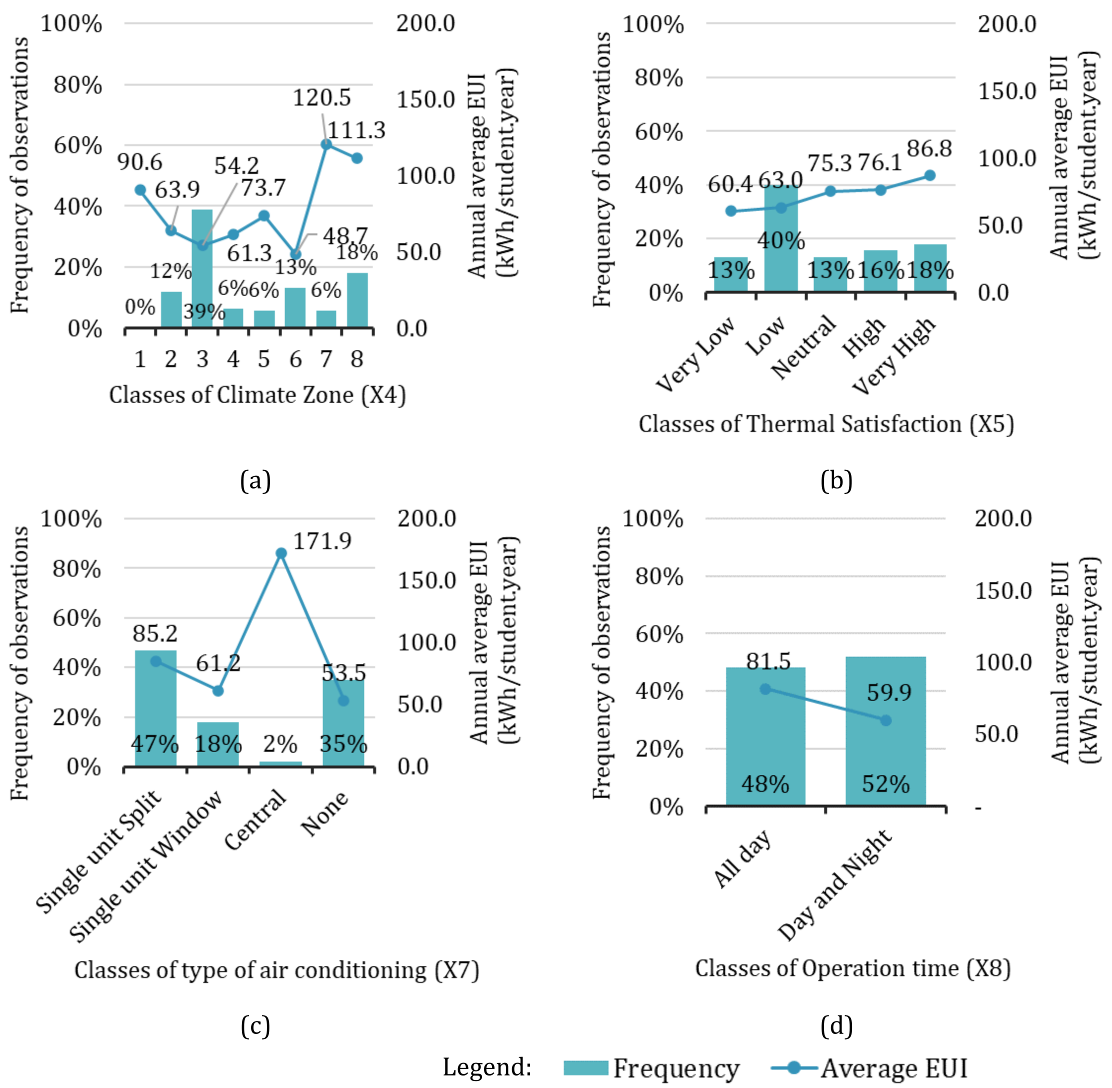


Figure 4.4 – Frequency of observations and average EUI for the classes of the qualitative variables (a) Climate zone, (b) Thermal satisfaction, (c) Type of air-conditioning, and (d) Operation time.

Figure 4.4.a shows that buildings in warmer climates, such as zones 7 and 8, tend to have average EUI (respectively 120.5 and 111.3 kWh/student/year) higher than buildings in other climate zones, probably due to the higher usage of air-conditioning.

Figure 4.4.b shows that the average EUI increases with the increasing of the thermal satisfaction of the schools. In fact, most of the schools with high levels of thermal satisfaction have higher cooling capacity, indicating that schools need air-conditioning to provide thermal comfort to the users. Also, this outcome shows the need to consider passive strategies for improving thermal performance in school building designs in Brazil, as highlighted by previous studies (GERALDI; GHISI, 2020b; SARAIVA *et al.*, 2019). Nowadays, thermal performance is poorly considered, and

thermal comfort relies on the use of air-conditioning to reduce humidity levels and on the use of fans to promote air movement (BUONOCORE *et al.*, 2018).

Regarding the type of air-conditioning, Figure 4.4.c shows that the most common type is split units (47%), and a significant number of buildings (35%) have no air-conditioning at all. Surprisingly, Figure 4.4.d shows that buildings that operate exclusively during day time presented EUI higher than buildings that also operate at night. This happened because schools that operate at night have significantly more students – those schools have three shifts of classes, morning, afternoon and night – in contrast, schools that operate during the day have classes in mornings and afternoons. Therefore, the energy consumption is divided by a greater number of students to compose the EUI. Again, this outcome reinforces the inference discussed in Figure 4.3, in which schools have a “residual load” (Basal Energy Consumption), probably due to office loads or refrigerators that do not depend on the number of students. This is clear in Figure 4.4.d because if the main loads were dependent on the number of students or the floor-plan area, the EUI should be higher for schools that operate all day and night once they have more students.

Importantly, the results of the discretisation process provide partial benchmarks of the building stock. For example, one could assume that the average EUI for a school located in Climate Zone 8 is 111.3 kWh/student/year. One could also assume that the average EUI for a school that operates during the day and night is around 59.9 kWh/student.year.

The average EUI, disregarding all particularities of each school and just taking the mean EUI for the 416 schools, was 72 kWh/student per year. For comparison with other studies, the average EUI in terms of floor-plan area was 30.54 kWh/m².year. This is a low EUI value compared to statistical benchmarks of other countries with similar climate conditions, for example, 86 kWh/m².year in Italy, 63 kWh/m².year in Cyprus and 123 kWh/m².year in Argentina (PEREIRA *et al.*, 2014). The determination of an average EUI considering all aspects together is performed by the Bayesian Network.

3.2. The Bayesian Network

A Bayesian Network is represented by a visual interface where the nodes are represented by boxes, the classes of each node have a belief bar to illustrate their probabilities (obtained from the training step), and arrows represent relationships between nodes. The numbers above the boxes of the continuous variables represent the mean and the interval of confidence of the corresponding variable. Figure 4.5 shows the outcome of the BN developed in this study.

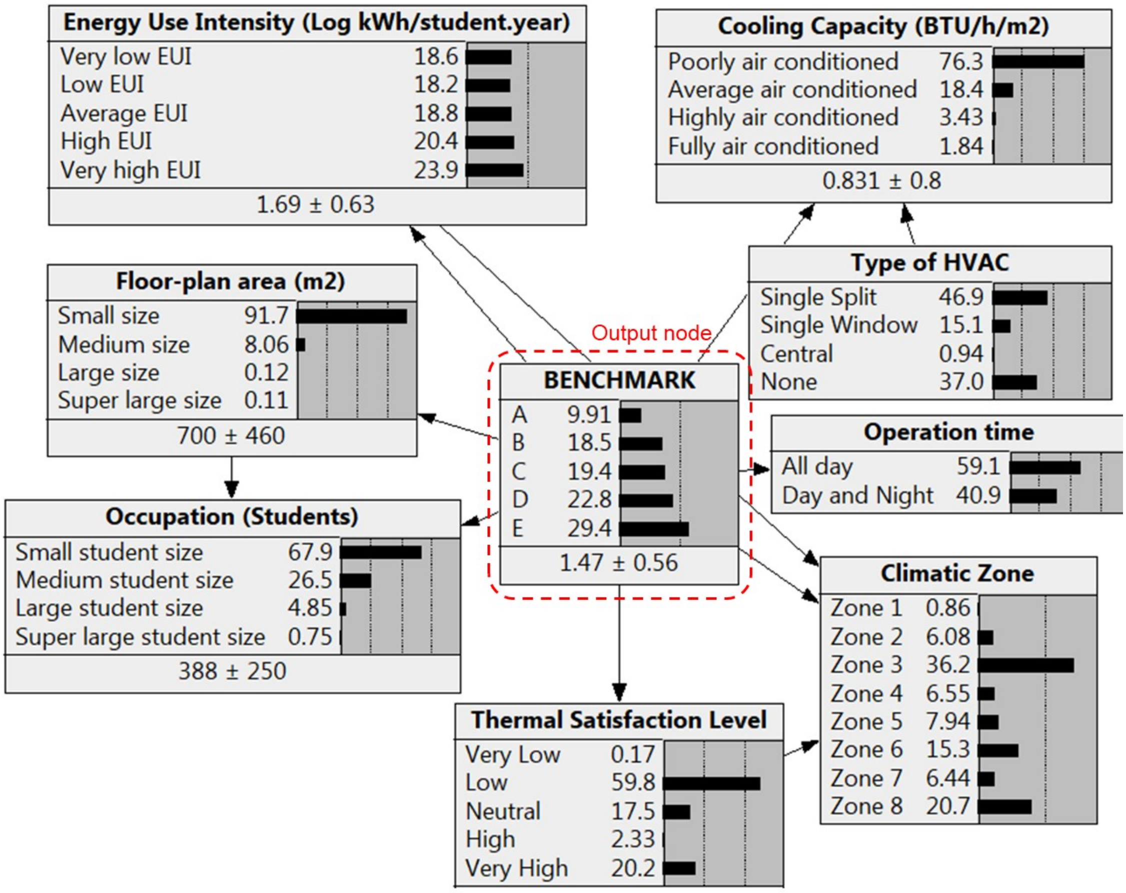


Figure 4.5 – Bayesian Network interface (obtained from Netica).

The result of the BN is the node BENCHMARK, which is a metric for the whole-building evaluation that considers all the input nodes. It is important to state that this metric delivers an outcome in terms of probability. This provides a degree of truth of the result instead of a single and closed number or class. It means that this method leaves the terrain of the deterministic, usually employed in building performance assessment, and get in probabilistic. Indeed, the use of statistic approaches are emerging to deal with the energy performance of building stocks (BORUNDA *et al.*, 2016). It is especially important to employ such approach in cases of buildings with intermediate performances, in order to provide a complete diagnosis of the context of that building.

In practice, a user can consult the BN by setting instances in each node. For example, to benchmark a demonstrative school "A", the user enters with the EUI of the school “A” in the corresponding class of the node “Energy Use Intensity”; the floor-plan area in the corresponding class of the node “Floor-plan area”, and so on, until the output node (BENCHMARK) will calculate the probabilities *a posteriori*. When a class is set with a certain instance, the node will appear green and show “100%” of probability for the instance that was set. Visually, the output node adjusts its belief bars to represent the probability of this school “A” to fit each class of the node BENCHMARK. For example, if an actual school has 2,500 m² of floor-plan area, the user will set the “Large size” (between 1,972.42 and 2,941.06) of the node Floor-plan area. The equivalence of class in each node was shown in Table 4.2 (unfortunately, the interface of Netica supresses long-texts in instances’ descriptions). A practical example of the network application is presented as follows.

3.3. Validated Bayesian Network

Validation is an important stage in BN construction. A sample composed of 213 schools (50% of the dataset) was used to test the BN performance. Such schools were not used to train the network, so these cases were unseen by the BN. Table 4.3 shows the confusion matrix showing the relationship between predicted and actual results during the validation stage.

Table 4.3 – Confusion matrix

Actual	**Predicted***					**TOTAL**	**Sensitivity**
	A	**B**	**C**	**D**	**E**		
A	12	2	5	2	0	21	57%
B	2	26	6	2	0	36	72%
C	1	3	32	3	1	40	80%
D	0	3	6	33	3	45	73%
E	0	0	4	7	60	71	85%
TOTAL	15	34	53	47	64	213	

* Highlighted values are corrected predictions.

Table 4.3 shows that the BN had a good performance in general. All sensitivity values were greater than 50%, showing an overall good prediction capacity in all instances. Specifically, the BN showed a good capacity to predict that a building is in the “E” class once it achieved 85% sensitivity.

There were 163 cases correctly predicted out of the total 213 cases tested. The error rate was 23.47% (Accuracy of 76.53%). By calculating the interval of confidence (using Equation 5), the error rate range was 5.69%, which means that the error rate for the population ranges from 17.78% to 29.17%, considering a 95% confidence level. Importantly, once this is a data-driven method, the results are restricted to this study population, which corresponds to the Brazilian public elementary school stock. Variables and results might change according to the dataset and application.

Compared to other studies that addressed machine learning methods for benchmarking buildings, Silva *et al.* (2019) achieved an error rate equal to 18.3% (C-RMSE) using support vector machines for benchmarking school buildings in São Paulo, Brazil. Targeting the same purpose but for office buildings, Dongmei *et al.* (2018) achieved accuracies from 85% to 71% using a regression model.

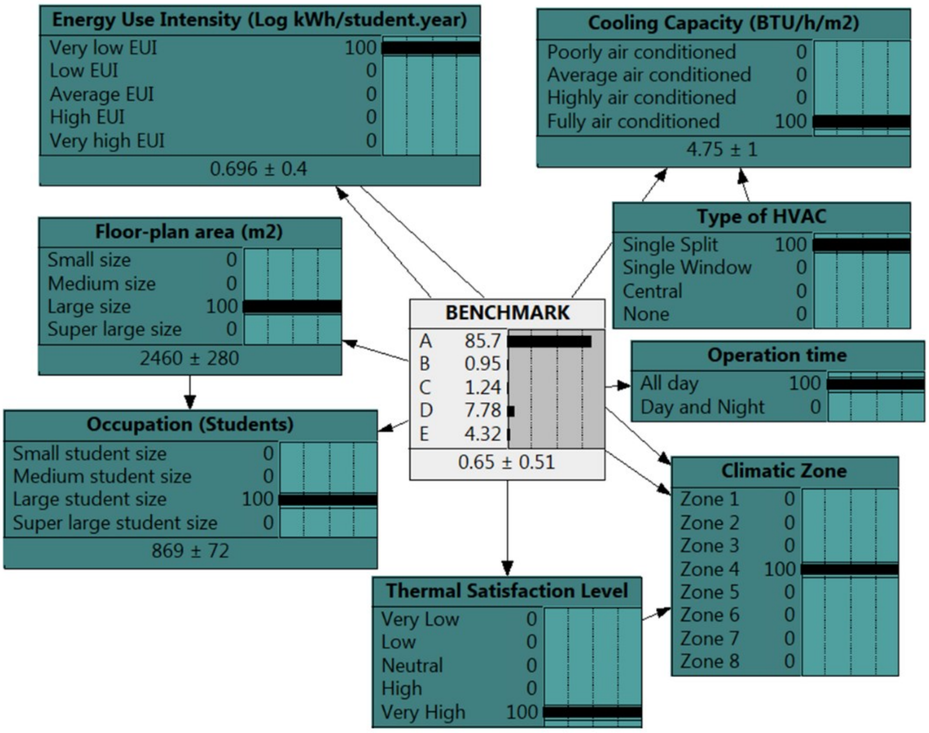
BN was used for other purposes related to building performance analysis in the literature but never for benchmarking energy performance. So, one could compare the BN performance for other purposes. For example, to estimate the occupation in office and residential buildings, Amayri *et al.* (2019) achieved an average accuracy of 84% of the BN. Barthelmes *et al.* (2017) used BN to predict window operation actions and achieved accuracy from 93% to 98%.

Therefore, it is possible to understand that the BN developed herein achieved a good performance compared to other studies and good practise thresholds. The structure can be generalised for other regions as long as the data used to train the BN is adapted using local evidence-based data.

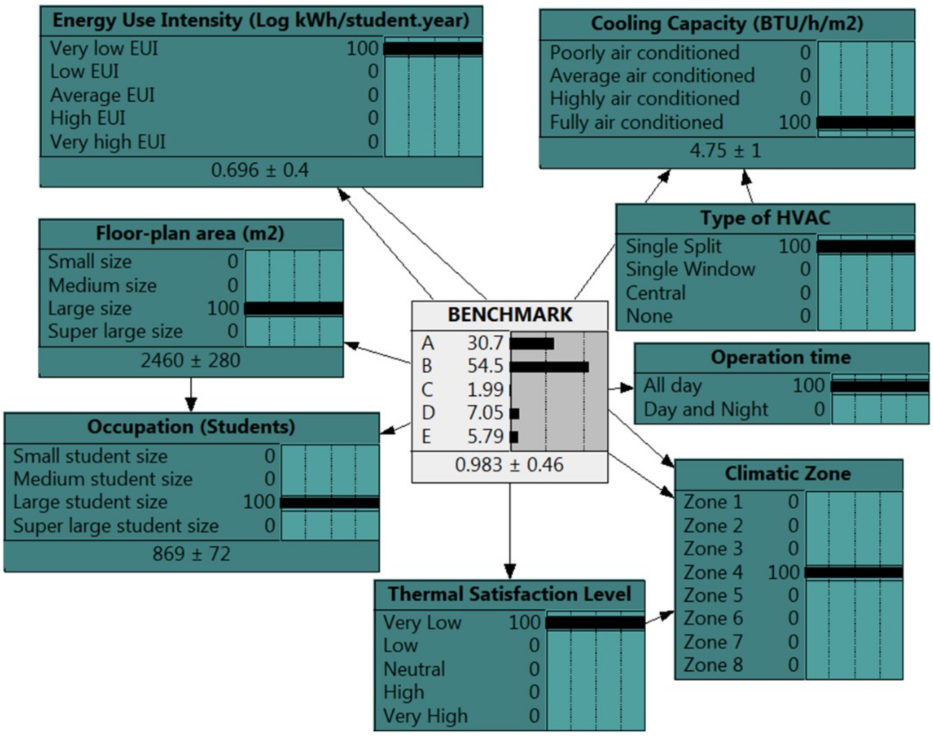
3.4. Practical application example

In this section we present a practical application of the benchmarking process in four actual situations, and explain how the method presented in this study impacts the final evaluation of real schools.

Firstly, two similar schools with low EUIs (Class "A" in LOG EUI node) and different thermal satisfaction levels were tested, one with "Very High" thermal satisfaction and other with "Very Low". Figure 4.6 shows an example of this scenario.



(a)



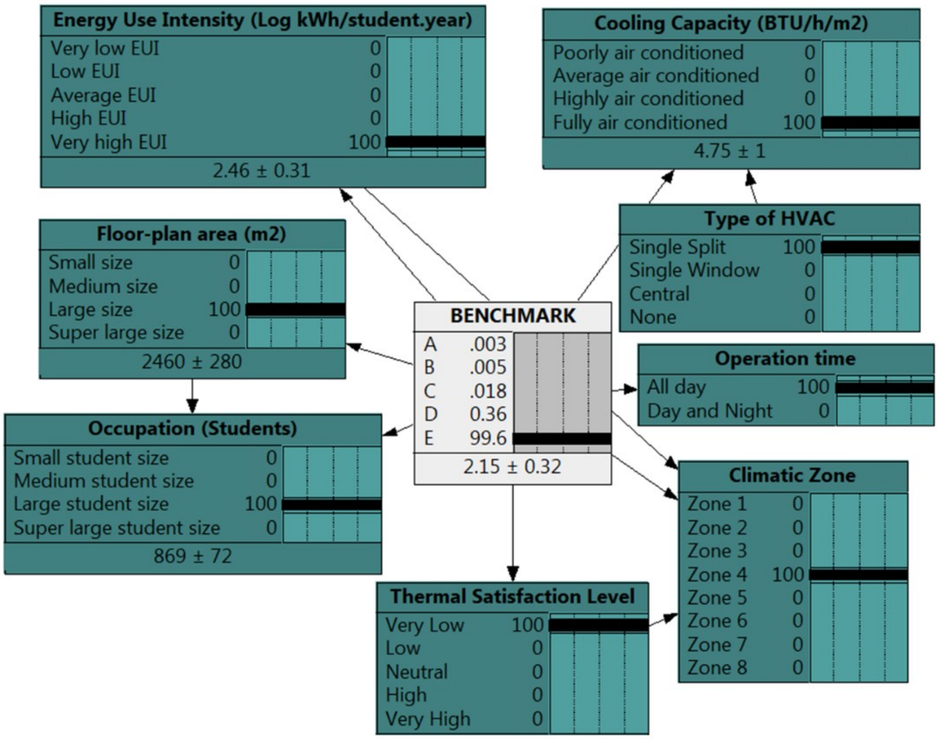
(b)

Figure 4.6 – Example of application of the Bayesian Network where: (a) is a school with very low EUI and very high thermal satisfaction; and (b) is a school with very low EUI and very low thermal satisfaction.

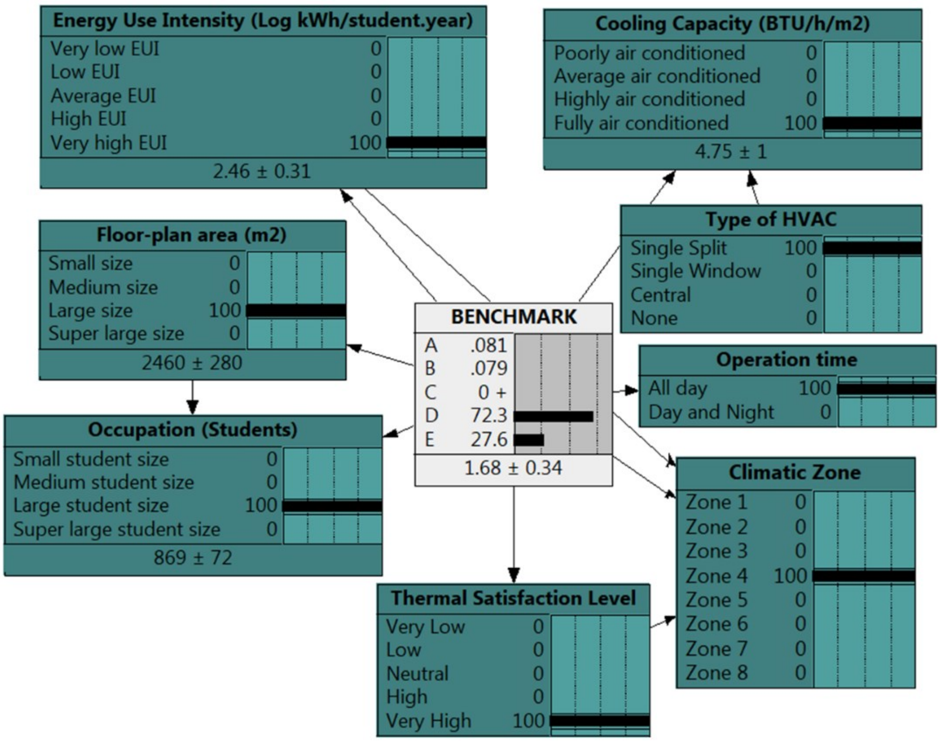
Figure 4.6.a shows an example of a building with very low EUI and associated with a very high thermal satisfaction level, which results in an 84.9% probability of this school obtaining a performance rated as “A”, as observed in the benchmark node. This means that this building is using energy efficiently to provide adequate thermal conditions to occupants, positively affecting their satisfaction. Otherwise, Figure 4.6.b shows the similar instances for a second building with very low EUI but associated with a very low thermal satisfaction level, showing that this building obtained a performance rated as “B” (66.1% probability) in the benchmark node. This means that this building is not really an energy-efficient one; its energy consumption is low but the rooms provide unpleasant thermal satisfaction, so it probably needs air-conditioning to provide adequate thermal conditions to occupants.

Although the second building still received a good performance rate, it is possible to note that thermal satisfaction is considered in the benchmark result (the benchmark is not “A”, it is only “B”). Nonetheless, the thermal performance is not the only factor that defines the benchmark result, neither solely the EUI. It is noteworthy that this building still presented a very low EUI compared to the whole stock and must be somehow efficient in other aspects (for example, lighting systems) compared to others.

A second example of two similar schools with very high EUI and different thermal satisfaction levels were tested (one with “Very High” thermal satisfaction and other with “Very Low”) is presented in Figure 4.7.



(a)



(b)

Figure 4.7 – Example of application of the Bayesian Network where: (a) is a school with very high EUI and very low thermal satisfaction and (b) is a school with high EUI and very high thermal satisfaction.

It is possible to see that Figure 4.7.a shows a school with very low performance (it consumes lots of energy and provides unpleasant thermal conditions). The benchmark result was a high probability (99.6%) for a “E” performance in the benchmark node. However, a similar building, with a similar energy consumption, associated with a very high thermal satisfaction level, and it was benchmarked as “D” performance (72.3% probability). This means that this second building may be using energy to provide adequate thermal satisfaction for occupants – but since its energy consumption is high, there must be some inefficient systems that could be improved. The important result is: the second building benchmark is not “E”, it is “D”.

The advantage of this method is the integration of different subjective aspects in rating building performance by using machine learning. This would be impossible by using traditional benchmarking methods that use entire numeric operations, such as regressions or frontier analysis. A regression benchmarking is applicable when buildings in the stock overall share similar environmental satisfaction levels. However, in developing countries, such as Brazil, energy regulations are still in a developing phase. The existing building stock is already constructed with low energy and thermal performance. Thus, an effective and disruptive method to evaluate those buildings is necessary. In fact, as shown by Elnaklah *et al.* (2021b), IEQ must be considered in the evaluations of energy performance of buildings in order to promote sustainability.

Bottom-up methods are comprehensive and refined once they use a representation of physical phenomena. However, as identified by previous studies (VELOSO *et al.*, 2020), there is a gap between reality and what could be modelled on a large scale due to the autonomy of buildings with a mixed-mode operation. This gap implies variability and, thus, the use of a bottom-up approach individually might not be effective (HONG *et al.*, 2014). The proposition of using a top-down approach tried to fill this gap by combining subjective aspects (such as thermal satisfaction), physical characteristics (such as the floor-plan area), and occupation aspects (such as the number of occupants). Many techniques and methods are emerging to make the building performance analysis increasingly integrative. For example, modelling the urban context (REINHART; CEREZO DAVILA, 2016) to include interactions of the building with its surroundings. Thus, in this study, we explored an approach to consider satisfaction levels in rating energy building performance and other systems and building factors.

As stated before, the issue identified in this study can be considered as an energy poverty problem. A future concern is the possible uprising of a counter-efficiency effect: while buildings receive air-conditioning systems to improve thermal satisfaction, their EUI will increase, implying in an increasing of the greenhouse gas emissions from the building stock. Therefore, two further steps for the subsequent studies can be outlined: (a) estimating the impact of this counter-efficiency effect by estimating how much the EUI of the building stock will increase according to scenarios of interventions (e.g., what happens if half of the buildings with no air-conditioning receive air-conditioning, and so on) and; (b) proposing energy-efficient strategies in those interventions by prioritising passive cooling strategies or integrating photovoltaic systems to reduce net energy amount. These propositions for further works culminate in integrating a bottom-up approach in the method proposed herein. Including simulation tools and using archetypes results in a promising method to predict future scenarios (MATA; SASIC KALAGASIDIS; JOHNSSON, 2014), especially considering the International Panel for Climate Change (IPCC) scenarios to consider climate change effects.

4. Conclusions

This paper presented a new data-driven method to integrate occupant-reported thermal satisfaction in the energy benchmarking of buildings. The main processes were the statistical analysis of variables in relation to the EUI of each school, the discretisation of each variable and the development of a machine learning tool for classifying the overall building performance. An approach of an expert system through Bayesian Network (BN) was employed. Training and validation stages were carried out. The main conclusions can be outlined as follows:

- The BN presented an adequate performance (94.76% accuracy) in comparison to other machine learning techniques used for benchmarking and other BN for other purposes.
- Using the BN to test similar buildings with discrepant thermal satisfaction reported by users proved to result in different benchmarking result – i.e. schools associated with higher levels of thermal satisfaction reported by users were scored with better performance grade. This outcome demonstrated that the method indeed considered the thermal

satisfaction for the benchmarking of the whole building performance. In summary, the thermal satisfaction was considered alongside with other aspects to compose a final result. The final result is sensitive to all input variables, and none of them alone performed a decisive part.

- The BN provides a result in terms of probabilities to fit in a class of efficiency. This is helpful because it did not provide a closed and blind result – instead, it provides a degree of truth for the evaluation, offering autonomy to stakeholders for understanding the result.
- Using evidence-based machine learning to develop an energy benchmarking method for buildings could lead to good results by combining variables to provide a fair comparison among buildings by integrating the EUI, building features, and subjective aspects such as occupants' thermal satisfaction.
- A key limitation is that this tool is highly dependent on the dataset. We used a dataset of 2018, but as the building stock changes, the BN results might change. Then, continuous collection of data and updating of the BN are needed.

The study presented herein shed light on the discussion of benchmarking methods to include the evidence-based subjective performance of buildings in their overall evaluation. Therefore, it was possible to conclude that the data-driven approach used in this study was adequate to perform a whole-building assessment especially in developing countries.

5. Bottom-up building stock model

This Chapter is the transcription of the following paper:

Data-driven framework towards realistic bottom-up energy benchmarking using an Artificial Neural Network: application for Brazilian schools

Authored by Matheus Soares Geraldi and Enedir Ghisi.

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Abstract:

Energy benchmarking of buildings has an important role in improving energy performance by establishing a reference for the energy efficiency of the building stock. The simulation of archetypes followed by a generalisation model has been widely used to obtain benchmarks. However, even though archetypes summarise the building stock's main features, the uncertainties of the building stock must be accounted for in the modelling process. Moreover, testing the response of the benchmarking model using the actual building stock data supports the reliability of the method. This paper aims to propose an innovative framework to reduce the uncertainty of archetypes for benchmarking buildings. A standard framework for data compiling is proposed and an assessment of the uncertainty of variables using entropy and cluster analysis defined representative archetypes. An Artificial Neural Networks (ANN) was used as a benchmarking tool, and it was applied to benchmark a sample of actual buildings. Also, the simulation outcomes were used to determine energy end-uses according to the climatic zones. The framework proposition is presented alongside with a practical application. The result is an unprecedented benchmarking method for the Brazilian school building stock. Additionally, the modelling process showed to be robust for combining different datasets, and the ANN achieved high-performance metrics. Conclusion indicates the potential of using the framework for other typologies. Moreover, the benchmarking of the sample of buildings showed a tendency to the inefficiency of the building stock while a specific case study was explored, showing the potential of the method to find faults in the building energy use.

1. Introduction

Buildings are complex systems, and their energy performance during the operational phase has been evaluated through energy benchmarking. Energy benchmarking of buildings is a helpful practice that compares a single building performance to others with the same typology in the building stock (WILDE, 2018).

Energy benchmarking helps to understand energy use in practice and provides opportunities to explore aspects that affect energy use. Moreover, there is evidence in the literature that energy benchmarking improves energy efficiency by promoting competition among buildings' stakeholders (CHUNG, 2011) and raising awareness about the efficiency of their systems (VAISI; PILLA; MCCORMACK, 2018). The building energy performance of a given building is evaluated through the comparison with a benchmark – a yardstick that represents the energy performance of a building under typical conditions. The benchmark needs to be determined through an adequate method to assure reliability.

Studies that evaluated methods to determine the benchmark are gaining ground. Li *et al.* (2014) classified benchmarking methods considering their complexity level (white, grey, or black-box approaches). Borgstein and Lamberts (2016) summarised the algorithms employed, the variables involved, and the accuracy level of several methods. Chung (2011) presented a complete review of methods for benchmarking, condensing the methods in the following topics:

- Simple normalisation: the benchmark is considered as statistical measures (e.g., mean or median). Further statistical analysis can be done, such as the determination of quantiles and histograms (BOEMI *et al.*, 2011; LI, 2008; SCOFIELD, 2013; SCOFIELD; DOANE, 2018; TAYLOR *et al.*, 2018);
- Regression analysis (or Ordinary Least Square, OLS): the benchmark is calculated through an equation considering a cause-effect function of the energy performance and relevant characteristics (BORGSTEIN; LAMBERTS; HENSEN, 2016; HONG *et al.*, 2014; PAPADOPOULOS; KONTOKOSTA, 2019; SABAPATHY *et al.*, 2010).
- Stochastic Frontier Analysis (SFA): the benchmark is also calculated through a regression equation considering the determination of a geometric element using data of high-performance buildings (BUCK; YOUNG, 2007; YANG; ROTH; JAIN, 2018).

- Data Envelopment Analysis (DEA): the benchmark is calculated through a regression analysis considering a boundary that includes all datasets (CHUNG, 2011; LEE, 2009a).
- Advanced methods: methods that take advantage of computational intelligence, for instance, geostatistical approaches (KOO; HONG, 2015; ÖSTERBRING *et al.*, 2018) and machine learning (CHUNG; YEUNG, 2017; PARK *et al.*, 2016; RUZZELLI *et al.*, 2010; SEYEDZADEH *et al.*, 2018).

The benchmark is obtained through an operation performed using a dataset of building energy performances in all methods. This dataset must adequately represent the building stock, i.e. it has to incorporate variations of energy performance due to the different characteristics of the buildings in the real world. The building stock is compared to a population and the buildings to individuals in an energy epidemiology approach (HAMILTON *et al.*, 2013). Benchmarks are calculated for each building typology – which implies that same-typology buildings share similar characteristics –, and the climatic conditions play an important role in energy performance variation (GOLDSTEIN; ELEY, 2014). Then, actual data can be used for benchmarking of building under the same climatic conditions (VELOSO *et al.*, 2020), but otherwise, a modelling process is necessary (BORGSTEIN; LAMBERTS, 2014). Thus, this dataset can be composed of actual data – obtained through Display Energy Certificates (DECs) (HAMILTON *et al.*, 2017; HAMILTON *et al.*, 2014); or simulated data – obtained through the building performance simulation (BPS) of archetypes (HERNANDEZ; BURKE; LEWIS, 2008; NÄGELI *et al.*, 2018). Although the literature supports that data-driven benchmarking approaches are more reliable (ROTH *et al.*, 2020), these methods rely on open data policies. Hence, the countries or cities that do not have DEC policies must adopt archetype-based benchmarking methods.

Archetypes – also called reference buildings – summarise the building stock into representative BPS models (MATA; SASIC KALAGASIDIS; JOHNSSON, 2014; REINHART; CEREZO DAVILA, 2016). The literature outlines methods to obtain archetypes, and, in summary, they can be obtained through clustering methods by grouping a sample of buildings into a single model (COTTAFAVA *et al.*, 2018; SCHAEFER; GHISI, 2016). The archetype can be simulated by considering the characteristics found in the actual stock to represent typical conditions. Generally, average or median parameters for each BPS model are used. A manipulable model is helpful to obtain representative energy end-uses (BORGSTEIN; LAMBERTS, 2014), to prospect improvements due to innovative solutions in scale (STREICHER *et al.*, 2018), and to evaluate scenarios, for example, considering the effects of climate change (HAMILTON *et al.*, 2016; INVIDIATA; GHISI, 2016). Therefore, the archetypes can be used to develop a tailored benchmarking using correction factors (e.g., weather, occupancy, systems) as strategies to adjust benchmarks to specific conditions, using methods described above (OLS, SFA, DEA, or machine learning techniques (TSO; YAU, 2007)). Inaccuracies of benchmarking approaches were studied in the literature, evidencing errors due to the static nature of the benchmarks (HEESEN; MADLENER, 2018). The weak spot of using archetypes is that this method carries uncertainties in its formulation. Since broad information has to be condensed into narrow models, uncertainties might lead to significant errors. However, the literature supports those methods to minimise the uncertainty can enhance archetypes' representativeness (ZHURAVCHAK *et al.*, 2021). The reliability of the benchmarking method can be verified by means of testing the response of the actual building stock performance.

Thus, the response of the building stock to a benchmarking process can bring evidence towards the energy efficiency of buildings. Some studies explored the data-driven benchmarking policy outcomes. Hsu (2014) analysed a dataset of energy audits in New York City and highlighted those operational improvements might bring better results than upgrading systems. In China, an evidence-based benchmarking using a sample of 165 office buildings was developed (WEI *et al.*, 2018); it showed the enormous range of building performances in Beijing. Other examples can be found, such as identifying retrofit improvements (BURMAN; KIMPIAN; MUMOVIC, 2018; ZINZI *et al.*, 2016), assessing low performance (KOLOKOTSA *et al.*, 2018; LIZANA *et al.*, 2018), and characterising and modelling the building stock (BURMAN; KIMPIAN; MUMOVIC, 2018; MARRONE; GORI, 2018; WILLIS *et al.*, 2011).

Along these lines, on the one hand, there is the use of archetypes as a path to model the building stock through representative simulation models. On the other hand, there is the comprehensive study of the building stock in terms of statistical analysis. Therefore, given the statistical nature of the archetype composition, it always holds uncertainties within – so, how can one be sure that the selected parameters are representative of the building stock archetype?

Consequently, a knowledge gap exists between the current methods for developing archetypes and the obtention of data from building stock, by evaluating the information embodied in the dataset used to compose the archetypes. The uncertainties of the archetypes were pointed out as a major problem that jeopardizes the wide application of benchmarking and limits regional applications such as UBEM (Urban Building Energy Modelling) simulations (ALI *et al.*, 2019).

To mitigate this gap, this paper proposes a framework to model a building stock archetype using information theory and cluster analysis to select the variables in the simulation. The solution proposed is based on increasing the number of cases of a parameter to reduce its uncertainty by including variability in the stock model. In other words, the higher the variability of a given parameter in the stock, the higher its variability should be in the simulations. The novelty of this study relies on the proposition of a schematic data-driven method to reduce uncertainty in modelling archetypes for energy benchmarking of buildings. The method can be adapted for other regions and building stock clippings, especially for developing countries, since building stock information is hardly available.

This paper outlined the first integration of the Information Theory and machine learning models in the context of building stock modelling. Related studies have worked towards the updates in the accuracy of models for benchmarking, but this paper outlined the first use of Entropy analysis and the proposition of a manipulable stock model towards interpretability and applicability of models. Finally, the proposed framework was demonstrated and compared with an actual building performance sample and a comprehensive benchmarking applicability was explored.

Thus, the objective of this article is to propose a reducing-uncertainty framework to obtain a bottom-up energy benchmarking model using Artificial Neural Networks (ANN). A test-bed data of the school buildings in Brazil is used to demonstrate the framework function. Applying the energy benchmarking method in an actual building stock demonstrates the assessment of its energy efficiency in a stock-level approach. The framework employs Information Theory to identify the variables with more uncertainty in the model, reducing the uncertainty of the BPS model by including more evidence data into the parametric simulation process. Cluster analysis was used to select the variables. After the archetypes were built and simulated, an ANN was constructed to generalise the model, and the actual building stock was benchmarked. Energy end-uses were aimed to be identified to allow the breakdown of the energy usage of the benchmark. Finally, a specific building was analysed as a case study to show the potential application of the method.

2. Method

The method is composed of seven steps. A test-bed dataset from school buildings in Brazil was used to demonstrate the method. The first step is the definition of the targeting building stock. Then, a standard inventory structure is proposed to compile the building stock features and assign variables and their values. From this inventory, the entropy analysis aids the decision of which parameters should be varied and which should be fixed in the simulation model. A cluster analysis was employed for those variable parameters to set their values, while the median value was selected for the fixed parameters. Then, a set of cases was performed through parametric simulation using EnergyPlus. Next, the results were used to develop an artificial neural network (ANN) to serve as the benchmarking model. Finally, the actual building stock performance could be benchmarked to measure its energy efficiency and validate the stock modelling framework. The energy end-uses can be obtained for each one of the eight climate zones analysed. A single case study is analysed particularly. Figure 5.1 shows the method workflow.

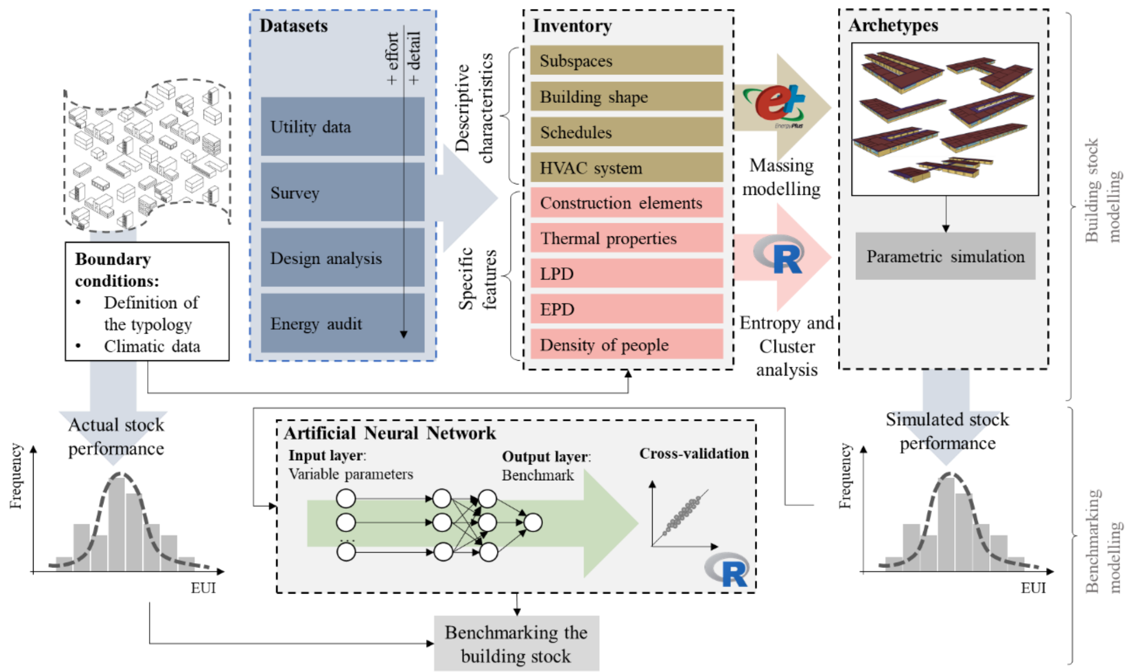


Figure 5.1 – Flowchart of the method.

2.1. Defining the target building stock

The target building stock is the group of buildings that is aimed to be modelled. The definition of the building stock is important to assure the validity of the archetype. A target building stock can be defined through the following boundary conditions:

i. The buildings are consistent: buildings share similar social function for the occupants (for example, schools, hospitals, office activities, and so on);
ii. The buildings have similar monthly operations throughout the year. This condition is related to the social function, and since the function is similar, it is likely that the operation is also similar;
iii. There is a comprehensive dataset of a representative sample of buildings to represent the building stock.

Then, from the target building stock, datasets of the stock are needed to extract information to model the archetypes. In order to apply the framework proposed, a test-bed dataset to represent the public-school building stock in Brazil was employed. This dataset was presented and explored through a comprehensive analysis in our previous work (GERALDI; GHISI, 2020b). This dataset is representative for the targeting building stock, and it is composed of:

i. Electricity bills: obtained through a survey in several cities in Brazil. Data of 417 schools in all of the eight climatic zones were obtained for the year 2018.
ii. Survey analysis: to enrich the information of the electricity bills, a survey was conducted with the occupants in the same 417 schools. A questionnaire aimed to fully describe building features and occupants' patterns in all schools.
iii. Design analysis: Drawings of 31 schools were carefully analysed in three climatic zones.
iv. Energy audits: Three energy audits in schools in Florianópolis (southern Brazil) were carried out. Site inspections helped to gather data of actual buildings. Guidelines of ISO 50002/2016 and ASHRAE Energy Audit level 2 (Energy survey) were followed. Results supported the massing model creation and validation of the surveyed values.

Then, a multi-level information dataset of the targeting building stock was accomplished. The quality of the data is inversely proportional to the effort of gathering it. Energy audits display high detail information while survey analysis and energy bills have little information. However, it is easier to gather data on more buildings through survey analysis than through energy audits. Design analysis provided relevant information regarding building spaces, constructions, and materials. It is essential to encompass all information available in the stock modelling process in light of this reality. The framework proposed herein relies on the datasets' compilation into a standard structure that converges into an archetype for simulation in EnergyPlus. Then, this method is robust to combine different sources of information to model the archetypes. It is important to mention that only electricity was assessed since fuel sources are usually related to heating water or cooking in Brazil.

2.2. Arranging the inventory

Outlying pieces of evidence from actual features of the building stock are essential to guarantee the archetype's accuracy. To construct a representative building stock model, the archetype must contain parametrisations to mirror the actual building stock variability. If the dataset contains information for every building in the stock, just choosing the exact parameters combination of each building would result in the simulation of each building of the stock. However, the dataset rarely contains every building of the stock. Thus, we need to obtain a relevant set of values from a stock sample that reflects the actual conditions to be represented through simulation. The results of the simulation are used in an extrapolation method (the benchmarking model). Thus, other buildings that are not in the building dataset (but fit in the building stock boundary conditions) can benefit from the benchmarking model.

The framework for gathering such building stock relevant features is proposed at the subspaces level. Subspaces are groups of similar spaces that the buildings of the stock share. The subspaces definition is helpful to aid the energy modelling process, for example, to set schedules of operation and internal loads.

For every building in the datasets, it is important to arrange their information into an inventory, considering a standard sequence of fields that should be filled. The characterisation of the building stock (filling the inventory) is performed in two stages: (a) descriptive characteristics; and (b) specification of features.

Descriptive characteristics are qualitative explanations regarding the building configuration (subspaces identification) and operation (schedules), where the buildings are placed (weather), how the buildings are shaped (massing model), what types of Heating, Ventilation, and Air-Conditioning (HVAC) are often used (HVAC system(s)). Each building will have a single response for every descriptive aspect; however, the final analysis is a subjective evaluation of those aspects that summarises the building stock's subjective features. Table 5.1 summarises the descriptive analysis and presented how it is included in the simulation model. Examples are provided for Brazilian school building stock.

Table 5.1 – Summary of descriptive characteristics of the building stock

Parameter	Application (E+ object)	Description	Example for schools in Brazil	Source
Identification of the subspaces	Thermal Zones	Identification of the similar spaces that the buildings share.	Schools have seven subspaces: Classrooms, library, computer cluster, office rooms, cafeteria, bathrooms, and aisles.	- Design analysis, - Energy audits
Shape rules	Geometry and Building Surface	Recognition of the shape rules that describe the building massing composition, i.e. the distribution of the internal spaces and storeys.	Classrooms are placed together and accessed through an aisle. Bathrooms, cafeteria, and kitchen are next to each other. Office rooms, library, and computer cluster are typically placed together. Seven predominant building shapes were identified: Shape E, L, H, O, U, Rectangular, and Multiple Buildings.	- Design analysis, - Energy audits
Weather	Weather file	Identification of the standard weather conditions where the target building stock is inserted.	Schools are uniformly distributed in all eight Brazilian climatic zones. Thus, it is important to include all climatic zones in the parametric simulation.	- Electricity bills, - Survey
HVAC type (for each subspace)	HVAC template	Identification of the predominant types of air-conditioning for each subspace in the building.	All schools in the dataset have air-conditioning in office rooms, computer cluster, and library. Half of them have it also in classrooms. All HVAC systems are unitary (split type or window type).	- Design analysis, - Energy audits, - Survey
HVAC operation	Energy Management System	Definition of the HVAC system pattern for each subspace.	All school buildings have a mixed-mode operation.	- Design analysis, - Energy audits, - Survey,

Table 5.1 – Summary of descriptive characteristics of the building stock (continuation).

Parameter	Application (E+ object)	Description	Example for schools in Brazil	Source
Water heater system	Water heater system	Register of the proportions of the systems to heat water and the hot water end-uses.	15% of the schools have electric showers, 85% have no water heating systems. Solar, gas heater or heat pumps were not found.	- Design analysis, - Energy audits, - Survey,
Hot water usage	Schedules: Compact	Identification of the daily hot water usage pattern.	Schools often do not use hot water. The electric showers are a precaution to solve accidents with children.	- Energy audits, - Survey
Annual operation (for each subspace)	Schedules: Compact	Documentation of the building operation throughout the year for each subspace in the building.	Schools operate every weekday, from 8:00am to 12:00am and from 1:00pm to 6:00pm.	- Electricity bills, - Survey
Daily operation (for each subspace)	Schedules: Compact	Documentation of the daily building operation pattern for each subspace in the building.	Schools operate every weekday, from 8:00am to 12:00am and from 1:00pm to 6:00pm.	- Electricity bills, - Survey

Based on the information shown in Table 5.1, it is possible to create the core concept of the building archetype: layout of the rooms, daily and annual operation patterns and climate. The HVAC system should be modelled according to the predominant type of systems found in the building stock. The scenarios for the descriptive parameters are employed considering the primary outcomes from Table 5.1. Since those are subjective parameters, accounting for the frequencies of occurrence provides a good path to select the scenarios. For example, if more than one representative HVAC system is found in the targeting building stock, “n” scenarios of HVAC system should be modelled where “n” is the number of representative HVAC systems. The definition of the representative system is still subjective since those parameters are subjective characteristics.

For the building stock analysed, seven subspaces were identified:

- Subspace 1: Classrooms;
- Subspace 2: Library;
- Subspace 3: Computer lab;
- Subspace 4: Office rooms;
- Subspace 5: Aisles, cafeteria, and open spaces;
- Subspace 6: Bathrooms;
- Subspace 7: Kitchen.

The specification of features is used to arrange the specific parameters of the simulation model. It includes all parameters relevant for a generic building energy simulation, such as the size of the subspaces, thermal properties, and lighting loads. Once several values are registered for each parameter, each parameter becomes a continuous variable. Then, a variable identification number was assigned for each one. One emphasises that this framework proposition is a table that should be filled with building stock information for every building in the dataset.

Table 5.2 presents the variables considered in the specification of features to model the archetype and how they are interpreted in the simulation model in EnergyPlus.

Table 5.2 – Specification of features structure.

Aspect	Group	Description	Application (E+ object)	Unit	Source	Variable ID
Building size	Subspace area	Subspace 1, 2, ..., S	BuildingSurface: Detailed	m²	Design Analysis	X1
	Floor height	Subspace 1, 2, ..., S	BuildingSurface: Detailed	m	Design Analysis	X2
Envelope	Exterior wall	Thermal transmittance	Material and Construction	W/m²K	Energy Audit	X3
		Thermal capacity	Material and Construction	J/m²K	Energy Audit	X4
		Thermal absorptance	Material and Construction	m	Design Analysis	X5
		Thickness	Material and Construction	%	Energy Audit	X6
	Interior wall	Thermal transmittance	Material and Construction	W/m²K	Energy Audit	X7
		Thermal capacity	Material and Construction	J/m²K	Energy Audit	X8
		Thermal absorptance	Material and Construction	m	Design Analysis	X9
		Thickness	Material and Construction	%	Energy Audit	X10
	Roofing	Thermal transmittance	Material and Construction	W/m²K	Energy Audit	X11
		Thermal capacity	Material and Construction	J/m²K	Energy Audit	X12
		Thermal absorptance	Material and Construction	m	Design Analysis	X13
		Thickness	Material and Construction	%	Energy Audit	X14
	Glazing	Thermal transmittance	Material: AirGap	W/m²K	Energy Audit	X15
		Solar Heat Gain Coefficient (SHGC)	WindowMaterial	%	Energy Audit	X16
		Opening Factor	AirflowNetwork:MultiZone: Surface	%	Energy Audit	X17
	Infiltration rate	Airflow rate through windows	AirflowNetwork	kg/m.s	Energy Audit	X18
		Airflow rate through doors	AirflowNetwork	kg/m.s	Energy Audit	X19
	WWR	Subspace 1, 2, ..., S	FenestrationSurface:Detailed	%	Design Analysis	X20
	Horizontal shading	Subspace 1, 2, ..., S	Shading:Building: Detailed	m²	Design Analysis	X21
	Vertical shading	Subspace 1, 2, ..., S	Shading:Building:Detailed	m²	Design Analysis	X22
Systems	Equipment loads	Subspace 1, 2, ..., S	ElectricEquipment	W/m²	Design Analysis	X23
	Lighting loads	Subspace 1, 2, ..., S	Lights	W/m²	Design Analysis	X24
	HVAC load	Subspace 1, 2, ..., S	HVACTemplate: Unitary	BTU/h	Energy Audit	X25
	Water heater	Heater Thermal efficiency	Water heater and Thermal Storage	W/W	Energy Audit	X26
Occupancy	Density of people	Subspace 1, 2, ..., S	People	people/m²	Database	X27
EUI	-	Whole building EUI	-	kWh/m².year	Database	Y

Table 5.2 provides the set of values found in the dataset for each variable of the framework considered in the simulation model. The set of values can be interpreted considering their range (minimum and maximum values) and their distribution (frequencies according to bins – a class interval). For example, by analysing the dataset of the school building stock in Brazil, the variable X2 (floor height) varied from 2.8 m to 3.2 m, and the median value was 3.0 m.

Table 5.1 provided general guidelines for the energy building model and its scenarios with the completion of the inventory, and Table 5.2 provided a distribution of values for the set of variables.

Hence, to prepare the energy simulation model, the variables in Table 5.2 have to be assigned with discrete values to parametrise representative conditions of the building stock. Running an energy simulation is often a time-and-resources consuming process; then, it is important to select typical cases for each parameter in the model. The building stock often presents a wide range of values in a variable; then, more than one value for some parameters should be set in the simulation to represent the stock adequately.

Therefore, in terms of specification of features, one may ask: how to select the parameters that should be varied in the parametric simulation? This can be performed by integrating Information Theory and analysing the entropy of each variable.

2.3. Entropy analysis

Claude E. Shannon originally proposed the information theory in 1948, and it is a concept that translates the study of uncertainty, quantification, and communication of information. Shannon proposed entropy, which quantifies the uncertainty (or information) involved in the random variable distribution. There are several interpretations for the entropy, including the "degree of surprise" or the "number of questions" it is needed to be asked to find a given answer (COVER; THOMAS, 2006). For a given continuous variable, the entropy is calculated through Equation 1 (here, we adopted Shannon Entropy (COVER; THOMAS, 2006), with the logarithm in base 2).

$$H(X) = -\sum_{x}^{i=1} p(x) \times log_2 p(x) \quad (1)$$

Where H(x) is the entropy of a continuous variable "x" (bits), and p(x) is the probability of the variable "x" (%).

In this paper, we employ entropy as a metric of uncertainty. The higher the entropy, the higher the uncertainty that a variable holds. The maximum entropy corresponds to the lower information available for a given variable. It is reasonable to associate the maximum entropy of a variable with the uniform distribution – the probability of a variable to be any value is equal for all bins. Maximum entropy only depends on the number of bins and can be obtained through the simple logarithm of the number of bins (DARSCHEID; GUTHKE; EHRET, 2018). Then, relative entropy is a valuable metric obtained by comparing the entropy of a given variable discretised by a given number of bins with the maximum entropy for the same number of bins. Relative entropy is calculated using Equation 2 (THIESEN; DARSCHEID; EHRET, 2018).

$$R(x) = \frac{H_n(x)}{H^{m,n}(x)} \times 100 \tag{2}$$

Where R(x) is the relative entropy (%), H(x) is the entropy of the variable "x" for "n" bins (bits), and $H^{m,n}$ is the maximum entropy of a distribution with "n" bins (bits).

To allow comparison between entropies, the entropy of each variable must be calculated using the same number of bins. The number of bins is a definition made by the specialist in the information analysis, depending on the number of observations and the variable distribution aspect. In this work, we adopted eight bins to discretise all variables. This results in the maximum entropy of 3 (logarithm of 8 bins in the base 2), as suggested by other studies (DARSCHEID; GUTHKE; EHRET, 2018). We employed the R package "Entropy" (HAUSSER; STRIMMER, 2009) to perform all entropy calculations.

All variables were normalised before calculating the entropy using Equation 3.

$$x'_{min} = \frac{x_i - x_{min}}{(x_{max} - x_{min})} \tag{3}$$

Where x' is a given "i" value of the variable "x", x_{min} is the minimum value of the variable "x" and x_{max} is the maximum value of the variable "x".

Then, the variable is presented in a range from zero to one. By calculating the relative entropy of all variables in Table 5.2 and considering the same number of bins and the normalisation, all entropies can be compared using the relative entropy. Relative entropy can rank the parameters with high and low uncertainty. In this case, parameters with relative entropy higher than 50% were considered with high uncertainty, while parameters with relative entropy lower than 50% were considered with low uncertainty.

Then, parameters with low uncertainty were kept fixed, and no parametrisation was performed (since we are more confident about their values in the building stock). Otherwise, parameters with high uncertainty were selected to be variable parameters in the simulation through parametrisation. Fixed parameters were adopted as their median values, but how to select the values for parametrisation? Cluster analysis was employed for such purpose.

2.4. Cluster analysis

The previous step provided the variables with more uncertainty in the dataset. Thus, a cluster analysis was employed in two steps: defining the optimal number of clusters and the parameters' values for each scenario. Cluster analysis is a multivariate technique that aims to group cases of a variable in the same class (cluster), considering similarities and dissimilarities (GENTLE; KAUFMAN; ROUSSEUW, 1991). Hierarchical and non-hierarchical approaches can be used. In this work, we employed a non-hierarchical process using the k-means method. K-means has been used in other studies to obtain reference buildings (SCHAEFER; GHISI, 2016; ZHAN *et al.*, 2020a).

Since k-means needs the number of clusters as input, the optimal number of clusters was calculated through the average silhouette method. The average silhouette method calculates scenarios of the silhouette coefficient (Equation 4 (GENTLE; KAUFMAN; ROUSSEUW, 1991)).

$$SC = \frac{x-y}{\max(x-y)} \tag{4}$$

Where SC is the silhouette coefficient, x is the mean distance to the instances to the next closest cluster; and y is the mean intra-cluster distance. SC varies from zero to one.

The silhouette coefficient determines the fit of an object within its cluster. By taking the average silhouette of all objects in a cluster, it is possible to calculate the average silhouette width. The optimal number of clusters is defined as the one with the highest silhouette width (best objects fit in the clusters). Figure 5.2 shows an example of the result of the silhouette method for the variable X27.

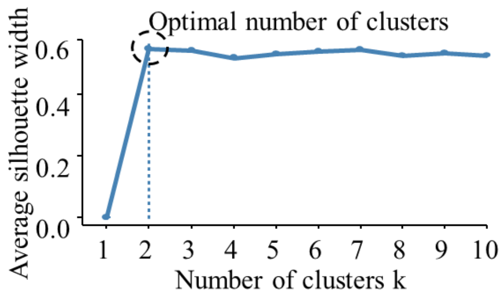


Figure 5.2 – Example of an optimal number of clusters (Silhouette method) for the variable X27 (density of people).

This process is performed for each variable considered for parametrisation (high uncertainty). R package Nbclust was used for such assessment (CHARRAD *et al.*, 2014). Then, having defined the optimal number of clusters, the cluster analysis for each variable parameter was obtained through the k-means method. K-means has been widely explored in data science, and various descriptions and variations are found in the literature. The main purpose consists of grouping the observations in clusters so that the variation within the cluster is minimal and the variation between clusters is maximum. The standard calculation method relies on determining the total within-cluster sum of squares and considers the squared Euclidean distances between each item and the corresponding centroid (Equation 5).

$$W(k) = \sum_{k=1}^{k} \sum_{x \in k} (x_i - x'_k)^2 \quad (5)$$

Where: W is the total within-cluster sum of squares for the cluster k; x_i is an instance of a given variable X and x' is the centroid value of a given variable X.

The process to calculate the cluster is iterative. "k" firsts random centroids are selected, one for each cluster, and used to calculate the total within-cluster sum of squares. Then, each instance is assigned to a cluster (as the proximity to the centroid chosen). After the assignment, the centroids for each cluster are recalculated, and the process is repeated. The iterations are performed until the clustering process converges (minimise the total within-cluster sum of squares). The centroids of each cluster are selected to be the values in the parametric simulation. For example, the cluster centroids were 1.20 m²/student and 2.29 m²/student for variable X27 (density of people).

2.5. Parametric simulation

The previous steps provided evidence to model the archetypes. The massing models were defined according to the subspaces identified in the descriptive analysis. This is a subjective process that has to be performed by an analyst. This framework proposes to begin with a minimal model, once an archetype intends to generalise conditions. OpenStudio® was used to support the modelling process.

More than one building massing model was developed since variations in the subspace's areas were significant for the entropy analysis. This analysis is particular for each building stock; once there are architectonical rules that are hardly interpreted by algorithms. Then, we considered the shape rules identified when composing the different massing models. The shape rules provide information about the typical building shapes and layout that supports the creation of simulation models. Regarding the current example, seven building shapes were identified for school buildings in Brazil.

Then, the simulation models are composed of fixed parameters and variable parameters. Variable parameters were programmed using parametric simulation tools (Parametric object in EnergyPlus and R environment support). In this framework, we employed a factorial experiment for the parametric simulation. Thus, all variations considered for every variable are combined with each other, i.e. the number of total simulations is the product of all number of clusters considered.

The entropy analysis defined which variables should be varied in the simulations, and the cluster analysis defined the values for each scenario for those variables. For the example used in this paper, Table 5.3 shows the scenarios evaluated in the parametric simulation.

Table 5.3 – Scenarios evaluated in the parametric simulation

Aspect	Object	Number of clusters	Description
Descriptive characteristics*	Building shape	7	Scenario 1: Shape E Scenario 2: Shape L Scenario 3: Shape H Scenario 4: Shape O Scenario 5: Shape U Scenario 6: Rectangular Scenario 7: Multiple Buildings
	Operation time	2	Scenario 1: School with day shift (8 hours)
			Scenario 2: School with day and night shift (14 hours)
	HVAC type	2	Scenario 1: HVAC in office rooms, library, and computer lab;
			Scenario 2: Scenario 1 + classrooms
	Weather	8	Eight climatic zones (Table 5.4)
Specific features	Subspaces' area	-	Variations according to the building shape
	Density of people	2	Scenario 1: High density in classrooms (1.20 m²/student)
			Scenario 2: Low density in classrooms (2.29 m²/student)
	Refrigerators	2	Scenario 1: High EPD in the kitchen (5.77 W/m²)
			Scenario 2: Low EPD in the kitchen (3.05 W/m²)
	Lights	2	Scenario 1: High LPD (11.09 W/m²)
			Scenario 2: Low LPD (3.37 W/m²)

* Clusters obtained through subjective analysis, not k-means method.

Other variables were adopted as fixed values according to the entropy analysis. These values are presented in Table 5.6 (Results and discussion section). For example, EPDs equal to 50.5 W/m² and 99.4 W/m² were considered for office rooms and computer labs, respectively.

In this case, 1,792 simulations were run for one year. The simulations were performed using the EnergyPlus engine (version 9.4). Some specific parameters of the simulations are described as follows:

- Ground domain model: a ground domain slab model was modelled considering an undistributed finite-difference algorithm. General soil thermal conductivity of 1.5 W/m.K, soil density of 1,250 kg/m³, and soil specific heat of 1,500 J/kg.K were considered.
- HVAC system: An Ideal Loads HVAC template was considered for each room for the air-conditioning model. A system with cooling system with direct expansion with a cooling setpoint of 24°C and a heating setpoint of 18°C was considered. An average coefficient of performance (COP)

was used to convert the thermal energy into electricity consumption; as suggested in the Brazilian Regulation (CB3E, 2017), a reference COP of 2.6 W/W was adopted.

- Energy Management System (EMS): To properly model the natural ventilation effect in buildings (mixed-mode building operation), which is common in Brazil, an EMS algorithm was applied to regulate the turning on/off of air-conditioning and opening/closing the windows in each air-conditioned room. The criterion was to turn on the air-conditioning (and windows closed) when the operative temperature of the zone was higher than 26°C (cooling) and lower than 16°C (heating), considering that there are people in the room. Outside this range, windows were considered open and air-conditioning off.
- Schedules: Occupancy schedules were defined according to the analysis of the descriptive characteristics. Understandably, occupancy behaviour plays an important role in building performance assessment, and several pieces of research have been conducted to enhance the representation of the user in simulations. However, this framework proposes modelling for benchmarking; thus, standard occupation patterns were set. Figure 5.3 presents the values adopted for the example analysis. A further improvement for this framework might be including an interpretation of obXML to enhance the representation of the occupant behaviour in a probabilistic way.

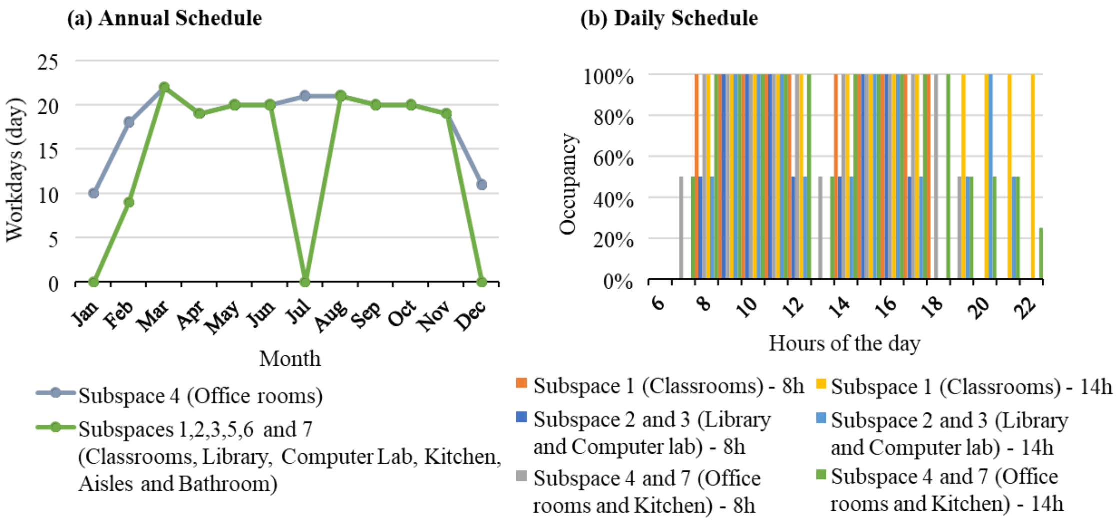


Figure 5.3 – Schedules considered in the simulation.

Eight weather data were used in the simulations to consider all eight Brazilian climatic zones proper. The data was obtained from the Climate One Building website, in TMY format with the database of 2018. Table 5.4 shows the cities chosen to represent each climate and their characteristics.

Table 5.4 – Climates considered in the parametric simulation.

City	Brazilian Climate zone (NBR 15220 2005)	ASHRAE classification (ASHRAE 169-2013)	Lat. (°)	Long. (°)	Alt. (m)	Cooling Degree Hours*
Curitiba (PR)	1	3A (Warm Humid)	-25.43	-49.27	924	9,397
Pelotas (RS)	2	3A (Warm Humid)	-31.72	-52.33	18	18,657
São Paulo (SP)	3	2A (Hot Humid)	-23.85	-46.64	792	14,172
Brasília (DF)	4	2A (Hot Humid)	-15.78	-47.93	1160	16,624
Santos (SP)	5	2A (Hot Humid)	-23.93	-46.32	14	40,003
Goiânia (GO)	6	1A (Very hot and humid)	-15.37	-48.78	770	31,081
Picos (PI)	7	1A (Very hot and humid)	-7.07	-41.40	233	53,316
Cuiabá (MT)	8	0A (Extremely hot humid)	-15.62	-56.00	151	59,551

* CDH calculated considering the base temperature of 15°C.

The outputs of the simulations that were analysed were the energy use intensity for each end-use (kWh/m².year), i.e. the annual electricity consumption of each end-use divided by the total gross floor-plan area of each building model. The end-uses were lighting, equipment, cooling, and heating.

Different building orientations were tested. A simple comparison showed that this factor did not impact the final results of this typology; thus, a single orientation was defined.

2.6. ANN model

The simulation results were used to developed an Artificial Neural Network (ANN) model. An ANN is a non-linear multivariate model composed of nodes (neurons) organised in layers and connected by synaptic weights to replicate the functioning of the human brain. There is an input layer, a hidden layer (or several hidden layers), and an output layer. The arrangement of the ANN makes this method a robust approach to model complex relationships between input and outputs. The ANN is modelled through a supervised procedure that contains a training process (using 80%

of the dataset) and a testing process (using the remaining 20%). During the training process, the output variables are known, and the weights and coefficients of the nodes and synaptic connections are calculated. An activation function is responsible for starting the calculations, providing random values for the synaptic weights, while iterations are performed to approximate the output calculated by the ANN to the output values in the training dataset. During the testing process, new input values are submitted to the ANN, and the predicted output is compared to the actual output to determine the ANN performance (AHMAD *et al.*, 2018). In this paper, the R environment (package "neuralnet") was employed to create the ANN using the logistic activation function.

The ANN was employed as a robust and useful estimator to serve as the benchmarking model. Thus, the EUI predicted by the ANN is the benchmark (a reference value of energy performance in typical conditions) that can be compared to the actual EUI of a given school in order to measure its performance.

The inputs of the ANN are the parameters used in the simulations, and the output was the EUI. The dataset used for training and testing was the simulation results (1,792 observations). Table 5.5 presents the inputs and outputs. Since the output is the EUI (which is already normalised in terms of the floor-plan area), the size of the building was not an input.

Table 5.5 – Input and output parameters of the ANN model.

Type	Parameter	Unit	Data range
Input	Cooling Degree Hours (base temp.: 15°C)	degree-hours	9,397-40,003
Input	Operation time	hours	8 - 12
Input	Total occupancy	people/m²	0.50 - 1.35
Input	Air-conditioned area ratio	%	16% - 75%
Input	Total equipment power density	W/m²	6.39 - 10.59
Input	Total lighting power density	W/m²	3.37 - 11.09
Output	Whole-building EUI	kWh/m².year	8.8 – 157.8

The dataset was partitioning, considering a random selection of 80% of the dataset (1,433) for training and 20% (359) for testing. A normalisation step was carried out in all variables (through the same process described in Equation 3), as recommended by good ANN development practices. Each input and output neuron ranged from 0 to 1. After the ANN development, the output value was transformed again in EUI by multiplying it by the average simulated EUI.

Different ANN arrangements were tested during the training and testing stages to find the optimum configuration for the given data. Several combinations of layers and neurons were tested, considering the maximum of six layers and neurons (the same number of input nodes). The best performance was obtained using two hidden layers with six neurons each.

The performance of the ANN was measured through the Root Mean Squared Error (RMSE) (Equation 6), considering the two datasets (training and testing datasets). The lower the RMSE, the greater the capacity of the ANN in predicting EUIs similar to the actual EUIs. This is a valuable metric to measure the performance of continuous estimators as the ANN used in this paper.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - x'_i)^2}{N}} \tag{6}$$

Where: RMSE is the Root Mean Squared Error (kWh/m².year); x_i is the EUI of a given "i" case (kWh/m².year); x' is the EUI predicted by the ANN (kWh/m².year); N is the number of cases, i.e. 1,792.

Also, the Coefficient of variance of RMSE was calculated (Equation 7) to relativise the result in terms of percentage. The lower the CV(RMSE), the greater the capacity of the ANN in predicting the output correctly.

$$CV(RMSE) = \frac{RMSE}{Y'} \tag{6}$$

Where: CV(RMSE) is the RMSE is the Coefficient of variance (%); the RMSE is the Root Mean Squared Error (kWh/m².year); and Y' is the s the mean target output (kWh/m².year).

Moreover, a cross-validation was carried out by fitting the actual versus predicted plot for both datasets. The closer to the main diagonal the points converge, the greater the capacity of the ANN in predicting the typical conditions of the building stock.

2.7. Benchmarking the actual stock

The benchmarking model can be used to benchmark the actual building stock. The input dataset of 417 school buildings in Brazil was used for such an aim. The actual dataset features were inserted in the ANN, and the predicted EUI from the ANN was compared to the actual EUI of each building. Then, it was possible to benchmark each building of the dataset. A graphical analysis shows green bars for EUIs lower than the benchmark and red bars for EUI higher than the benchmark.

End-uses are important to address in order to evaluate the efficiency of a building. This model was not meant to estimate the end-uses in the ANN because the inputs are already indications of the end-uses (EPD and LPD). However, it is possible to assess typical end-uses for the building typology for each climatic zone evaluated by calculating the average end-uses of the simulation scenarios evaluated. Two scenarios were considered, one for highly air-conditioned schools (scenario 2 of HVAC type in Table 5.3) and one for lower air-conditioned schools (scenario 1 of HVAC type in Table 5.3).

Finally, a case of a specific school building was analysed individually. The school "Almirante Carvalhal", located in Florianópolis (southern Brazil) was benchmarked using the ANN. The school has a total floor-plan area of 1,428 m². The input parameters are:

- CDH_{15}: 28,602 degree-hours;
- Operation time: 8 hours;
- Total occupancy: 0.98 people/m²;
- Air-conditioned area ratio: 50%;
- Total EPD: 14.78 W/m²;
- Total LPD: 3.12 W/m².

This building was one of the three buildings with an energy audit; then, an end-use level comparison was performed by comparing the end-uses proportions identified in the energy audit and the end-uses of the benchmark predicted by the ANN.

3. Results and Discussions

3.1. Building stock modelling

The stock modelling process includes a composition of an inventory of parameters followed by an entropy and a cluster analysis of those parameters. This step originated the parameters to be inserted in the archetype simulation.

The entropy analysis measures the degree of uncertainty of each parameter considering the available information in the dataset. The relative entropy (the rate between the maximum entropy, or uncertainty, and the entropy of the parameter) is a useful metric to visualise how much uncertainty a parameter holds in terms of percentage. Parameters with relative entropy lower than 50% were fixed in the simulation, while parameters with relative entropy higher than 50% were varied through cluster analysis. Table 5.6 presents the entropy, the relative entropy, and the adopted value for each fixed parameter of the inventory.

Table 5.6 – Fixed parameters used in the simulations

#	Parameter	Unit	Range	Entropy (bits)	Relative Entropy	Median (adopted)
X2	Floor height	m	2.8 - 3.2	1.48	49%	3.0
X3	ExtWalls-Transmitance	W/m²K	1.8 - 2.5	0.83	28%	2.4
X4	ExtWalls-Thermal Capacity	J/m²K	180 - 240	0.83	28%	240.0
X5	ExtWalls-Solar absorptance	%	0.6 - 0.8	0.68	23%	0.7
X6	ExtWalls-Thickness	m	15 - 30	1.03	34%	20.0
X7	IntWalls-Transmitance	W/m²K	1.8 - 2.5	0.83	28%	2.4
X8	IntWalls-Thermal Capacity	J/m²K	180 - 240	0.83	28%	240.0
X9	IntWalls-Solar absorptance	%	0.6 - 0.8	0.68	23%	0.7
X10	IntWalls-Thickness	m	15 - 30	1.03	34%	20.0
X11	Roof-Transmitance	W/m²K	0.8 - 2.7	0.86	29%	2.1
X12	Roof-Thermal Capacity	J/m²K	220 - 258	0.55	18%	238.0
X13	Roof-Solar absorptance	%	0.6 - 0.8	0.68	23%	0.7
X14	Roof-Thickness	m	1.3 - 1.5	0.55	18%	1.3
X15	Glazing-Transmitance	W/m²K	5.3 - 5.7	0.21	7%	5.7
X16	Glazing-SHGC	%	0.8 - 0.8	0.21	7%	0.8
X17	Glazing-Opening Factor	%	0.3 - 0.7	0.55	18%	0.5
X20.1	WWR-Subspace 1	%	0.1 - 0.8	1.10	37%	0.4
X20.2	WWR-Subspace 2	%	0.1 - 0.8	1.10	37%	0.4
X20.3	WWR-Subspace 3	%	0.1 - 0.8	1.10	37%	0.4
X20.4	WWR-Subspace 4	%	0.1 - 0.8	1.10	37%	0.4
X20.5	WWR-Subspace 5	%	0.6 - 1	0.79	26%	1.0

Table 5.6 – Fixed parameters used in the simulations. (continuation).

#	Parameter	Unit	Range	Entropy (bits)	Relative Entropy	Median (adopted)
X20.6	WWR-Subspace 6	%	0 - 0.8	1.42	47%	0.2
X20.7	WWR-Subspace 7	%	0.1 - 0.3	1.02	34%	0.2
X21.1	HorShading-Subspace 1	m²	0.5 - 0.9	0.41	14%	0.8
X21.2	HorShading-Subspace 2	m²	0.5 - 0.9	0.41	14%	0.8
X21.3	HorShading-Subspace 3	m²	0.5 - 0.9	0.41	14%	0.8
X21.4	HorShading-Subspace 4	m²	0.5 - 0.9	0.41	14%	0.8
X21.5	HorShading-Subspace 5	m²	0.5 - 0.9	0.41	14%	0.8
X21.6	HorShading-Subspace 6	m²	0.5 - 0.9	0.41	14%	0.8
X21.7	HorShading-Subspace 7	m²	0 - 0.8	0.41	14%	0.8
X22.1	VerShading-Subspace 1	m²	0.2 - 0.6	1.42	47%	0.4
X22.2	VerShading-Subspace 2	m²	0.2 - 0.6	1.19	40%	0.4
X22.3	VerShading-Subspace 3	m²	0.2 - 0.6	1.19	40%	0.4
X22.4	VerShading-Subspace 4	m²	0.2 - 0.6	1.19	40%	0.4
X22.5	VerShading-Subspace 5	m²	0 - 1	0.21	7%	0.0
X22.7	VerShading-Subspace 7	m²	0 - 0.1	0.21	7%	0.0
X23.1	EquipLoads-Subspace 1	W/m²	15.2 - 239.4	1.19	40%	21.2
X23.2	EquipLoads-Subspace 2	W/m²	3.3 - 20.7	0.41	14%	20.7
X23.3	EquipLoads-Subspace 3	W/m²	37.9 - 346.5	1.41	47%	99.4
X23.4	EquipLoads-Subspace 4	W/m²	43.5 – 57.0	0.41	14%	50.5
X23.6	EquipLoads-Subspace 6	W/m²	-	-	N/A	0.0
X23.7	EquipLoads-Subspace 7	W/m²	-	-	N/A	0.0
X26	HeaterThermalEfficiency	W/W	1-1	0.00	N/A	0.0
X27.2	People-Subspace 2	people/m²	2 – 8	0.29	10%	4.0
X27.3	People-Subspace 3	people/m²	0 - 20	0.39	13%	7.0
X27.4	People-Subspace 4	people/m²	2 - 6	0.24	8%	7.0
X27.5	People-Subspace 5	people/m²	-	-	N/A	0.0
X27.6	People-Subspace 6	people/m²	-	-	N/A	0.0
X27.7	People-Subspace 7	people/m²	-	-	N/A	0.0

Most of the envelope characteristics were considered as fixed parameters since school buildings follow very similar standards for construction. Equipment loads per floor-plan area in classrooms, libraries, and computer labs, were surprisingly consistent and were adopted as fixed parameters. Equipment loads in kitchens are due to refrigerators and freezers, which presented significant variation in the building stock. Equipment loads in bathrooms and aisles were not considered in the model. Whenever empty observations happened in the analysis (such as the equipment loads in bathrooms), it was represented with zero entropy and a non-applicable tag (N/A) in relative entropy. Another example like this is the occupation of aisles, bathrooms, and the kitchen.

Very few schools presented water heaters since it is not part of the culture in Brazil that elementary and high schools provide baths. Then, the water heater was disregarded in the simulation since it was not considered a typical condition.

Table 5.7 shows the parameters with relative entropy higher than 50% and considered variables in the simulation model. Additionally, the last column presents how the parameters were varied in the parametric simulation and the result of the cluster analysis, i.e. the values adopted in each scenario of parametrisation.

Table 5.7 – Variable parameters used in the simulations

#	Parameter	Unit	Median	Range	Entropy (bits)	Relative Entropy	Scenarios for parametrisation (clusters)
X1.1	Area-Subspace 1	m²	604.0	223.3 - 1579.2	2.4	79%	Seven floor-plan areas according to each building shape
X1.2	Area-Subspace 2	m²	67.7	20.7 - 131.3	2.7	89%	
X1.3	Area-Subspace 3	m²	50.3	1 - 131.8	2.0	68%	
X1.4	Area-Subspace 4	m²	84.8	14.9 - 282.1	2.5	82%	
X1.5	Area-Subspace 5	m²	190.0	80.1 - 873.6	2.0	68%	
X1.6	Area-Subspace 6	m²	61.8	28.4 - 265.7	2.0	66%	
X1.7	Area-Subspace 7	m²	31.0	7.1 - 96.4	2.2	73%	
X23.4	EquipLoads-Subspace 7	W/m²	4.7	4.4 - 9.7	1.5	50%	Scenario 1: EPD of 5.6 W/m² in the kitchen Scenario 2: EPD of 3.5 W/m² in the kitchen
X24.1	LightLoads-Subspace 1	W/m²	12.5	0.5 - 23.5	1.9	62%	Scenario 1: High average LPD (11.09 W/m²) Scenario 2: Low average LPD (3.37 W/m²)
X24.2	LightLoads-Subspace 2	W/m²	9.0	0.5 - 24	1.9	62%	
X24.3	LightLoads-Subspace 3	W/m²	9.0	0.5 - 25.5	1.5	51%	
X24.4	LightLoads-Subspace 4	W/m²	9.7	4.9 - 18	1.6	52%	
X24.5	LightLoads-Subspace 5	W/m²	5.5	1.2 - 15.5	1.8	61%	
X24.6	LightLoads-Subspace 6	W/m²	5.0	1.2 - 16	1.6	54%	
X24.7	LightLoads-Subspace 7	W/m²	15.5	1.2 - 15.5	1.8	61%	
X25.1	HVAC-Subspace 1	%	68.0	0 - 97.9	2.6	87%	Scenario 1: HVAC in office rooms, library, and computer lab; Scenario 2: Scenario 1 + classrooms
X26.1	People-Subspace 1	student/m²	0.5	0 - 5.1	2.7	89%	Scenario 1: High density in classrooms (1.20 m²/student) Scenario 2: low density in classrooms (2.29 m²/student)

The areas of all subspaces were variables. Since the subspace's composition consists of a subjective evaluation, the variation of each subspace area was considered in different shape compositions (Table 5.8). Equipment loads in the kitchen were considered a variable when different refrigerators and freezers were found. The cluster analysis resulted in two scenarios. Lighting loads were also very irregular – which carries uncertainty to the stock model. Two scenarios were also defined to represent this distribution of different lighting loads.

Table 5.8 – Summary of the floor-plan area of the simulation models.

Subspace	Name	Floor-plan area (m²)						
		Shape E	**Shape H**	**Shape L**	**Shape O**	**Shape U**	**Rec.**	**Multiple buildings**
Subspace 1	Classrooms	799.7	609.0	623.3	637.0	500.5	700.7	638.4
Subspace 2	Library	67.8	72.0	70.0	59.5	50.1	82.0	72.0
Subspace 3	Computer lab	50.0	72.0	49.0	54.6	50.1	70.0	50.0
Subspace 4	Office rooms	100.0	217.8	120.0	100.0	52.5	98.0	80.1
Subspace 5	Aisles	240.9	597.7	317.7	260.5	109.8	318.3	146.0
Subspace 6	Bathroom	44.8	38.8	68.6	58.8	58.9	89.0	103.0
Subspace 7	Kitchen	51.0	87.8	42.0	74.2	60.0	83.3	80.0
Total		**1,354.1**	**1,695.0**	**1,290.6**	**1,244.6**	**881.8**	**1,441.3**	**1,169.5**

During the subjective evaluation of the building stock sample, seven building shapes were identified. It was important to represent those different building shapes in the archetype once the shape has an important role in the energy performance of the building, as shown in the study of several features to categorise buildings according to their performances (ZHAN *et al.*, 2020b). It is important to keep in mind that the benchmarking is meant to represent typical conditions and the output available is the EUI (in terms of kWh/m².year); then, the size of the building is relativised considering the indicator employed. Figure 5.4 presents the seven archetypes obtained.

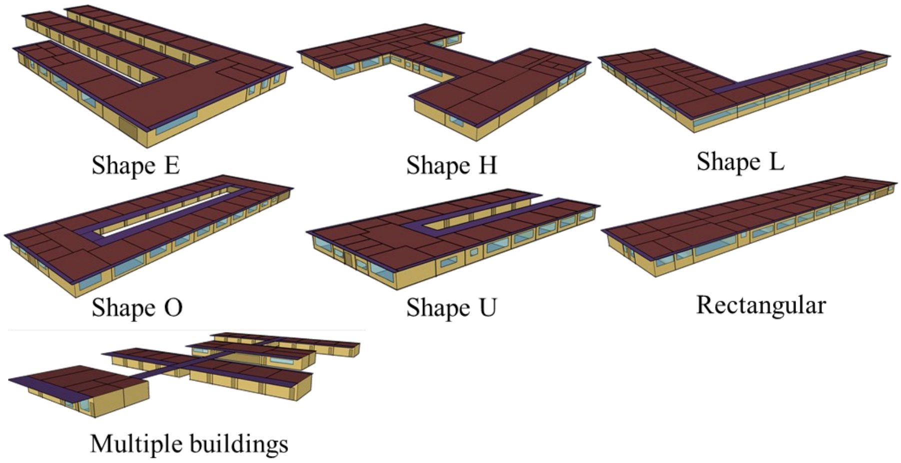


Figure 5.4 – Archetypes obtained for each building shape.

Differences in shapes imply different building envelope interactions with the exterior, especially considering the self-shading dynamic. The building orientation was not significant for this typology because the central part of the building comprises the same subspace (classrooms), making each building shape have a similar number of classrooms oriented equally. Although the building massing model and the shape configuration were a product of a subjective evaluation in this study, and there is an uncertainty accumulated in this process, we understand that the identification of shape rules is used for similar purposes (GRANADEIRO *et al.*, 2013). However, with the emerging tools for generative design and parametric modelling (YU; GERO; GU, 2015), there is an opportunity to improve this method considering integrating such tools. Other studies took advantage of modelling buildings using Grasshopper to improve building energy performance through parametric design (KITCHLEY; SRIVATHSAN, 2014). The descriptive analysis of this method could be translated to a set of Grasshopper rules, and generative archetypes can be modelled using an auxiliary script. This approach was disregarded in this method because it demands a specific study considering the programming implications and shape grammar definitions process; however, we see it as the following steps to automatise the framework proposed.

3.2. Benchmarking model and validation

The archetypes were simulated considering the scenarios for the parameter variables and the different climates. The results of the simulation models served as parameters to model an ANN for benchmarking the actual stock. The benchmarking model is necessary to generalise the typical results obtained in the simulations. The simulations were responsible for providing typical and extreme cases. Then, a statistical generalisation process is needed to allow the placement of an actual building performance among these typical and extreme cases. Other studies used regression analysis (BORGSTEIN; LAMBERTS, 2014), convex non-parametric least-square analysis (CHUNG; YEUNG, 2017), and two-stage regression analysis (CHUNG; YEUNG, 2021), among others. In this paper, an ANN considering two hidden layers with six and three neurons was built. Figure 5.5 shows the visual aspect of the ANN built.

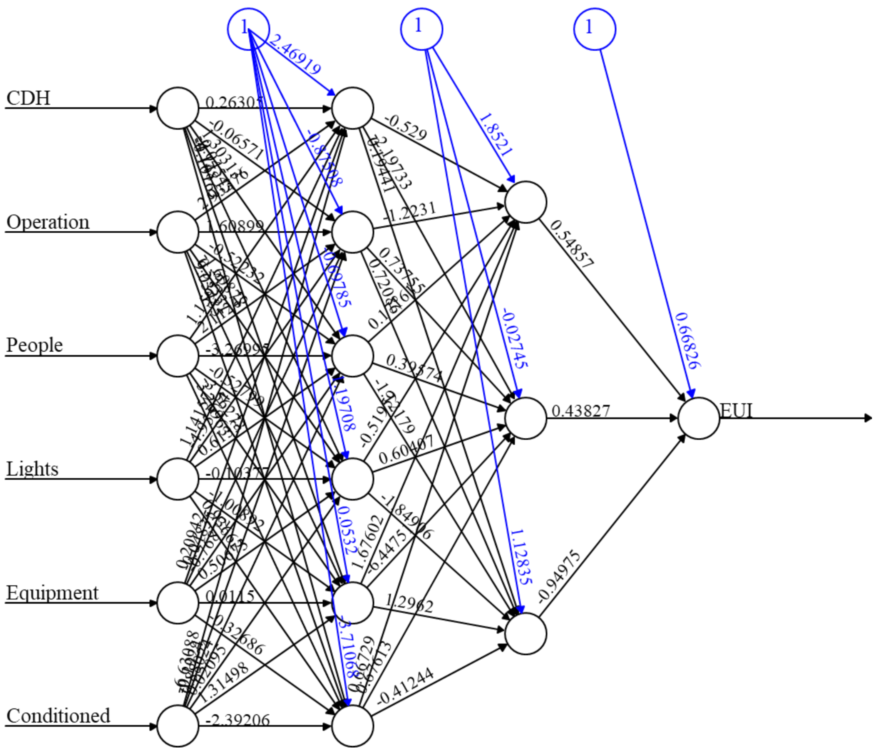


Figure 5.5 – ANN of the benchmarking model.

Several ANN arrangements were tested to a final structure, considering RMSE and CV(RMSE) reduction. The ANN serves as a regressive estimator by inputting new values in the input neuron and providing the predicted value by the output neuron. A validation step was performed by examining both training and testing datasets and measuring the capacity of the ANN in predicting the EUIs correctly. Figure 5.6 shows the plot of the predict versus training and testing data. The closer the points are to the diagonal line, the best the predicting capacity of the ANN. The dashed lines represent the interval of confidence for the model.

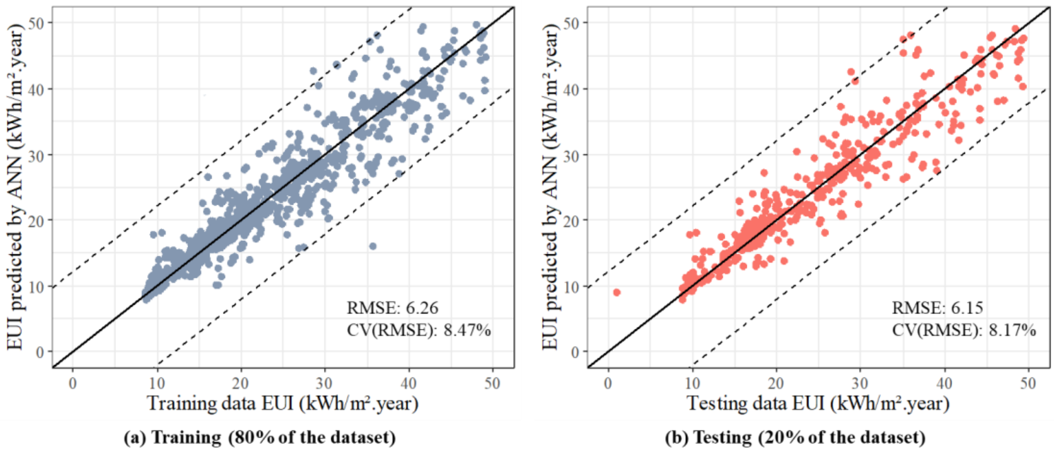


Figure 5.6 – ANN performance evaluation.

For the training data, the RMSE was 6.26 kWh/m².year, and the CV(RMSE) was 8.47%. For the testing data, RMSE was 6.15 kWh/m².year, and the CV(RMSE) was 8.17%. It is possible to see that, in general, the ANN had a good prediction capacity once most points are placed inside the interval of confidence, except for a few cases. Although a lower RMSE indicates a good ANN performance, there is no consensus regarding an optimal value once the RMSE is restricted to each ANN and its analysis. The CV(RMSE) corresponds to a more understandable metric, ranging from 0% (zero error) to 100% (maximum error).

Other studies in literature achieved similar performance indexes. The study of Hong *et al.* (2014) also proposed an ANN for benchmarking school buildings in the UK and achieved an RMSE equal to 11.6 kWh/m² and a CV(RMSE) equal to 23.5% for predicting electric uses (HONG *et al.*, 2014). Wong *et al.* (2010) used an ANN to assess daily performance in office buildings and achieved an RMSE of 2578 kWh and CV(RMSE) of 9.4% for predicting the whole-building energy consumption (WONG; WAN; LAM, 2010). Wang *et al.* (2019) used an ANN and achieved CV(RMSE) from 10% to 35% for predicting plug loads (WANG; HONG; PIETTE, 2019), and Zhang *et al.* (2015) achieved an RMSE of 12.09 and CV(RMSE) of 14.01% for energy performance prediction on a daily-basis (ZHANG *et al.*, 2015). Veiga *et al.* (2021) proposed a Support Vector Machine for Bank Branches and achieved an RMSE of 4.45

kWh/m².year. Thus, it is possible to understand that the RMSE achieved is acceptable considering the aim and approach employed.

Figure 5.7 shows the breakdown of the predicted versus testing data plot for each city considered in the study. Since the climate is a crucial factor in the building performance analysis, it is important to assess how the ANN addresses the predictions under different climate conditions. It is possible to see that zones 1, 2, and 8 correspond to good predictions. Results showed that the ANN predicts slightly lower EUIs for buildings in zones 3, 5 and 7, and slightly higher EUIs for buildings in zones 6 and 4. In any case, the output values were always inside the interval of confidence.

A possible solution to mitigate this issue is to create an ANN for each climatic zone. However, we constructed the ANN using the CDH as a parameter for estimating (using eight CDH to train and test the network, one for each climate used in the simulations). This means that the network can be generalised for other cities with other CDH.

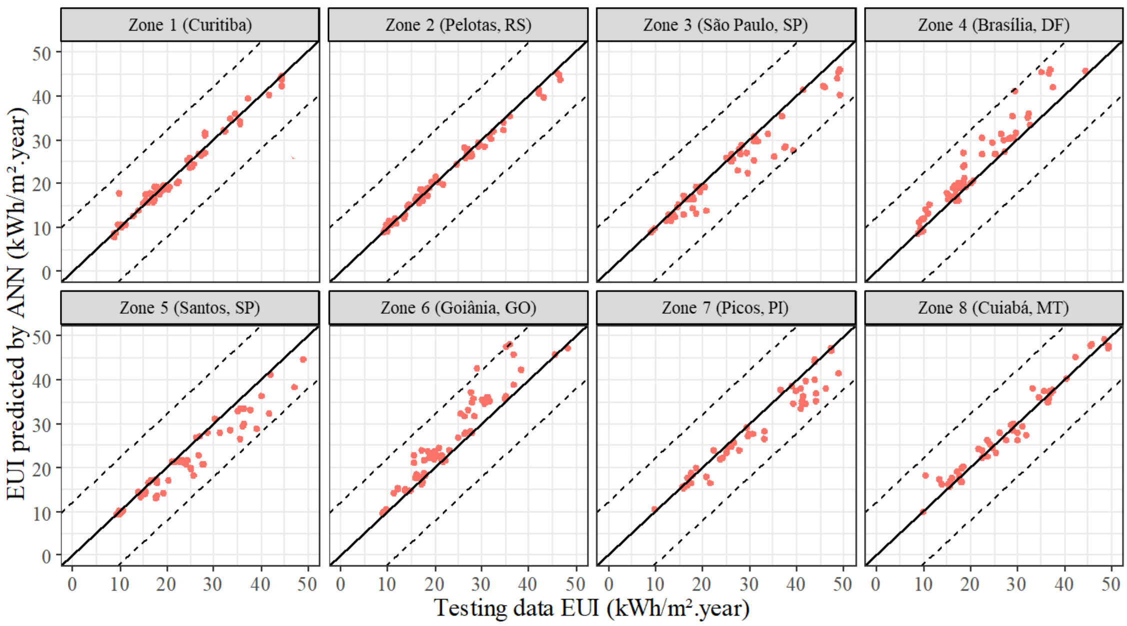


Figure 5.7 – Evaluation of the ANN performance for the cities analysed.

The ANN is used to benchmark the energy performance of buildings in the stock. To assess the actual application of such benchmarking method, we used the ANN to benchmark the 427 buildings used in this study. This sample was gathered in our previous study (GERALDI; GHISI, 2020b) and presented in Section 0. Figure 5.8 presents the EUI predicted by the ANN as the benchmark (blue bars in inverse order);

and the actual EUIs in the x-axis. Green bars represent buildings in which the actual EUI was lower than the benchmark, referring to an efficient outcome, while red bars represent buildings in which the actual EUI was higher than the benchmark, marking reference to an inefficient outcome.

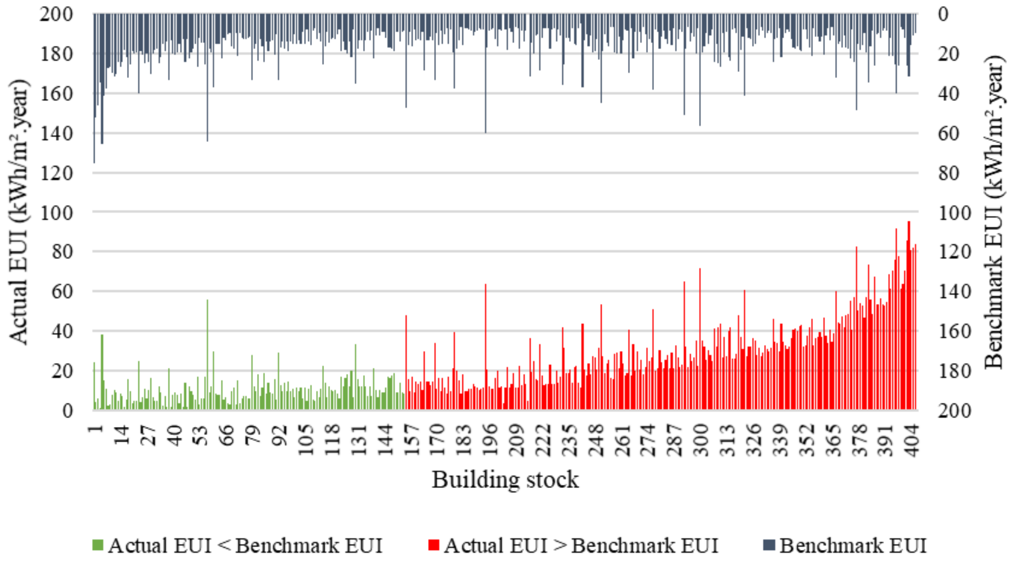


Figure 5.8 – Application of the benchmarking method in the actual building stock.

Figure 5.8 shows the actual EUI shorted in an increasing aspect regarding the difference of actual and benchmark EUI (to group green and red bars). However, the corresponding benchmark EUI for each actual EUI was consistent no matter how the actual EUI increased. In other words, the benchmarking model (ANN) always predicts inside some range. This is important for a benchmarking model because it makes the model robust to identify inefficiencies. After all, the benchmarking model is meant to replicate the actual building stock performance and provide reliable typical performance values instead. Figure 5.9 shows the histograms for both modelled and actual EUIs for the dataset analysed. It is possible to see that the average EUI in the actual stock was 19.29 kWh/m².year, while the average EUI for the benchmarks was 18.63 kWh/m².year. Although the distributions had an overlap, it is possible to see that the actual EUI distribution had more frequency in the higher bins (between 20.10 to 54.60 kWh/m².year), while the modelled EUI distributions had more frequency in lower bins (between 7.40 to 20.10 kWh/m².year). This denotes that the actual EUI distribution indeed has more observations with higher EUIs. Moreover, the modelled EUI distribution has more observations around the mean value, demonstrating that extreme values are not modelled by the benchmarking model. This is exactly what is expected of a benchmarking model which intends to model typical EUIs.

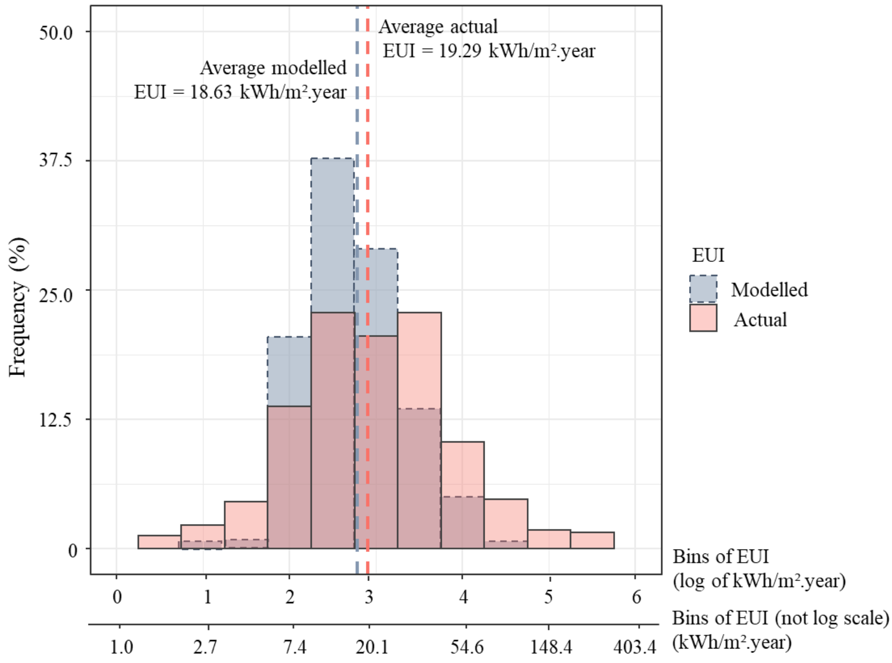


Figure 5.9 – Histograms of the modelled and actual EUI for the school building dataset (417 schools). Note: Napierian logarithm.

Both average actual and modelled EUIs were significantly low compared to EUIs in schools in other countries, for example, 86 kWh/m².year in Italy, 63 kWh/m².year in Cyprus (PEREIRA *et al.*, 2014). However, those are developed countries. By comparing the average EUI with a reference school in South Africa (ranging from 10 to 24 kWh/m².year Samuels and Booysen, 2019), the average EUIs were similar.

Both Figures 8 and 9 showed that the building stock showed a tendency to inefficiency. The average benchmark EUI was 3.4% lower than the average actual EUI. It is noticeable that most of the buildings in the stock (62.2%) had an actual EUI higher than the benchmark, while only 37.8% had a EUI lower than the benchmark. The building stock in Brazil is mostly composed of schools without air-conditioning in classrooms, around 92%, according to Geraldi and Ghisi, (2020b). Then, lighting systems and inefficient equipment can be pointed as the leading causes for inefficiency since they are the primary energy end-uses. As pointed by other studies, lighting can account for the expressive share of the total EUI in schools in developing countries (SAMUELS; BOOYSEN, 2019). Reinforcing this, in our previous research regarding the main issues related to the school building, the Principals reported main problems with the electrical system and old appliances (GERALDI; GHISI, 2020b). Moreover, a lack of planning and management to implement new appliances and systems in the schools might lead to difficulties in replacing inefficient systems.

It is possible to see that some specific bars in Figure 5.8 in the actual EUI dataset were adequately reproduced by the benchmarking model for both cases (actual EUI higher and lower than the benchmark). For example, schools with a high air-conditioned area rate (bars between 53 and 66 in Figure 5.8) will not necessarily implicate an inefficient classification. This school might present some efficiency in its operation compared to the typical condition established.

It is important to mention that here we employed simple efficient/inefficient categories just for evaluation of the method proposed. It is essential to mention that labelling the efficiency of buildings is not a trivial solution (CLARKE *et al.*, 2009), and it has been explored by specific studies (WEI *et al.*, 2018). In fact, "black and white" evaluations are not encouraged, and building performance analysis – especially building operation – is more like a grey area. The definition of scales of efficiency needs further discussion. For example, Veloso *et al.* (2020) discussed labelled the efficiency of office buildings according to percentiles of the EUI distribution. Other example are the Brazilian labelling scheme, which proposes a calculation of scales based on the relationship between the high-efficient and poor-efficient conditions (CB3E, 2017). We did not discuss the labelling scheme here because we believe that this classification is related to a broader debate. Instead, we discussed the validity of the ANNs as a benchmarking model and the implications in applying the ANN considering actual buildings.

3.3. End-uses analysis

The following step in the benchmarking model is to assess the end-uses. Assessing the end-uses is important to identify the energy usage pattern in building performance analysis.

In this benchmarking model, typical end-uses for the building stock were determined for each climatic zone through the breakdown of the average EUI obtained from the simulation results. Since two HVAC scenarios were addressed, the proportions were calculated considering each HVAC scenario individually. Figure 5.10 presents the end-uses.

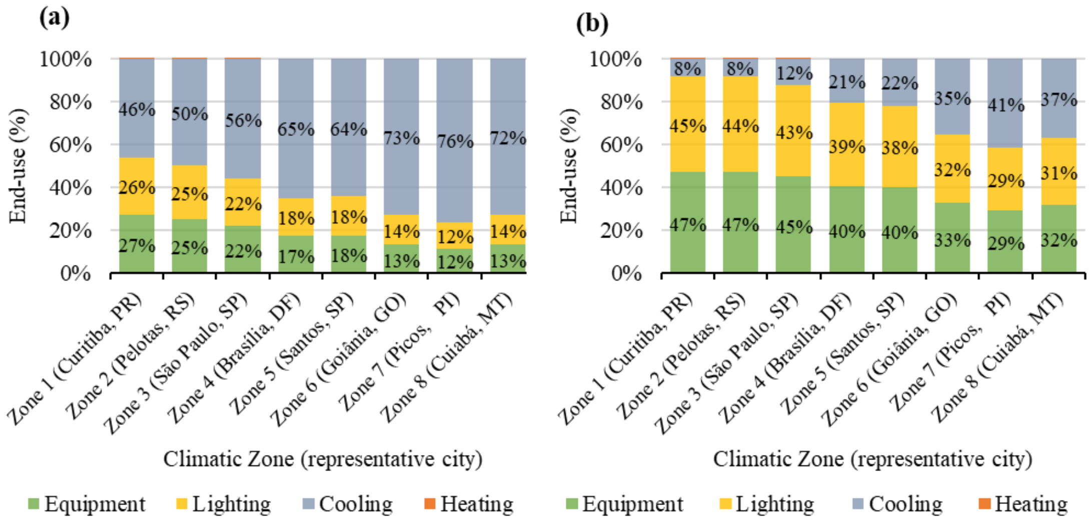


Figure 5.10 – Typical end-uses for schools for each climatic zone in Brazil. (a) End-uses for high air-conditioned schools; (b) End-uses for low air-conditioned schools.

The cooling loads increase as the CDH increases for both HVAC scenarios. It is important to remember that the scenario of high air-conditioned schools considers HVAC in classrooms, library, computer lab, and office rooms, while low air-conditioned schools consider HVAC only in library, computer lab, and office rooms. There is a noticeable difference in end-uses for both scenarios since classrooms are the leading share in the total area of the schools. The lighting end-uses are similar to other studies that addressed end-uses for South Africa (SAMUELS; GROBBELAAR; BOOYSEN, 2020), which found 31% to 40% of the total energy consumption for schools without air-conditioning, and 14% to 25% for schools with air-conditioning. Heating end-uses were almost not present in any case, confirming that heating loads can be disregarded in the Brazilian context.

Hence, the end-uses can be used in the benchmark value output by the ANN to serve as a reference for typical conditions that a target building should be performing.

Finally, a specific school was analysed through the benchmarking model proposed. The features of a school in Florianópolis, southern Brazil, was input in the ANN to determine the benchmark. Moreover, we applied the proportions of the end-uses of the climatic zone 3 to perform an energy breakdown of the benchmark – i.e. what the expected energy usage in the building evaluated is. Figure 5.11 presents the comparison among the actual EUI of the school, the benchmark, and the energy audit performed. The energy audit aimed to estimate the actual energy usage of the school, considering an ASHARE level 2 approach and resulted in a reasonable estimation (5% difference).

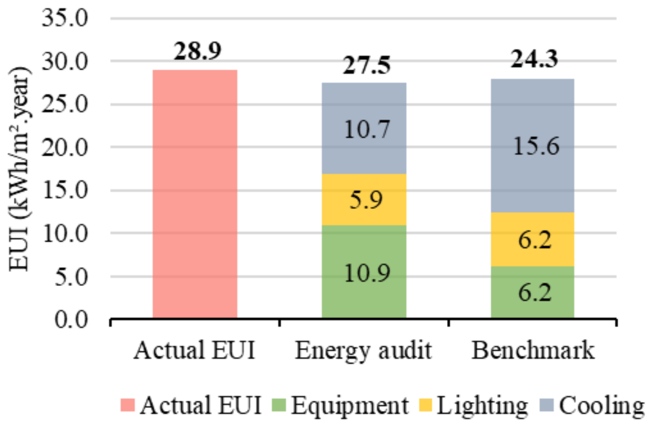


Figure 5.11 – Benchmarking of a specific school in Florianópolis. Comparison between the actual EUI, the energy audit EUI, and the benchmark estimated by the ANN.

The case analysed presented an actual EUI higher than the benchmark (28.9 > 24.3 kWh/m².year). By comparing the end-uses estimated by the energy audit to the end-uses of the benchmark, it is possible to notice that the energy consumption due to equipment was very high (101% higher). The energy audit estimated a lower share for cooling compared to the benchmark (20% lower); however, the consumption due to equipment not only exceeded the benchmark estimation but also counterweighed the reduced cooling consumption. The energy consumption with lighting was consistent with the benchmark (only 9% higher). The leading cause for this high energy consumption due to equipment is the high number of refrigerators in this school compared to the average in the stock. There were observed eight refrigerators in this school during the energy audit. Also, the refrigerators were very old and inefficient.

Therefore, this is the kind of analysis that a benchmarking model can assess. The proposition of the framework in this study supports an in-depth evaluation of the performance of the building, considering a reliable and fair comparison with the building stock. Since it is an evidence-based approach (because the inventory analysis sustains the archetypes), it translates to the typical conditions of reality. By comparing the actual performance of a building with its typical condition, it is possible to identify possible causes for inefficiencies or prospect examples of efficiencies, whenever is the case. This analysis aims to improve the overall performance of the buildings of the entire building stock. This study comprises both building-level and stock-level perspectives (GERALDI; GHISI, 2020a), because it uses specific building features through a bottom-up approach to assess the building stock performance and, finally, supports the specific building evaluation.

As a final remark on this topic, it is important to address future estimations for the building stock studied. Although the current scenario presents a lack of air-conditioning in schools in Brazil, there is a tendency to installing air-conditioning over the time, as estimated by the increase of the EUI in the past decades and prediction until 2060 (ZHONG *et al.*, 2021). This is a reality already reported in other developing countries. China reported an increase of the EUI from 86 kWh/m².year in 2003 to 105 kWh/m².year in 2017 (CHUNG; YEUNG, 2020) due to an air-conditioning implementation policy. Currently, public schools in Brazil lack structure management (GERALDI; GHISI, 2020b) and internal environmental quality (SARAIVA *et al.*, 2019), implying air-conditioning installation to mitigate this issue. Thus, if the *status quo* is maintained, an increase of the average EUI can be expected for Brazil just as occurred in China. This is obviously against the international guidelines to reduce energy consumption to mitigate climate change effects – while passive strategies such as envelope improvement and photovoltaic generation are encouraged. At the same time, the lack of air-conditioning can be faced as an energy poverty issue – as reported by other developing countries (SAMUELS; GROBBELAAR; BOOYSEN, 2020).

Thus, a comprehensive evaluation has to be carried out to propose an integrative solution. This study was essential to reveal the current energy performance state of the building stock analysed – and outlined possible evaluations that the framework proposed can reach.

4. Conclusions

This study aimed to propose a framework for benchmark modelling considering the uncertainty reduction of the archetype parameters. Data-driven approaches were used to compose the archetypes, considering both Information Theory to measure and identify uncertainties and Cluster Analysis to select parameter values. The archetypes were simulated considering several scenarios through parameter combinations. An ANN was used to develop the benchmarking model to generalise the results and an actual sample of buildings was benchmarked. Therefore, the main conclusions of this study are outlined as follows:

- A protocol was proposed to organise the building stock information into a standard manner that can be adapted for any building typology. The inventory structure supports the input of objects in the EnergyPlus model, simplifying the modelling and the parameterisation process.
- The entropy analysis measured the uncertainty of the parameters filled in the inventory, and the cluster analysis selected the relevant scenarios. Combining both approaches was useful to improve variability in the benchmarking model (and reducing uncertainty by inserting in the model several observations instead of a single or fixed values) while also contributing to optimising the number of simulations.
- The benchmarking model using ANN resulted in high accuracy levels. The model could predict with satisfactory accuracy both training and testing datasets (which is composed of inputs unseen by the ANN).
- The energy performance of the building stock sample evaluated demonstrated a tendency to inefficiency, once around 62.2% of the building stock showed actual EUIs higher than their benchmarks (in average 3.4% higher). The leading cause for the inefficiency might be an inefficient use of the lighting systems and inefficient equipment.
- Energy end-uses for each climatic zone were obtained from the simulation outcomes, considering two scenarios: high air-conditioned schools (in which cooling loads represented the main end-use share); and low air-conditioned schools (in which equipment loads represented the main end-use share). Heating loads were not significant in any climate for the Brazilian schools.
- By evaluating a specific case, the application of the benchmarking method was demonstrated in practice. The comparison of the actual EUI with the benchmark demonstrated an inefficiency due to old and inefficient refrigerators.

The limitations of the study are addressed as follows:

- The modelling of subspace geometries is still dependent on subjective evaluations. This issue could be improved by using parametric design tools such as Grasshopper in an additional improvement of the method.
- The framework disregards the modelling of surroundings – which is hard to establish typical realistic conditions. In this case, the typical surrounding condition was set as none; but this condition should be deeply studied in further studies.
- As in all simulation modelling, the framework is limited by computational capacity. In the example carried out, 1,792 cases were run, but as the uncertainty increases, the number of simulation runs increases.

The limitations addressed can be accepted as opportunities to improve the framework.

Finally, the main conclusion is that an innovative method to improve the reliability of the archetype-based benchmarking model was proposed and showed good useability when tested using actual cases. The proposed framework has a strong potential for application in other cities in Brazil and other typologies.

6. Application of the building stock model

This Chapter is the transcription of the following paper:

> **Impact of implementing air-conditioning systems on the school building stock in Brazil considering climate change effects: a bottom-up benchmarking**
>
> Authored[1] by Matheus Soares Geraldi, Mateus Vinicius Bavaresco, Veronica Gnecco Martins, Enedir Ghisi and Michele Fossati
>
> Published in the Proceedings of Building Simulation 2021, and presented in 2nd September 2021

Abstract

This study aimed to investigate future energy benchmarks for the school building stock in Brazil, considering the gradual implementation of air-conditioning systems in those buildings and the influence of future climate conditions. Archetypes were simulated using EnergyPlus for four cities in Brazil, representing predominant weather data in the country. The models were simulated considering air-conditioning implementation in two scenarios: a) administrative and lab environments; b) administrative, labs and all classrooms. Modified-weather data considering IPCC scenario A2 was used to include climate change trends for 2050 and 2080. The average and standard deviation of Energy Use Intensity (EUI) were analysed. Results showed an increase of the average EUI of the school building stock in Brazil considering the air-conditioning implementation, raising 88% concerning the actual EUI if the systems were implemented today, 8% in 2050 and 43% in 2080. Conclusions support that upgrading thermal comfort conditions in those buildings require attention towards improving energy efficiency strategies.

[1] The authors agreed with the utilisation of this paper to compose this thesis through the shared authorship agreement presented in Appendix F.

Introduction

The need for improving energy efficiency in buildings is urgent. In Brazil, buildings were responsible for 43% of the electricity consumption in 2019 (Brazil 2020). The amount of energy consumed in this sector tends to increase in the following years if the *status quo* is maintained.

As extreme climate events become more frequent and the overall global temperature increases, both the effects of Climate Change and the use of HVAC systems in equatorial, tropical and subtropical climates can become health issues (ELNAKLAH *et al.* 2021). Additionally, as HVAC equipment becomes more socially inclusive (KIGALI PROJECT, 2019), people of developing countries tend to buy and install more of this equipment (MACRAE *et al.*, 2008).

This is especially true in school buildings in Brazil. Air-conditioning systems are responsible for enhancing indoor thermal conditions and increasing the energy use intensity (SARAIVA *et al.*, 2019). Geraldi and Ghisi (2020) performed a top-down analysis of this type of building across the country, showing that HVAC is not frequently installed in all buildings. In fact, it is installed in only about 13.0% of the classrooms, 32.7% of the administrative rooms, and 31.9% of the labs of public schools. In the same study, the performance of schools with and without air-conditioning systems were compared; schools with air-conditioning had an annual EUI 64% higher than schools without air-conditioning.

However, this is not a static situation. Schools tend to buy air-conditioning sets over the years, and this gradual implementation will cause an increase in the school building stock energy consumption. For example, the EUI of two schools in which air-conditioning was installed increased from 8.1 to 15.8 kWh/m² and 11.9 kWh/m² to 34.6 kWh/m² (GERALDI; GHISI, 2020b). Also, as reported in several recent case studies, improving air quality through air-conditioning systems is an urgent task and has been increasing with the outbreak of the coronavirus pandemic.

Since the implementation of air-conditioning in public schools in Brazil is a large-scale action, this issue can be addressed by a stock-level analysis. Modelling the building stock is a useful practice to assess statistical key information of a group of buildings (GERALDI; GHISI, 2020a; HAMILTON *et al.*, 2017). Some studies applied this approach to assess the energy performance of buildings and find different insights for energy efficiency, for example, to improve best practices in the United Kingdom

(HONG *et al.*, 2014), to model buildings relationships at an urban scale (REINHART; DAVILA, 2016), and to estimate energy savings potential at national-level (BRØGGER; WITTCHEN, 2018).

An example of a stock level analysis application is the development of energy benchmarks, which evaluates the energy efficiency of a building against its pairs (WILDE, 2018). Reference buildings (denominated archetypes) are usually adopted to represent the main characteristics of typical buildings of the stock to develop benchmarks. The archetypes are used to simulate a reference building in various conditions that represent the stock reality – i.e., different climate conditions, occupations, materials, and others. Benchmarks are obtained through regressive models of simulation results, according to variables that are important for the type of building (CHUNG, 2011). Advances in benchmarking methods are available in the literature; however, they are usually related to high-granularity data, particular focuses or specific to their countries or regions (BORGSTEIN; LAMBERTS; HENSEN, 2016). In Brazil, a benchmarking approach was developed for bank branches (BORGSTEIN; LAMBERTS, 2014) and high-rise buildings (ALVES *et al.*, 2017). Synthesizing the building stock into archetypes is a handy approach to predict trends in the energy use of similar buildings through computer simulation.

Therefore, it is pertinent to measure the carbonisation effect due to the implementation of air-conditioning systems in Brazilian schools to estimate their impact at the stock level.

The objective of this study was to investigate future energy benchmarks for the school building stock in Brazil, considering two scenarios of air-conditioning systems implementation in the building stock and future climate data. To do so, comprehensive building stock data were analysed and used to model seven building archetypes to represent the stock. Those models were simulated considering four cities (that represent the types of weather in Brazil) and calibrated using the actual energy consumption of the stock. Then, the calibrated models were simulated considering air-conditioning implementation in two scenarios: a) administrative and lab environments; b) administrative, labs and classrooms. Three reference years were selected: a baseline year (compound by an TMYx 2020 database file), and two modified-weather data considering IPCC (International Panel for Climate Change) scenario A2 to include climate change trends for 2050 and 2080. Electricity consumption for cooling was analysed in these combinations. The new aspects adopted in the approach proposed herein comprise the combination of interrelated aspects that might have been treated in an isolated manner in previous research. For instance, a comprehensive analysis of the built stock in Brazil enabled to achieve realistic archetypes considering local characteristics; and the consideration of mixed-mode operation in archetypes. Then, exploring future scenarios of the energy performance of the building stock consolidates the need for improving whole-building performance also in developing countries. Also, despite the application of stringy regionalised data, the method could the adapted for other locations. Nevertheless, this study also serves as a report of the carbonisation of the stock occurring in developing countries – although the causes are locally regionalised, the consequences are global.

Method

Figure 6.1 illustrates the flowchart of the method employed.

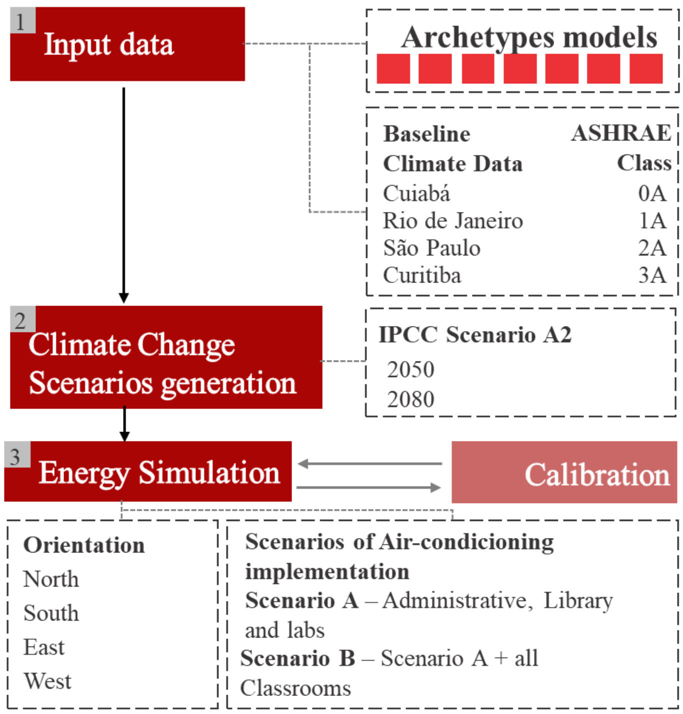


Figure 6.1 – Flowchart of the method

Modelling the school building stock

In order to build the representative archetype models, a database of 284 educational buildings was analysed. These buildings were provided by the Educational

Administrative Organism as the buildings under their jurisdiction. They represent educational buildings in southern Brazil. However, although they belong to a specific region, all public schools in Brazil share similar design guidelines. A well-known method to create archetypes was employed (ATTIA *et al.* 2020). Seven building shapes were identified as predominant (Rectangular, H-shape, E-shape, U-shape, O-shape, L-shape and Multiple buildings). The main characteristics used to outline the building stock were: (1) annual energy consumption (kWh/year); (2) gross-floor area (m²); (3) number of students (people), and; (4) building shape. Among the buildings analysed, 35 building designs were assessed, which allowed a detailed investigation in terms of materials properties, fenestration details, window-to-wall ratio (WWR) (%), and number and layout of rooms, classrooms, aisles, office rooms, bathrooms, kitchen and additional spaces. Furthermore, the design analysis also provided information on the lighting power density (LPD) and equipment power density (EPD) in every room. Such information supported the construction of seven models in EnergyPlus Input File (.idf) format, one for each building shape. Average values were adopted from the design analysis. The variability of shapes assists the representation of the variability inherent to the building stock. OpenStudio® was used to support the modelling process. Table 6.1 shows the average values of gross-floor area, and the number of classrooms for all models and the values adopted equally for all models. Adopting average values for building mass and thermal properties may have different outcomes. For building-mass aspects, which had a higher variation throughout the models, average values are a good proxy for the stock characteristics since they may balance the differences found among samples. Additionally, each prototype had its values based on the stock analysis. Considering the thermal properties of the facilities, it is worth mentioning that adopting average values will not hinder the applicability of results as most buildings share the same constructions and materials used.

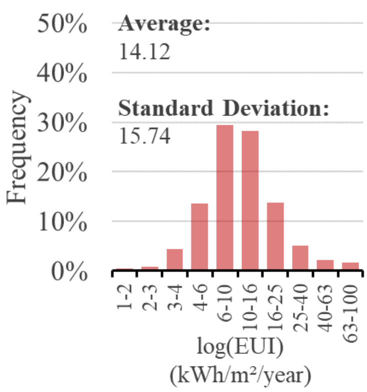
Table 6.1 – Summary of the archetype's parameters

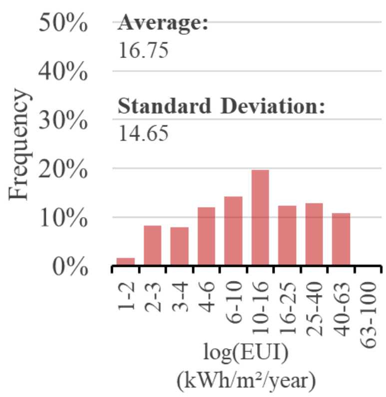
Parameter	**Unit**	**Value**
Average gross-floor area	m²	2,547.0
Average number of classrooms	rooms	14
Wall thermal transmittance	W/m²K	2.13
Roof thermal transmittance	W/m²K	1.77
Slab thermal transmittance	W/m²K	3.30
Wall thermal capacity	kJ/m²K	151

Table 6.1 – Summary of the archetype's parameters. (continuation).

Parameter	Unit	Value
Roof thermal capacity	kJ/m²K	230
Glazing U-value	W/m²K	5.70
Glazing Solar Heat Gain Coefficient	-	0.87
Average wall absorptance	-	0.50
Average roof absorptance	-	0.65
Administrative room WWR	%	29.00
Library/Computer lab WWR	%	40.00
Classrooms WWR	%	35.00
Average LPD	W/m²	6.57
Average EPD	W/m²	116.00
Occupancy in admin. rooms	people	10
Occupancy Library/Computer lab	people	10
Occupancy in classrooms	people	25

To ensure that the building models represent the actual stock model, pilot simulations were used to compare actual and simulated building performances. Then, a calibration step was employed to refine the simulation models using International Performance Measure and Verification Protocol guidelines (IPMVP, 2001), considering the occupancy schedule during the year in all rooms as the parameters for calibration. Small adjustments in this occupancy provided good calibration considering a comparison of the simulated EUI with the actual EUI of a set of schools. It is important to highlight that the performance gap is a noticeable issue reported in the literature, and in this study, we did not intent to accurately replicate the stock's actual energy consumption. Instead, we intended only to approximate the simulated and actual energy performances to establish a baseline for comparison – simulation results will be compared with themselves. Figure 6.2 presents the distribution of the log EUI for (a) the actual building stock analysed and (b) for the calibrated simulated models. Averages and standard deviations for actual EUI are presented as well.

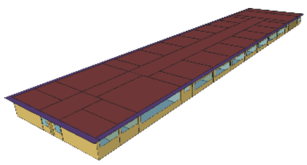




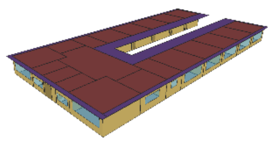
(a) (b)

Figure 6.2 – Comparison between (a) actual and (b) simulated EUI of the school building stock in Brazil.

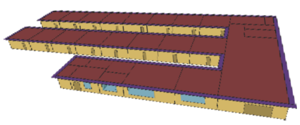
The comprehensive description of the stock analysis to obtain the representative building models and the discussion regarding the representativeness of the archetypes obtained were reported in a research of the Laboratory of Energy Efficiency in Buildings (LabEEE/UFSC) in Brazil. The study is currently being developed, and it aims to investigate the impact of building shape on the energy consumption and to analyse the impact in different Brazilian cities. Figure 6.3 presents the graphical aspect of each building model.



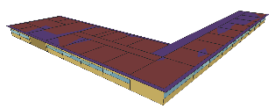
(a) Rectangular



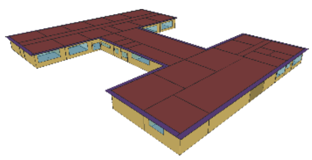
(b) U-shape



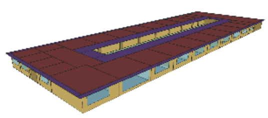
(c) E-Shape



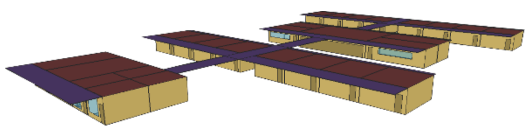
(d) L-Shape



(e) H-Shape



(f) O-Shape



(g) Multiple buildings

Figure 6.3 – Archetype models identified from the stock.

Simulation for future scenarios

Three reference years were adopted. The first is a year corresponding to the actual scenario (the baseline year). TMYx data files were used from ClimateOneBuilding website. Then, IPCC scenario A2 for 2050 and 2080 time-slices was used to perform the simulations for future climate. The scenario A2 characterizes the medium emission scenario, which preserves local identity and economic development, with fragmented and slower introduction of new technologies. The "morphing method" (BELCHER *et al.* 2005) was used as a reference. The morphing method is one of the most widespread methods to generate future climate files, as seen in previous works (CHAN, 2011; GAGLIA *et al.*, 2017; JENTSCH; BAHAJ; JAMES, 2008; TROUP; FANNON, 2016). This approach is normally used because it preserves the real weather sequences and is specific to a certain location. The tool "Climate Change World Weather File Generator for World-Wide Weather Data", the CCWorldWeatherGen (JENTSCH *et al.*, 2013), developed by the University of Southampton was applied for this purpose.

The weather files adopted in this research were determined to represent the four main climate zones of Brazil, defined by ASHRAE 169 Standard. Table 6.2 presents the locations adopted to represent the climates and correlates the ASHRAE 169 (ASHRAE, 2013) and the Brazilian climate classification (NBR 15220, 2005) of each location.

Table 6.2 – Weather data adopted and Correlation between ASHRAE 169 and Brazilian standard NBR 15220-3.

Location	ASHRAE 169	NBR 15220-3	Description
Cuiabá	0A	ZB 7	Extremely Hot and Humid
Rio de Janeiro	1A	ZB 8	Very Hot and Humid
São Paulo	2A	ZB 3	Hot humid
Curitiba	3A	ZB 1	Warm humid

Figure 6.4 presents the main climatic characteristics (average monthly temperature and relative humidity) for the cities used in this study.

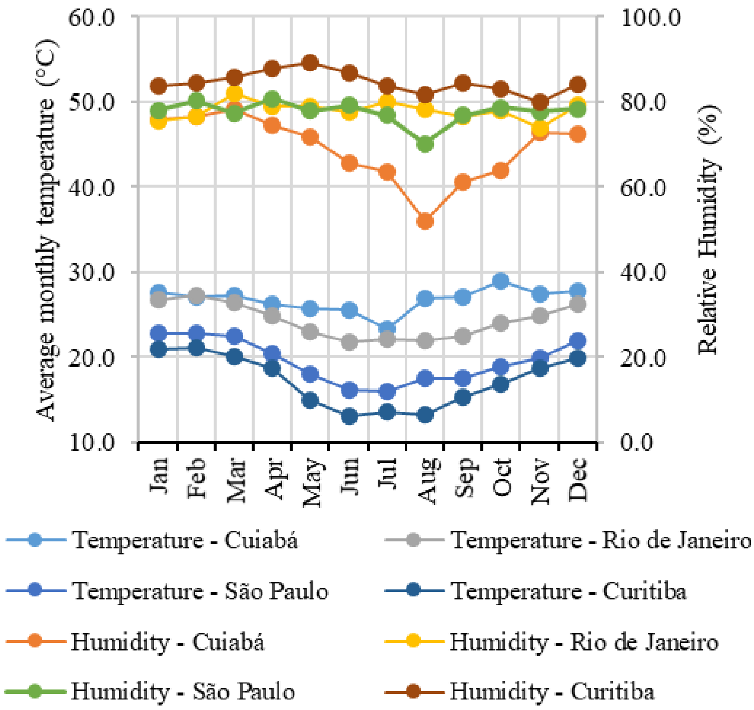


Figure 6.4 – Temperature and humidity of the cities analysed.

As observed in the stock analysis of a previous work (GERALDI; GHISI, 2020b), air-conditioning systems in schools are mainly installed in administrative rooms, computer labs and libraries. Retrofits to install air-conditioning systems in classrooms are often observed. When it happens, it is likely that all the classrooms get air-conditioning sets.

In all cases observed in the stock, the preponderant type is mini-split (90%), which means that each room has a single unit. This facilitates the implementation by the Education department, once they can install, replace or maintain the units individually and with no big retrofits. However, the energy efficiency of adopting such an approach is debatable. In this study it was adopted the most frequent case observed in the stock: each room conditioned separately. The system type was cooling with direct expansion. The cooling setpoint was 24°C, and the heating setpoint was 18°C. The average coefficient of performance was 3.6 W/W. The setpoints were assumed according to the Brazilian Centre of Energy Efficiency in Buildings (CB3E, 2017), which provides referenced values for energy simulation of buildings considering the Brazilian context. These setpoints are also used in Energy Performance Certification (EPC) in Brazil.

Then, two scenarios of air-conditioning systems implementation in schools were considered:

- Scenario A: air-conditioning in administrative rooms, libraries and computer rooms, and;
- Scenario B: air-conditioning in administrative rooms, libraries, computer rooms and all the classrooms.

EnergyPlus 9.4 engine was chosen to carry out the computer simulations. The use of natural ventilation mixed with air-conditioning is common in Brazil. Then, the control of conditioned and naturally ventilated areas was performed using the Energy Management System (EMS), which is a script programmed to control diverse building systems (ELLIS *et al.* 2007). Sensors of operative temperature and outside air temperature were used to determine the air-conditioning activation or deactivation, considering the setpoints of 26°C and 19°C, respectively. Also, occupancy and operation sensors determine the use of the system, preventing the system from being activated in empty rooms.

Parametric simulation

Finally, four different orientations for each scenario were considered, i.e., each model facing North, South, East and West. With the combination of all seven models, two scenarios of air-conditioning, four orientations, four locations and three weather data (Baseline year, 2025 and 2080), 672 simulations were run. The occupancy schedules were considered according to the standard period of functioning of the school buildings in Brazil: classes from 8:00 am to 12:00 am and from 1:30 pm to 5:00pm. The student year begin in February 15th and finish in December 15th, with a winter-break of two weeks in July. Administrative rooms, libraries and labs have the same occupancy. Lighting and equipment were considered to be on when there is occupancy in the rooms.

Energy performance analysis

The energy performance simulation results were analysed for each weather scenario in terms of each building's total EUI. Using the outcomes from the parametric simulations, an initial description of the results was performed using boxplot-like graphs. Such an approach showed the contrast of both scenarios of air-conditioning implementation according to the current climates and their corresponding projections influenced by climate change trends. Besides that, a general overview of the results shows the expected average of EUI for each year tested, as well as standard deviations for each scenario.

Results and discussions

The results of the parametric simulations are synthesized in Figure 6.5. The boxplots provide information on each city evaluated (Cuiabá, Rio de Janeiro, São Paulo, and Curitiba) according to both scenarios of air-conditioning implementation and projections of climate change.

Figure 6.5 shows the important role that local weather plays on the average energy use of the building stock. For instance, even considering the worst-case combination (scenario B in 2080), the energy consumption of schools in Curitiba (below 40 kWh/m²/year) are likely to be lower than those currently observed in Cuiabá if all the classrooms were air-conditioned (generally above the 40 kWh/m²/year threshold).

Such information emphasizes that building stakeholders in large countries like Brazil, which has different climates, should be aware of their current decisions' implications on the future. Indeed, an important takeaway from this study is that one trend does not fit all the realities in Brazil. Different regions are likely to be impacted by climate changes in varying intensities. Along these lines, the hottest city evaluated, Cuiabá, is likely to require a massive amount of energy to keep the indoor conditions of public schools in comfortable ranges in the future. The median EUI for this city is 63.4 kWh/m²/year, while no school has reached the threshold of 60.0 kWh/m²/year in the other cities. As the state governments are responsible for maintaining such schools, national decision-making should be oriented to guarantee that students across the country will have access to acceptable learning environments.

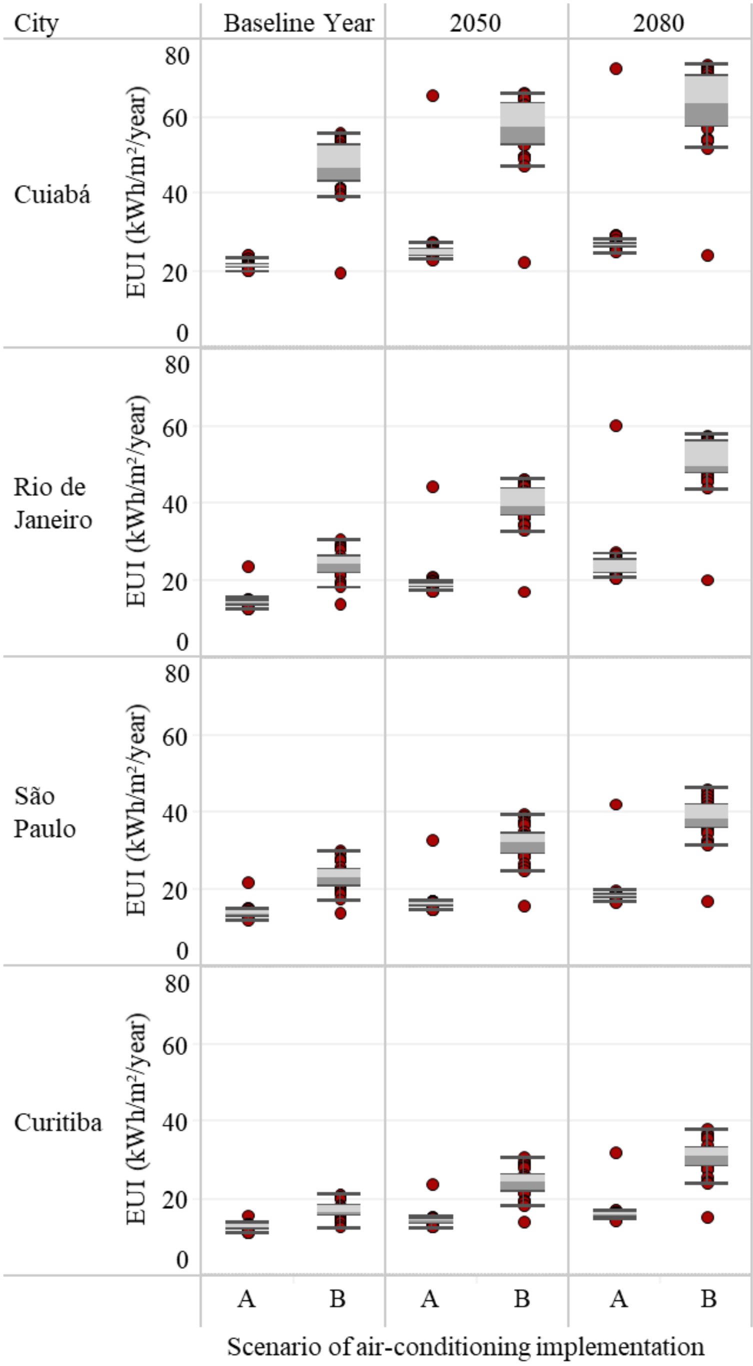


Figure 6.5 – Energy use intensity for Brazilian schools according to different projections of climate.

A general overview of the stock EUI is shown in Figure 6.6. It comprises both scenarios of air-conditioning implementation in the school stock. The averages of EUI are highlighted. First, it is important to stress that besides most Brazilian schools that do not have air-conditioning yet, the simulations also included scenario B for the reference year for comparison purpose.

This approach aimed to show a tendency from the baseline year up to 2050, as there is no specific timeline for such a massive air-conditioning implementation across the country. Additionally, a dashed line linking the average for scenario A in the baseline year and the average of scenario B in 2050 is an alternative estimate for continuous air-conditioning implementation throughout these years.

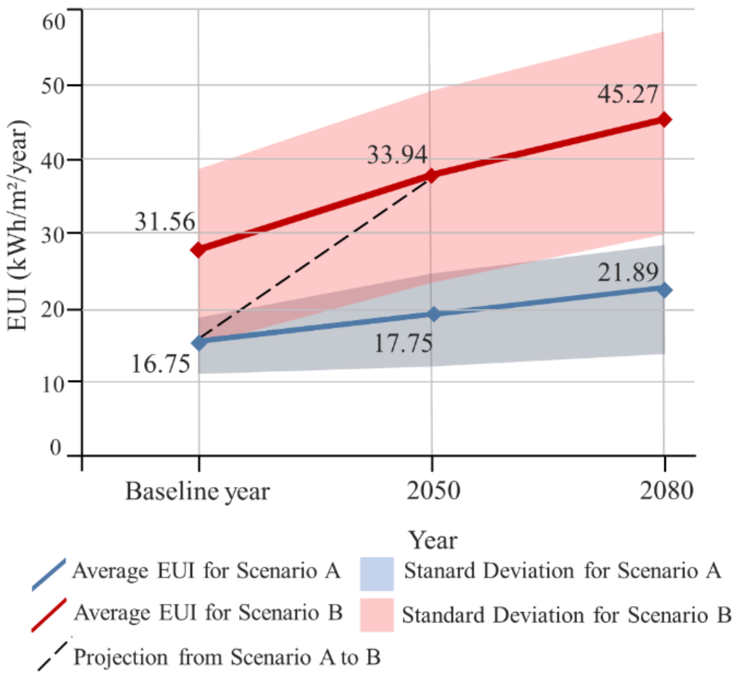


Figure 6.6 – Average and standard deviations of energy consumption in Brazilian schools

It is evident that if the current condition of schools is maintained (Scenario A), there will be an increase in the energy use of the school stock of about 6% in 2050 and 31% in 2080. Considering the implementation of Scenario B in the buildings today (baseline year), there will be an increase of 88% on the average EUI (from 16.75 to 31.56 kWh/m²/year). Of course, this is a theoretical scenario since it is very unlikely that all schools get air-conditioning today. Thus, a projection from Scenario A in baseline year to Scenario B in 2050 is shown in Figure 6.6.

Considering the actual scenario without air-conditioning in classrooms (average 16.75 kWh/m²/year), if such systems are implemented up to 2050 – which is probable –, the average increases to 33.94 kWh/m²/year, i.e. a growth of 103%. And this tends to be even higher in 2080 (45.27 kWh/m²/year), resulting in an increase of 170% compared to the baseline year. Of course, this outcome is expected if the *status quo* is maintained, which means installing poor-efficient air-conditioning systems with no upgrade of the building envelope.

Additionally, scenario B also showed higher standard deviations on the average EUI of schools and an increasing tendency for further years. For instance, the lower limit (average minus the standard deviation) for scenario B in 2080 is greater than the upper limit (average plus the standard deviation) for scenario A in the same year: 31.06 kWh/m²/year and 29.59 kWh/m²/year, respectively.

It is important to highlight the implications of the approach used in this study. Since it is based on stock modelling, there is an uncertainty inherent of the process of simplification that comprehends simulation models. Indeed, standard deviations were maintained to show that the results might vary. Sensitivity analysis performed in other studies (Silva and Ghisi 2014) showed that occupancy schedules, equipment power, and occupants are relevant parameters in energy simulation in general. Thus, a sensitivity analysis could reveal the major aspects that impact stock modelling and energy benchmarking.

Another key point evidenced in Silva and Ghisi (2014) is the possibility of relying on simulation-based results to strategically plan future steps towards decarbonisation (and prevent carbonisation) of the local building stock. Indeed, by combining emerging topics from the literature (stock modelling, energy benchmarking, building performance simulation and climate change), a solid overview of the implications may be captured to aid a country-sized planning building intervention. These outcomes do not support the idea of avoiding the air-conditioning implementation or even installing them only in colder climates to minimize such an increase in energy use. Instead, students' performance may be negatively affected by suboptimal indoor conditions (PALACIOS *et al.* 2020). In fact, this study sheds light on the need to assess the impacts of current decisions on the future comprehensively. Achieving decarbonisation target in buildings is a complex demand, which involves different stakeholders (HAMILTON *et al.*, 2017). Therefore, our results support that building designers, researchers, school principals, and policy-makers must be aligned to achieve comfortable yet energy-efficient and climate-change-resilient learning environments in Brazil.

Naturally, achieving such ambitious targets demand high efforts. However, if authorities do not consider this issue from now on, both problems (global warming and thermal comfort) will contribute to aggravate each other. Indeed, without a resilient, energy-efficient transition in Brazilian schools, those buildings will worsen climate change effects with their associated high amount of carbon emissions. As a consequence, the same buildings will be likely to use even more energy to operate.

From a building designers' perspective, our results support the need to include energy efficiency measures on new buildings constructed throughout the years. As highlighted in the method section, the envelope of current schools in Brazil is not provided with materials able to minimize the energy use (see Table 5.1). Previous research conducted in Brazil emphasized the major role of incorporating energy efficiency measures to reduce the effect of climate change in the coming decades (Triana *et al.* 2018). Indeed, preparing the envelopes to such trends on climate change is necessary.

Researchers are also expected to continuously provide new information to other stakeholders about good practices in this field. For instance, understanding acceptable indoor conditions is a key aspect to tailor the building operation to guarantee higher satisfaction and productivity for the students without compromising those buildings' energy performance. Along these lines, there is evidence that thermal comfort in classrooms in Brazil is highly influenced by airspeed, which provides an opportunity to avoid air-conditioning overuse by relying upon natural ventilation (BUONOCORE *et al.*, 2018).

As a consequence, both school principals and policy-makers can define their practices according to the best strategies. Policy-makers can implement strict requirements on the minimal performance of systems installed and the properties of new buildings. In Brazil, energy labelling of buildings is still voluntary, and the transition to a mandatory requirement would facilitate the achievement of an energy-efficient stock in the future.

Conclusion

This paper has shown a study on the EUI of the school building stock in Brazil considering two scenarios of air-conditioning implementation and two scenarios of future climate. The objective was to measure the impact of the implementation of air-conditioning that is occurring in those types of buildings in Brazil, with no other interventions to decrease energy consumption – which causes carbonisation of the building stock. The main conclusions can be outlined as follows:

a. Considering the scenario of implementing air-conditioning in classrooms (Scenario B) in the baseline year, the average EUI of the school building stock in Brazil might increase about 88%.
b. If the trend to install air-conditioning without any other energy efficiency measures is kept, the energy consumption tends to increase more 8% in 2050 and 43% in 2080.
c. To reduce energy consumption in schools and continually provide thermal comfort to students and employees, stakeholders must include energy efficiency programmes for buildings once the actual buildings' conditions are not prepared to integrate air-conditioning systems.

The detailed reasons for the findings above will be investigated in future studies, for example, specific strategies of energy efficiency and photovoltaic panels implementation to mitigate this carbonisation effect.

7. Discussions

The Brazilian electricity matrix is currently based on renewable energy sources (around 84.8%) when compared to the average world generation matrix (23.0%)(EPE, 2021). This implies in a low carbon emission rate (1.9 tCO_2eq/person) in comparison to developed countries (carbon emission rate in the USA is 15.0 tCO_2eq/person) (EPE, 2021), but there is still a concern regarding the increasing energy demand in buildings.

The overview of the current school building stock in Brazil presented in Chapter 3 revealed that most school buildings need better thermal conditions. A significant share of the analysed schools (78%) does not have air-conditioning in classrooms, and 39% do not have air-conditioning at all. Other studies report that Brazilian schools lack adequate thermal comfort to students (SARAIVA *et al.*, 2019). Since retrofits to improve passive thermal comfort strategies (such as envelope upgrades) are not common in such typology, there is a trend to install air-conditioning sets. The study of Chung (2020) reported that a very similar phenomenon occurred in China (schools received a massive implementation of HVAC) and caused an increase of 22% in the EUI from 2003 (86 kWh/m².year) to 2017 (105 kWh/m².year) (CHUNG; YEUNG, 2021). Thus, it is reasonable to assume that the lack of air-conditioning is an energy poverty issue.

Energy poverty is demonstrated by the lack of environmental quality due to the scarcity of financial resources to implement systems that provide adequate thermal comfort (PALMA; GOUVEIA; SIMÕES, 2019). For example, in South Africa, a study compared two different schools, i.e. one in a high-income neighbourhood and another in a low-income neighbourhood. Although the schools were located in the same city (same climatic conditions), the high-income school had a very high EUI and electricity consumption due to cooling in addition to lighting and equipment; while the low-income school had a very low EUI and energy consumption mainly due to lighting (SAMUELS; GROBBELAAR; BOOYSEN, 2020).

Chapter 3 also explored the variables related to the building energy performance, and the impact of each variable on the EUI was accounted for. The survey used for data collection shown in Chapter 3 is available in Appendix B. The correlation of all variables of the building stock with their corresponding EUI was performed using statistical analysis, non-parametric methods (Kruskal-Wallis and pair-wise Wilcoxon tests) and Likert-like scales related to environmental satisfaction of occupants. When a variable caused a considerable variation on the EUI, it is possible to conclude that such a variable is relevant for the EUI. The analysis showed that the number of students, the number of air-conditioning units, the operation shift, and the number of classrooms (related to the floor-plan area) were relevant, together with the climatic zone. Another pertinent result was that the building manager (in the case of the schools: the principal) is not responsible for the energy bills, and 75% often do not know how much energy is consumed in the building. However, the statistical test did not show a difference of EUIs between schools where the principal knows the energy bill cost from schools where the principal does not.

A benchmarking model that does not take into account the quality of the indoor environment is not a model that shows the proper performance of a building. However, including subjective variables such as environmental satisfaction in benchmarking models can be challenging. Chapter 4 presented a proposition of a Machine Learning method to mitigate this gap. A Bayesian Network was constructed to predict a subjective benchmark (a level of efficiency, varying from A to E) of the whole-building performance.

While the analysis presented in Chapter 3 achieved the relevant variables of the building stock regarding energy consumption, those relevant variables were employed in the Bayesian Network. The relationship among variables was calculated through a probabilistic approach using the Bayes Theorem, which results in a degree of truth and not in an individual and final result. This means that the classification of the performance of a building is presented in probabilities instead of deterministic terms. Since this method is based on evidence, it shows more properly what happens in the real world. The variables used to model the Bayesian Network were: the floor-plan area, climatic zone, number of students, type and number of air-conditioning units, operation shifts, and thermal satisfaction in the classrooms. The dataset obtained in Chapter 3 was split in two sets: one for training and another one for testing. The training dataset was used to calculate the conditional probabilities among variables of the Bayesian Network, and the testing dataset was used to calculate the network's performance. The Bayesian Network was chosen for such an aim because it is widely used in health science, especially for diagnosing diseases, because it is strong to solve "if-then" problems.

A challenging step in this process of proposing the top-down method was the discretisation of the continuous variables. The variables floor-plan area, number of students, number of air-conditioning sets, and EUI needed categorisation because they were continuous ones and the model requires categorised data. There are several methods for this practice, but there is no consensus in the literature regarding this topic – actually, it depends on the variable and the purpose of the discretisation. Therefore, one tested three methods in an exploring paper (GERALDI; BAVARESCO; GHISI, 2019). Since the aim of that paper was different from the aim of this thesis, such a paper was not included in the core of this thesis. Instead, it is shown in Appendix C. In that paper, it was found that the Equal Width Discretisation (EWD) method was the best to discretise the variables in the dataset in order to provide better Bayesian Network performance. Then, one used EWD to discretise the total dataset to build the Bayesian Network shown in Chapter 4.

The Bayesian Network presented a high performance when compared to similar Machine Learning methods developed in other studies. The accuracy of 76.53% found by our Bayesian Network was similar to studies that used Bayesian Network for different purposes, for example, Dongmei *et al.* (2018) (accuracy of 71% to 85%), Amayri *et al.* (2019) (accuracy of 84%), and Barthelmes *et al.* (2017) (accuracy from 93% to 98%). An important result of this method was that by employing a classification model such as Bayesian Network, it was possible to classify in different categories buildings with similar EUIs but distinct thermal satisfaction of occupants. In other words, both EUI and thermal satisfaction of occupants were considered in the benchmarking (alongside with other factors). The model was sensitive to all input variables, and none of them alone played a decisive part.

A tailored benchmarking method is important to allow subjective assessment in the evaluation process. In this sense, the method might take into account other phenomena that impact operational energy usage besides building features and climatic data. For example, how did the pandemic of COVID-19 affect building energy usage? The Brazilian National Energy Report of 2021 informed that the pandemic in 2020 caused a reduction of around 1.0% of the total electricity consumption compared to 2019. Commercial and public sectors experienced a reduction of, respectively, 10.4% and 7.3% in 2020 compared to 2019, while the residential sector faced a growth of 5.8% (EPE, 2021).

Regarding the Brazilian school building stock, the specific analysis of the impact of the lockdown measures was not carried out because the data used in this thesis was pre-COVID. Since, the pandemic is still an ongoing challenge, post-COVID investigation might take time. However, a partial analysis of the first (and more restrictive) lockdown measures in Florianópolis showed that the municipal schools had an average 50% reduction in energy consumption (GERALDI *et al.*, 2021). Since school buildings were supposedly unoccupied, why was this reduction not 100%? The same study showed that this was due to essential loads that keep the building operating even though it is unoccupied – in a "ready-to-operate" mode. This residual energy consumption was defined as basal EUI, an analogy to the basal metabolic rate in human bodies: the minimum energy consumed by the organism to maintain the body alive without activity. The basal EUI comprises lights that remain turned on for safety, refrigerators and freezers, residual safety system loads, stand-by loads, and emergency systems. Each typology might have other essential loads, for example, health centres or hospitals will include stand-by loads for some specific equipment.

Therefore, a building with no modifications on its envelope and under the same weather conditions will have changes in its EUI only caused by the interaction of the occupants with the buildings' systems. Since "Buildings don't use energy: people do" (JANDA, 2011), the occupant behaviour was included as a primary factor that contributes to energy consumption (YAN *et al.*, 2017). Thus, by correlating the energy consumption and a key performance indicator (KPI) for occupants, in terms of some subjective aspects (such as environmental comfort or productivity), it is possible to outline four assumptions that compose this interface:

(I) Inactivity: It is the condition in which there is no performance of the building (there are no occupants), but yet there is energy consumption to maintain the building "read-to-operate". It goes from zero consumption to the basal EUI;

(II) Under-consumption: It is the condition in which occupants are not comfortable or might be more productive considering the current building systems usage. This means the HVAC systems or lighting, for example, have to be activated to provide adequate environmental quality. If there is no HVAC system, there is a need for implementation. If HVAC systems and comfort are not adequate, the HVAC needs to be turned on or adjusted. It goes from the basal EUI up to the optimal state;

(III) Optimal: It is the condition around the best performance of comfort or productivity that the building could provide to occupants considering only upgrades of their systems. In this case, the energy is used adequately to provide satisfactory indoor environmental quality to occupants;

(IV) Over-consumption: It is the condition in which the occupants are not in the comfort zone, i.e. the HVAC is too hot or too cold, or a lighting system is causing glare. It goes from the optimal region towards the maximum energy consumption possible.

These four schematic assumptions show that within the optimal region lies the best practice possible for these given buildings. Therefore, it is with this best practice that the performance of a building has to be compared, which makes it the most suitable benchmark possible, because it is specifically tailored for the given building. Figure 7.1 shows a theoretical diagram of the four regions concept for the specific-building operational benchmarking.

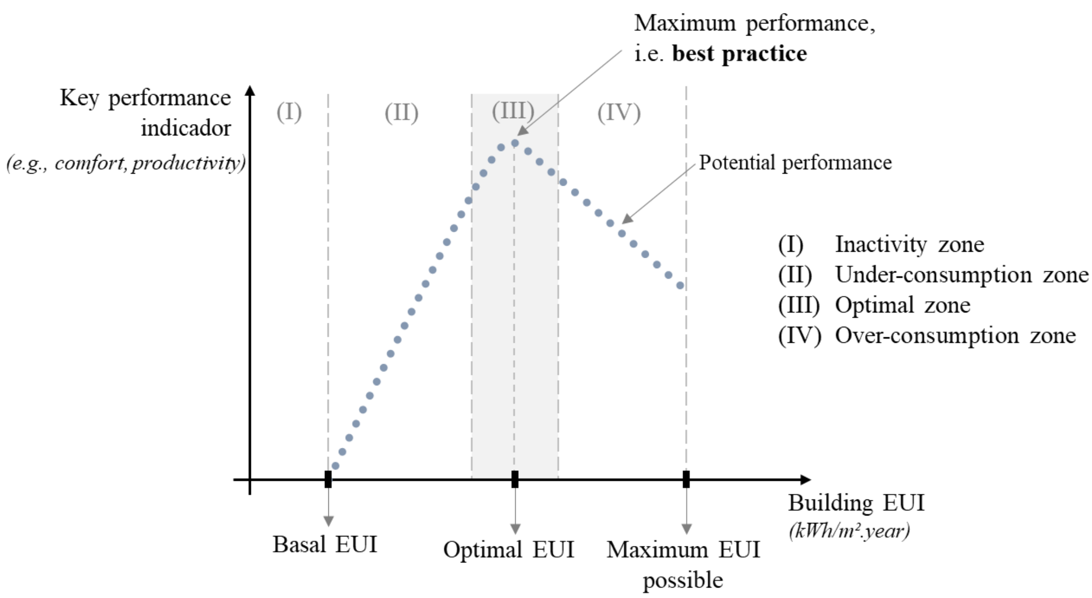


Figure 7.1 – Theoretical concept of the specific building operational performance evaluation.

The attainment of this diagram and the reference benchmark for an actual building might be challenging. The definition of a single KPI for the building performance was explored in the literature (ZHAO *et al.*, 2019), but it is debatable (CHEN *et al.*, 2020). However, a single KPI that summarises all subjective aspects of the interface between occupants and the building is hard to obtain for a simple assessment (MCARTHUR; POWELL, 2020). Certification processes, such as LEED, can incorporate human aspects to obtain a single rating (JIANG *et al.*, 2020), but these processes are exceptions, not the rule for a large-building stock. The method proposed in Chapter 4 could provide such KPI once it is a method that integrates subjective aspects and building features. However, there is room for discussion about this subject. Experimental analysis might be conducted to respond to such a riddle.

Since the schema presented in Figure 7.1 deals with subjective variables, it needs experimental analysis to collect evidence from the occupants. Further investigations can be outlined in a large sample to allow a high-resolution schema detailing. In this thesis, such an analysis was not carried out because the lockdown measures of the COVID-19 pandemic made impossible the *in-situ* data collection. The work initially proposed would be to collect information in the schools to improve the model's resolution in Chapter 4. A comfort survey and a high-resolution energy consumption monitoring (in a resolution of seconds) would be conducted. However, the suspension of school activities demanded a changing of plans.

Hence, although the top-down approach worked adequately to benchmark the whole-building performance considering the subjective aspects from occupants, this approach is limited to the dataset used. A generalisation model is more suitable to benchmark buildings considering standard (typical) conditions. Then, a bottom-up method using archetypes plays an important role because it emulates standard conditions for a given typology.

Along these lines, there is an evident need for a building stock model based on archetypes. Such models allow the creation of benchmarks to adequately study trends and analyse impacts of unseen scenarios on buildings and allow specific studies of strategies for interventions.

Obviously, the archetypes that represent the building stock need to be constructed based on actual data. However, the current methods found in literature always employed some archetypes' parameters based on actual data of the stock, but others based on values obtained in standards. Still, those parameters based on actual data are often based on averages of the stock and might not represent the whole distribution data. More advanced techniques to compose archetypes were found in literature, such as performance-based clustering processes to obtain reference buildings (SCHAEFER; GHISI, 2016) and segmentation criteria for whole-building index (ALI *et al.*, 2019). However, the representation of archetypes' parameters is still limited to single values, and there is no accounting for the amount of information in the building stock dataset. Therefore, the framework proposed in Chapter 5 aimed to bridge this gap. A reducing-uncertainty framework to obtain a bottom-up energy benchmarking model using Artificial Neural Networks (ANN) was proposed. The framework combines Information Theory through entropy and cluster analysis to determine the archetype parameters used to model an ANN as the benchmarking tool.

Three energy audits were carried out in schools in Florianópolis. Energy audits are in-deep analyses that aim to understand a specific building context related to energy usage and propose energy efficiency measures. ASHRAE defines three energy audits types:

- Level 1 (Walk-through survey): a brief visit to the building to recommend straightforward energy efficiency measures (EEMs);
- Level 2 (Energy survey and analysis): a survey conducted to raise equipment and systems, including operation and maintenance. The EEMs recommended included cost analysis;
- Level 3 (Detailed analysis of capital-intensive modifications): It is a level 2 including an equipment monitoring and more detailed site inspection. Energy simulation can be used to find economic-engineering analysis. It is the most detailed approach and holds the higher the level of confidence.

In this study, a proper energy audit protocol was developed. It is shown in Appendix D. This protocol is an enhancement of ASHRAE level 2, and it is suitable for non-complex and non-domestic buildings. The energy audit was important in this process to raise *in-situ* information and find detailed energy consumption data. The reports of the energy audits are presented in Appendix E, and they were used in Chapter 5 to compose the model and validate it.

Also, a data collection step was carried out through the analysis of the drawings of 31 schools. From the drawings' analysis it was possible to characterise the school building considering construction detail information, such as the thickness of the walls, type and size of roof, absorptance (colour) of the walls, type of floors, window-to-wall ratio for each type of room, among others.

The dataset of the Brazilian building stock was used to demonstrate the method application; however, the framework is not restricted to the data obtained in this study.

By adopting actual (and assertive) values on the archetypes' parameters, one can achieve a representative model of the building stock. The main innovation relies on the formulation of this framework: the schematic data-driven method was created to reduce uncertainty in modelling archetypes for energy benchmarking of buildings. Moreover, the study innovatively reported the analysis of an actual building stock benchmarking evaluation on a large scale in Brazil. The method application demonstrated that the Brazilian school building stock tended to inefficiency, and a specific case study pointed out that inefficient equipment might cause such an inefficiency.

It is important to clarify that the tendency to inefficiency is related to the actual condition of the schools – not that the energy consumption is high. Actually, by comparing the average EUI of the school building stock in Brazil (19.29 kWh/m².year), one can see that this is a very low EUI compared to other countries. The more similar EUIs reported by the cross-country benchmarking of Pereira *et al.* (2014) were 86 kWh/m².year in Italy and 63 kWh/m².year in Cyprus. However, by comparing it with South Africa (10 to 24 kWh/m².year), it is possible to understand that the average EUI is within a developing country range (SAMUELS; GROBBELAAR; BOOYSEN, 2020). As reported by Samuels *et al.* (2020), even though there is an evident social inequality issue in South Africa, reported by the authors, the public schools in South Africa lack adequate IEQ as well. Thus, one emphasises the energy poverty question raised above: does the Brazilian average energy consumption decrease due to efficiency or the lack of adequate IEQ? Clearly, the results found in thesis leads to the latter.

Although the actual EUI was very low, the benchmarking determined a tendency to inefficiency because the method calculated a reference EUI considering the conditions of the schools. For example, for a given school which the main end-uses are for lighting and equipment (without HVAC), the model will predict a benchmark without HVAC as well, because it is unfair to compare the actual EUI with a standard condition considering HVAC. Consequently, if the actual EUI is higher than the benchmark predicted by the model, lighting or equipment is inefficient.

In fact, a case study showed that inefficient equipment, such as old refrigerators, was the cause of inefficiency in that school. By comparing the end-uses obtained through the energy audit and the end-uses estimated by the benchmarking model, it was possible to achieve what makes the school inefficient. The energy consumption with equipment was 75.8% higher than the benchmark, while the energy consumption for cooling was 31.4% lower. Energy consumption with lighting was very similar. This analysis was inspired by a similar study performed in literature for residential buildings, which concluded that estimations predicted by benchmarking models are as suitable as energy audits to predict energy end-uses (HSU, 2014).

A comprehensive building stock model proposed in Chapter 5 supports not only the prospection of inefficiency but also the testing of scenarios of unseen events such as the performance of the stock under future climatic scenarios or the implementation of strategies on a large scale.

In the final core part of this thesis, Chapter 6 presents the application of the building stock model presented in Chapter 5 to emulate two situations: the implementation of HVAC in the school building stock in Brazil and the performance of such a stock considering the future climatic data. Two scenarios of HVAC implementation were analysed: one considering HVAC only in administrative rooms, library and computer labs, and the other considering HVAC in administrative rooms, library, computer labs and all classrooms. As for the climatic data, the weather data of 2019 (TMYx format) was used for four cities (Cuiabá, Rio de Janeiro, São Paulo and Curitiba), representing the four ASHRAE climatic zones for Brazil. Then, the 2019 weather data was adapted using the morphing method to generate weather for 2050 and 2080 according to the IPCC scenario A2. Results of this study showed an important prediction: the average EUI of the school building stock would increase around 88% today if there was a massive HVAC implementation. If the *status quo* is maintained – i.e. the same implementation of HVAC systems with no consideration of retrofit actions – the EUI will increase from the current 16.75 kWh/m².year to 45.27 kWh/m².year, an increase of 170%. It is important to state that the dataset used in the analysis of Chapter 5 was slightly small than the dataset used in Chapter 4 (because of the size of the article for a conference, only four cities were chosen for Chapter 5 instead of the eight adopted in Chapter 4). Then, the average EUI of both papers (Chapter 4 and 5) was slightly different. This result is supported by the evidence obtained in Chapter 3, which revealed that schools with HVAC had a EUI 60% higher than schools with no HVAC.

These outcomes do not encourage avoiding the air-conditioning implementation to diminish such growth in energy use. Instead, occupants' satisfaction might be negatively affected by poor indoor conditions (PALACIOS *et al.*, 2020; VAN DEN BOGERD *et al.*, 2020). It is important to assess the impacts of current decisions on the future carefully. Accomplishing the decarbonisation target in the buildings sector is a complex demand, which involves different stakeholders (HAMILTON *et al.*, 2017).

Therefore, building designers, researchers, school principals, and policy-makers must be consonant in order to achieve comfortable, energy-efficient, and climate-change-resilient learning environments in Brazil.

As a final remark on this Chapter, one discusses the validity of the energy benchmarking application. In this thesis, two stock modelling methods were proposed: a top-down and a bottom-up method. The top-down method was an energy epidemiological solution based on evidence to model statistical relationships and provide a single performance scale. This method is suitable to include occupants' aspects in buildings operational performance evaluation. On the other hand, the bottom-up method started from the building stock dataset to model archetypes; artificial intelligence was used to generalise the benchmark prediction. This method is adequate to rate the building performance under standard conditions. As a result, both aspects are important to be considered differently because they measure different metrics and solve different problems. Thus, both methods are useful and valid, but they perform different evaluations.

8. Conclusions

The objective of this thesis was to develop methods to obtain representative building stock models to benchmark the energy performance of Brazilian schools considering building-level and stock-level perspectives. An energy epidemiological study was conducted to assess the distribution (frequency and patterns) and determinant factors of energy consumption in the school building stock in Brazil.

Five articles constitute the core of this thesis. The first article showed a literature review in which the main gaps of researches were identified. The second article showed information of the school building stock and a statistical analysis of the main features regarding energy consumption. The third article proposed a top-down modelling based on the data presented in the second article in order to propose an integrative benchmarking model considering subjective aspects (satisfaction with built environment) for benchmarking. The fourth article proposed a bottom-up modelling framework based on reducing the uncertainty of archetypes and the construction of an ANN to generalise the building performance evaluation. The fifth article reported a practical application of the stock model constructed in the fourth article to measure how the building stock will respond under future conditions considering climate change effects and large-scale HVAC implementations.

Each article addressed conclusions regarding their detailed application and their individual topics while sharing the encompassing problem of this thesis. The main contributions of this work are both theoretical and application-oriented, which drives the research to the following key conclusions:

- The current state of art evidenced two main perspectives: building-level and stock-level analysis of operational building performance. Building-level analysis employed higher resolution of data than stock-level analysis. Also, one concluded that building performance analysis benefits from the consideration of the climate, urban, and social context, encouraging researchers to specify the boundary condition adopted in the study;
- An energy epidemiological analysis was carried out showing that the determinant factors that impact the EUI in the school building stock in Brazil were the number of students, floor-plan area, operation time, and HVAC system specifications (type and quantity). Obviously, the climate

conditions where the building is placed impacts the energy consumption when there is HVAC in the building. Other factors such as thermal satisfaction and the need for improvements played an important role but were not decisive. The awareness of the schools' principal regarding the energy consumption and satisfaction with other aspects of the IEQ (such as acoustic satisfaction and lighting satisfaction) were not relevant for the EUI. Moreover, the survey responses showed that the schools in Brazil have poor IEQ, and occupants reported an urgent need for HVAC. Thus, the apparent low EUI of the stock (if compared to other countries) is an energy poverty issue due to the need for better thermal performance in those buildings;

- The consideration of subjective aspects is important to allow a fair benchmarking, especially on a country-size scale. A probabilistic model was proposed to integrate both qualitative and quantitative variables of the building stock to perform such an evaluation. The Bayesian Network provided good results;
- The method used to enhance the archetype composition (evaluating the entropy and defining clusters) provided a high-performance stock model to emulate the stock conditions. This manipulable stock model supported the analysis of unseen scenarios for the population of buildings, such as strategies for energy efficiency and building performance under future climates;
- The method proposed to develop bottom-up building stock model was successfully applied in a case study considering future scenarios of climatic data and interventions of HVAC installation. If the *status quo* is maintained (intensification of HVAC implementation and aggravation of climate change effects), the Brazilian school building stock will experience an increase of 88% in their average EUI by 2050 and 170% by 2080. Therefore, actions must be taken to provide a more conscious transition to a comfortable and energy-efficient school building stock in Brazil.

8.1. Limitations

Limitations were also addressed in each individual article and they can be summarised as follows:

- Only data of 2018 was used for the conducted analysis. As pointed out in the literature review, the benchmarking throughout the years is a question still open. The data collection process (through survey and design analysis) might imply in some loss of data due to the different databases. Also, the voluntary nature of the survey application disregarded some states of the country due to absence of responses. Moreover, the questionnaires were applied to a key person – which limits the perception of the data to the respondent person. Thus, an investigation of the actual environmental comfort conditions of each individual occupant was not considered because it is timing and money consuming;
- The top-down model is highly dependent on the dataset. As the building stock changes, the Bayesian Network results might change. Then, continuous collection of data and updating of the BN are needed.
- Regarding archetype modelling, the process is still dependent on the analyst. The modelling of subspace geometries needs subjective evaluations. Moreover, the framework neglects the modelling of surroundings.

8.2. Further research

Further investigations and follow-up research are outlined as follows:

- For further works, one suggests an expansion of this research, including the missing states. A suggestion is to apply the same questionnaire used herein (or other well-known approach), in order to obtain yearly systematic responses from occupants. By expanding the research scope, one could also include other dimensions of the environmental comfort, such as lighting and acoustic satisfaction – which play an important role in occupant experience in the building, but were disregarded in this research because they were secondary in relation to the thermal satisfaction;

- Although the collected data in this study was comprehensive, there is room for enhancement by collecting high-granularity data. This step was planned to be performed, but it was cancelled due to the COVID-19 pandemic. A high granularity of energy consumption data in a sample of school buildings could enlighten specific energy-consumption drivers and allow deep correlations with occupants' satisfaction. For example: time and setpoints to operate HVAC systems, lighting usage pattern, schedules of equipment operation, among others;
- It is possible to improve the method of archetype modelling by including parametric design in the massing model. Since the geometric parameters are variables, it is possible to systematise the process by linking the inventory proposed with an algorithm that automatically reads, analyses, and models the archetype. This is achievable using current parametric design tools, such as Grasshopper and Rhinoceros;
- Further research can be conducted to reproduce the data-driven models considering multi-year evidence. This analysis might reveal a direction of the building performance of the stock towards efficiency, inefficiency, or stability.

Therefore, the study of the building performance at the stock-level is a key knowledge to improve energy performance and enhance indoor environmental quality at the building-level. This thesis strengthens the state of the art of building stock modelling worldwide by proposing stock-level evidence-based techniques to assess building-level energy performance.

Exploring the energy performance of a population of buildings sheds light on the individual building's insights, supporting the understanding of energy usage in practice. Thus, only a representative building stock model sustains a reliable and collective analysis of strategies to reduce energy consumption and provide actions to move towards a more sustainable world.

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Appendices

Appendix A – First appendix to Chapter 3

This appendix presents a literature review table that is part of the article shown in Chapter 3.

Table A.1 – Summary of the selected previous works that addressed energy performance of school building stock.

Authors	Year	Country	Contribution	Reference
IEA EBC Annex 15 (Various authors)	1996	Various	Established a set of guidelines for the construction of school buildings in order to achieve a certain level of energy efficiency considering Heating, Ventilation and Air-Conditioning (HVAC) and water heating, insulation of the envelope, and window-to-wall ratio.	(IEA, 1996)
Hong *et al.*	2013	UK	Established a top-down approach to benchmark the school building stock using a broad perspective. Used ANN for benchmarking, adopting the building characteristics as inputs and the benchmarks of electric energy and heating energy demand as outputs. Conclusions pointed out that this approach is useful to compare building among pairs.	(HONG *et al.*, 2014)
Burman *et al.*	2014	UK	Established a bottom-up approach to benchmark the school building stock including end-use analysis. Authors proposed an intrinsic method to evaluate a building by comparing it with itself, using past performance as a baseline. A post-occupancy evaluation was applied in four school buildings for two years. The authors identified specific building characteristics by considering the social context, mapping operations issues and establishing the baseline. A very detailed simulation model was developed to analyse the energy performance and to propose energy conservation measures.	(BURMAN *et al.*, 2014)
De Santoli *et al.*	2014	Italy	By analysing the existent stock, it was possible to predict a reduction of around 20% by combining floor plan and material improvements.	(DE SANTOLI *et al.*, 2014)
Pereira *et al.*	2014	Portugal and Italy	Established a functional multiple-country benchmarking, summarised the main characteristics of the school building stock and concluded that indoor environmental conditions must be considered in benchmarking. Additionally, benchmarking must consider energy bill information in large-scale analysis.	(PEREIRA *et al.*, 2014)
Herrando *et al.*	2016	Spain	Found an average difference of 30% between measured and predicted consumption at stock level. This difference is mainly caused by the unrealistic consideration of the user behaviour and difficulties in simulating some types of loads.	(HERRANDO *et al.*, 2016)
Salleh *et al.*	2016	Malasya	Applied questionnaires to measure the perception of the users regarding energy efficiency	(SALLEH; KANDAR; SAKIP, 2016)
Ouf, Issa	2017	Canada	Level of study and age of the building had a significant impact on energy performance. New buildings showed a lower performance.	(OUF; ISSA, 2017)

Table A.1 – Summary of the selected previous works that addressed energy performance of school building stock (continuation).

Authors	Year	Country	Contribution	Reference
Lizana *et al.*	2018	Spain	A new energy assessment method using supporting decision-making process towards low-carbon energy schools was proposed. The method included the minimization of the input data according to the specific characteristics of schools.	(LIZANA *et al.*, 2018)
Burman *et al.*	2018	UK	Five high-efficient school buildings presented higher CO_2 emissions regarding operational performance than the median of the same typology stock. The performance gap is pointed as a possible cause: the buildings have been designed but are operated in a different way. Thus, it is important to address post-occupancy evaluations and measurement and verification of performance in-use. Also, the study suggests a holistic approach, assessing energy, environmental quality, and educational performance in order to potential conflicts between energy efficiency measures and indoor environmental quality (IEQ).	(BURMAN; KIMPIAN; MUMOVIC, 2018)
Vivian *et al.*	2018	UK	Experiment study of using passive ventilation systems (PVHR) in classrooms in order to reduce energy consumption with heating. This study addressed parameters such as Air permeability and air infiltration and concluded that airtightness significantly affects the performance of the PVHR as well as the human behaviour interactions (such as window opening).	(VIVIAN *et al.*, 2018)
Saraiva *et al.*	2019	Brazil	The study established a comparison between comfort indicators between schools in two different regions in Brazil. It was demonstrated that a specific methodology to assess sustainability school buildings is required for each region of Brazil.	(SARAIVA *et al.*, 2019)
Wang	2019	Taiwan	A broad panorama regarding the final energy consumption in senior and junior high and elementary schools in Taiwan was presented using measure EUI and energy consumption per student. A major conclusion point to the higher consumption for private schools than public schools.	(WANG, 2019)
Kim *et al.*	2019	South Korea	A summary of the schools' energy usage and their construction aspects in South Korea was presented. The main energy performance indicators were assessed, such as the EUI and the energy consumption in function of the number of students. Thus, it was suggested to estimate the school size considering the population density.	(KIM *et al.*, 2019)
Attiaa *et al.*	2020	Belgian	The study used stock data to develop two benchmark models of NZEB schools, based on EUI rated by floor-plan area. Models were validated using four-year dataset of energy consumption monitoring.	(ATTIA; SHADMANFAR; RICCI, 2020)
Barbosa *et al.*	2020	Portugal	Assessed the thermal discomfort in public schools in free-running conditions. The experimental work used a prototype of a real school in order to evaluate thermal discomfort, energy consumption prototype before and after refurbishment, considering heating strategies (winter and midseason analysis).	(BARBOSA; DE FREITAS; ALMEIDA, 2020)

Appendix B – Second appendix to Chapter 3

This appendix presents the questionnaire that is part of the article shown in Chapter 3. This questionnaire composes the form for data collecting of this thesis.

Table B.1 – Questionnaire used in the research.

Questions	Type of question
Basic data:	
1. School Name	Open-ended
2. School code	Open-ended
3. City	Open-ended
4. State	Open-ended
5. Phone number	Open-ended
6. Operating hours (Options: Morning, afternoon and night)	Multiple choice (more than one is allowed)
7. Year of construction	Open-ended
8. Floor plan area (in m²)	Open-ended
About the Facility:	
10. Which of those facilities the school have? (Options: Gymnasium, Sport Court, Cafeteria, Snack Bar, Library, Computer Lab, Auditorium, Swimming Pool, Kitchen, Other).	Multiple choice
11. How many classrooms the school have?	Open-ended
12. How many refrigerators and freezers the school have?	Open-ended
13. Are there fans in the school? (Options: Yes, in most of the classrooms; Yes, in least than half of the classrooms; No)	Multiple choice
14. Are there curtains in the school? (Options: Yes, in most of the classrooms; Yes, in least than half of the classrooms; No)	Multiple choice
15. Generally, when the light bulbs are turned on? (Options: Only during the night; Only during the day; During both night and day)	Multiple choice
16. In general, what are the type of the lights? (Options: LED light bulb; Fluorescent light bulb; Fluorescent Tub; Incandescent light bulb)	Multiple choice
18. Are there air-conditioning in the classrooms? (Options: Yes, in most of the them; Yes, in least than half of the them; No)	Multiple choice
18. Are there air-conditioning in the office rooms? (Options: Yes, in most of the them; Yes, in least than half of the them; No)	Multiple choice
18. Are there air-conditioning in the library and labs? (Options: Yes, in most of the them; Yes, in least than half of the them; No)	Multiple choice
19. In total, how many air-conditioning units the school have?	Open-ended
20. In general, when the air-conditioning units are often used? (Options: February/March; April/May; June/July/August; September/October; November/December)	Multiple choice (more than one is allowed)
20. In general, when the fans are often used? (Options: February/March; April/May; June/July/August; September/October; November/December)	Multiple choice (more than one is allowed)
21. What are the types of air-conditioning units the school have? (Options: Split-type; Window-type; Central-type; None)	Multiple choice
22. In average, how often the air-conditioning units got maintenance actions? (Options: Less than one time each 2 year; One time each 2-year; One time each year; More than one time each year; never; I don't know)	Multiple choice
About the energy use:	
23. Do you know how much the monthly energy consumption of this school is?	Yes / No
24. In your perception, how much the air-conditioning usage impacts on school's energy bill?	Likert scale

Table B.1 – Questionnaire used in the research (continuation).

Questions	Type of question
24. In your perception, how much the fans usage impacts on school's energy bill?	Likert scale
24. In your perception, how much the lighting system usage impacts on school's energy bill?	Likert scale
24. In your perception, how much the computer's usage impacts on school's energy bill?	Likert scale
25. Does the school motivate the employees to save energy?	Yes / No
26. What do you think about approaching the energy efficiency with the students?	Likert scale
About the indoor environmental satisfaction:	
27. In your perspective as principal, do the students/teachers are satisfied with the indoor temperature in February/March?	Likert scale
27. In your perspective as principal, do the students/teachers are satisfied with the indoor temperature in April/May?	Likert scale
27. In your perspective as principal, do the students/teachers are satisfied with the indoor temperature in June/July/August?	Likert scale
27. In your perspective as principal, do the students/teachers are satisfied with the indoor temperature in September/October?	Likert scale
27. In your perspective as principal, do the students/teachers are satisfied with the indoor temperature in November/December?	Likert scale
28. In your perspective as principal, do the students/teachers are satisfied with the lighting in the classrooms?	Likert scale
28. In your perspective as principal, do the students/teachers are satisfied with the external noises in the classrooms?	Likert scale
28. In your perspective as principal, do the students/teachers are satisfied with the airflow in the classrooms?	Likert scale
28. In your perspective as principal, do the users are satisfied with the lighting in the office rooms?	Likert scale
28. In your perspective as principal, do the users are satisfied with the external noises in the office rooms?	Likert scale
28. In your perspective as principal, do the users are satisfied with the airflow in the office rooms?	Likert scale
29. In your perspective as principal, there is any improvement to increase the environmental satisfaction with the temperature? (Options: Yes, a major retrofit; Yes, a medium retrofit; Yes, a minor retrofit; No)	Multiple choice
29. In your perspective as principal, there is any improvement to increase the environmental satisfaction with the lighting? (Options: Yes, a major retrofit; Yes, a medium retrofit; Yes, a minor retrofit; No)	Multiple choice
29. In your perspective as principal, there is any improvement to increase the environmental satisfaction with the airflow? (Options: Yes, a major retrofit; Yes, a medium retrofit; Yes, a minor retrofit; No)	Multiple choice
29. In your perspective as principal, there is any improvement to increase the environmental satisfaction with the acoustic? (Options: Yes, a major retrofit; Yes, a medium retrofit; Yes, a minor retrofit; No)	Multiple choice
30. Do the air-conditioning units need improvements? (Options: Need Installation; Need maintenance; Already have enough and works well; There is no need)	Multiple choice
30. Do the fans need improvements? (Options: Need Installation; Need maintenance; Already have enough and works well; There is no need)	Multiple choice
30. Do the curtains need improvements? (Options: Need Installation; Need maintenance; Already have enough and works well; There is no need)	Multiple choice
30. Do the lighting systems need improvements? (Options: Need Installation; Need maintenance; Already have enough and works well; There is no need)	Multiple choice
31. How much do you think that this improvement would cost?	Likert scale
32. Fell free to tell more about the needs of the school	Open-ended

Table B.1 – Questionnaire used in the research (continuation, end).

Questions	Type of question
33. In general, how much do you think that the actual conditions of the lighting system impact on the students' learning skill?	Likert scale
33. In general, how much do you think that the actual conditions of the natural lighting impact on the students' learning skill?	Likert scale
33. In general, how much do you think that the actual conditions of the acoustic impact on the students' learning skill?	Likert scale
33. In general, how much do you think that the actual conditions of the natural airflow impact on the students' learning skill?	Likert scale
33. In general, how much do you think that the actual conditions of the temperature impact on the students' learning skill?	Likert scale
34. Feel free to complement the previous question or to share your experience.	Open-ended
34. Do you want to share anything else?	Open-ended

Appendix C – First appendix to Chapter 7

This appendix presents the article published in the Building Simulation 2019 conference. This article was developed during the thesis and it was used as a complementary study to construct the Bayesian Network model presented in Chapter 4, and discussed in Chapter 7. The reference of the paper is:

GERALDI, M. S.; BAVARESCO, M. V.; GHISI, E. Bayesian Network for Predicting Energy Consumption in Schools in Florianópolis – Brazil. Proceedings of the 16th IBPSA Conference Rome, Italy, p. 4188–4195, 2019. doi: https://doi.org/10.26868/25222708.2019.210484.

Bayesian Network for Predicting Energy Consumption in Schools in Florianópolis – Brazil

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Abstract

It is important to study innovative approaches that consider real-world data to predict energy consumption, especially in existing buildings. This paper presents a data-driven model to predict energy consumption using Bayesian Networks. Monthly energy bills over three years were obtained from 90 public schools in Florianópolis, southern Brazil. Information such as floor-plan area, number of students, type of education, number of floors and occurrence of events were gathered for each building. The network output indicator was assessed using Energy Use Intensity based on floor-plan area or number of students. Three types of discretization methods and three network structures were tested, generating eighteen networks. A performance analysis comparing predicted as well as real Energy Use Intensity determined the Normalized Root Mean Square Error for each network and pointed out Equal Width Discretization as the best method and Naïve-Bayes as the most advantageous structure type. The discretization method had a high impact on the network performance. In addition, the Energy Use Intensity based on floor-plan area was more reliable than that based on the number of students.

Introduction

Predicting energy consumption is important for public buildings once it yields better resource management and improves optimization and retrofits. In Brazil, buildings were responsible for 43% of the total energy demand in 2017 (Brazil, 2017).

For new buildings, the energy consumption is commonly predicted using computer simulation or simplified models. However, predicting energy consumption for actual buildings lacks dependable methods along with challenges to be addressed, such as the non-availability of measured data and the unwillingness to share existing data (Borgstein and Lamberts, 2014). Thus, a statistical approach can be helpful to overcome those difficulties and obtain a representative result.

Computer simulations and statistical approaches are complementary techniques. Building simulation using software (e.g., EnergyPlus) is useful for forward modelling at the building design phase and data-driven modelling is useful for retrofits, building performance analysis and energy purchasing in smart grids (Kontokosta and Tull, 2017). Moreover, authors have emphasized the gap between simulation results and actual performance (Jones et al., 2015; Khoury et al., 2017; Menezes et al., 2012), and this fact leads researchers to look for new ways to predict energy consumption by calibrating forward models or using data-driven modelling (Tardioli et al., 2015; Wei et al., 2018). An evident need to forecasting energy consumption based on real data is expressed by recent studies, especially for existing buildings (Hamilton et al., 2015, 2016; Huebner et al., 2015; Huebner et al., 2016; Staepels et al., 2013).

Statistical approaches can be used to create data-driven models using information from the building stock. Usually, data-driven approaches are used to calculate baselines for measurement and verification proceedings (e.g., retrofits) (Burman et al., 2014; IPMVP, 2001). Human variables can also be taken into account to improve the accuracy of such data-driven models by considering user's behaviour (Liang et al., 2016).

Wei et al. (2018) categorized data-driven approaches in two major classes: to predict building energy consumption (using artificial neural networks, support vector machines, statistical regression, decision tree and genetic algorithm); or to classify building energy consumption (using *k*-mean clustering, self-organizing map and hierarchy clustering).

For example, using a data-driven approach, Lindelöf et al. (2018) developed a model to reduce the cost of retrofitting by estimating the baseline period through a Bayesian verification (no specific monitoring period was needed). In addition, the result was expressed by probability density function, which gives a confidence interval and not a static value. This confidence interval, rather than a blind result, supports the stakeholder to decide about the most suitable retrofit.

The Bayes theorem introduces the conditional probability, which is a powerful approach to face complex and interactive problems, such as energy consumption, due to its capacity to express results in a degree of uncertainty (Borunda et al., 2016). Bayesian Networks are acyclic graphical models used to assess inferences regarding the relationship between input and output variables, represented as nodes. This technique has been used for many purposes, such as calibrating simulation models (Heo et al., 2011; Heo et al., 2012), defining architypes for stock modelling (Menberg et al., 2017; Sokol et al., 2017) and evaluating resources operation and application (Borunda et al., 2016).

To forecast energy consumption, Bassamzadeh and Ghanem (2017) proposed a Bayesian Network to predict the demand for purchasing energy in Smart Grids based on high resolution data (5 min). The aim was to investigate the dependent relations between contributing variables and to build a model to help managers to buy the right amount of energy using high-granularity data. The main variables used were past demand, outside temperature, weekday or weekend day and price of energy. O'Neill and O'Neill (2016) proposed a Bayesian Network for forecasting hot water energy consumption in an office building. The model was based on an hourly dataset of outside temperature and energy demand collected during the cold season. The Network was very dependent on the discretization process and the uncertainty had increased when predicting consumption in other seasons.

However, both proposed frameworks required a high level of data resolution and lacked to predict consumption when the building was not monitored with smart meters. In developing countries as Brazil, buildings with monthly energy measurement (billing) are the majority and there is a need to develop models to consider this portion of the stock. In addition, despite the high applicability of the Bayesian Network to predict energy demand in buildings, there is a lack of a tool for forecasting electric energy use intensity (EUI), since it has been used to estimate HVAC demands in cold locations. The objective of this work is to introduce a data-driven model using Bayesian Network to predict electric energy use intensity in public schools based on monthly data. The model was constructed using billed data from 90 state schools in Florianópolis, southern Brazil. The method presents the step-by-step construction of the Bayesian Network and registers how the nodes, data classifications and node connections were settled to obtain an optimal network performance.

Method

The study is comprised of three steps: dataset characterization and discretization process, Bayesian Network construction, and performance analysis. Figure C.1 shows the method flow chart.

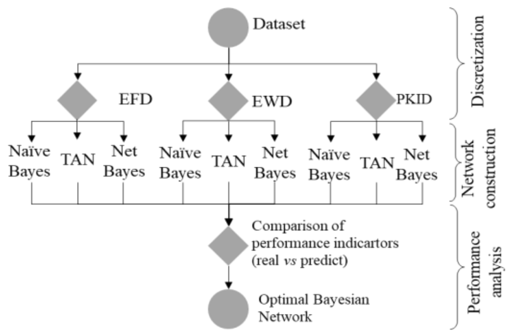


Figure C.1 – Method flow chart

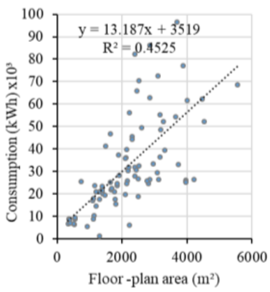
Dataset characterization

The first step was to collect and to characterize the dataset. Data from 118 schools were obtained and each school was characterized by including information such as monthly energy bills from 2016 to 2018, floor-plan area (in m²), number of students, type of education (basic, high or both). The presence or not of significant events was also identified for each monthly bill in order to indicate if the school had a situation, such as a party or science fair, which impacts on the energy consumption. The data collection process was based on the Energy Star® Portfolio

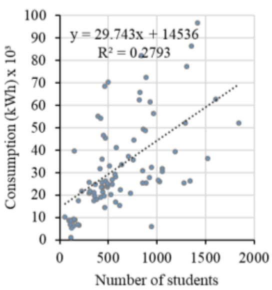
Management worksheet for schools K-12 (EPA, 2016).

A first exploratory analysis cleaned the dataset aiming to exclude missing data, removing outliers and correcting inconsistent data. Some inconsistent data that should be avoided (such as hotwire power supply) could lead to an unreliable modelling. This process included the comparison of the average and the standard deviation of the annual electricity consumption. Schools with average annual consumption differences greater than 50% and schools with monthly peaks greater than two standard deviations of the annual consumption were excluded. The result of this step was the dataset ready to be used for discretizing.

The EUI was obtained for each school in two ways: rating the monthly consumption by floor-plan area and by number of students. Despite the relationship between the consumption and the building characteristics, a Bayesian Network was proposed because it is not possible to predict energy consumption using a directly linear model. Figure C.2 shows electricity consumption versus floor-plan area and number of students and evidences that a linear model will be very unreliable.



(a)



(b)

Figure C.2 – Monthly energy consumption versus (a) floor-plan area and (b) number of students.

Discretization process

Values of an attribute are either discrete or continuous. The conditional probability of an attribute X_i that will take a particular state x_i, when the value of the class C that conditions X_i is c can be described as Equation C.1.

$$P(X_i = x_i \mid C = c) \qquad \text{(C.1)}$$

Where X_i is an attribute of the variable X; x_i is a given state of the attribute; C is a class of the attribute; and c is an adopted value for class C.

Attribute value c for the class C is considered a discrete value with a finite range. When the class C has a continuous attribute range, it is necessary to group them into classes to calculate a probability function. Even for attributes that have a discretized but large amount of values, it is often advisable to group ranges of values into a smaller range for the purpose of estimating the probabilities. So, it is needed to discretize the continuous variables to allow the calculation of the probabilities.

Some of the variables gathered were continuous and needed discretization, but some variables were discrete. Table C.1 shows a summary of the variables used to construct the Bayesian Network.

Table C.1 – Summary of the variables

Variable	Variable type	Node number	Node type	Nº of Classes
EUI	Continuous	1	Output	5
Area	Continuous	2	Input	3
Students	Continuous	3	Input	3

Table C.1: Summary of the variables (Continuation).

Variable	Variable type	Node number	Node type	Nº of Classes
Floors	Discrete (One or Two)	4	Input	2
Education	Discrete (Class 1, 2 or 3)	5	Input	3
Month	Discrete (12 months)	6	Input	12
Event	Discrete (Yes or No)	7	Input	2

To categorize the continuous variables, three discretization methods were used aiming the best network performance. Three methods were tested because, as concluded by O'Neill and O'Neill (2016), the discretization criteria have a high impact on the network output. The discretization methods were chosen according to Yang and Webb (2002) due the nature and amount of data available in this work.

The first discretization approach was EWD (Equal Width Discretization). This method divides the number of observations into *k* intervals of equal width, where *k* corresponds to the number of classes. The interval width is given by Equation C.2.

$$D_{EWD} = (v_{max} - v_{min})/k \qquad \text{(C.2)}$$

Where: D_{EWD} is the intervals width; v_{max} is the maximum observed value; v_{min} is the minimum observed value; and *k* is the number of intervals.

The cut points start in v_{min} and continue by summing D_{EWD} until v_{max}.

The second discretization approach was the EFD (Equal Frequency Discretization). This method divides the dataset into *k* intervals where each one contains approximately the same number of training cases (equal frequency). *k* is a predefined factor equal to the number of classes.

Both EWD and EFD methods possibly jeopardize attribute information since *k* is determined by an assumption and without considering the dataset properties. However, both methods are often used and work surprisingly well for Naïve-Bayes classifiers (Yang and Webb, 2002). To explore that limitation, the final discretization approach was the PKID (Proportional *k*-Interval Discretization) which discretizes the dataset into *k* intervals with *s* size. PKID adjusts discretization because it considers the relationship between interval size and number of intervals. The higher the number of intervals, the smaller the interval size. Consequently, the larger the interval size (the smaller the number of intervals), the lower the variance but the higher the bias. The opposite is true. PKID gives equal weight to discretization bias and variance decrease by setting both interval size and interval number equally and proportionally to the dataset size, as presented in Equation C.3.

$$s = t = (n)^{1/2} \qquad \text{(C.3)}$$

Where *s* is the interval size; *k* is the number of intervals; and *n* is the dataset size.

The result of this step was a table with all variables classified according to the three discretization criteria adopted.

Bayesian Network construction

The construction of the Bayesian Network was based on the Bayesian Theory and the calculation of conditional probabilities as shown in Equation C.4.

$$P(A|B) = P(B|A).P(A)/P(B) \qquad (C.4)$$

where P(A|B) is the probability *a posteriori* of the event A, conditioned by the event B; P(B|A) is the probability *a posteriori* of the event B that conditions an event A; P(A) is the probability *a priori* of the event A; and P(B) is the probability *a priori* of the event B.

The probabilities *a priori* were based on their own variable distribution and the probabilities *a posteriori* was calculated as a function of the conditioning event. The nodes represent the attributes of the observations, i.e., the variables gathered in the dataset. Node classes represent the variable states. The connections among the nodes are called directed arc of probability and express the likelihood that the arrow-headed node conditions the arrow-ended node. The structure of the network depends on the arrangement of those arcs among the nodes.

Those probabilities were assessed by calculating the frequency of occurrence for each variable state related to the variable state of the connected node using a frequency table. Table C.2 shows the questions asked whose response values complete the frequency table for two generic nodes.

Table C.2 – Analytical composition of a generic frequency table of two nodes with two classes.

Node A	**Node B**	
	Class 1	**Class 2**
Class 1	How many observations had Node A classified as Class 1 and Node B classified as Class 1?	How many observations had Node A classified as Class 1 and Node B classified as Class 2?
Class 2	How many observations had Node A classified as Class 2 and Node B classified as Class 1?	How many observations had Node A classified as Class 2 and Node B classified as Class 2?

Three structures of Bayesian Network were tested. The most basic one was Naïve Bayes, wherein the input nodes were settled by a direct arc to the output node. The Tree Augmented Naïve-Bayes type (TAN) was similar to Naïve Bayes, but arcs among input nodes were used. The Net Bayes type combines the arcs among input nodes and the use of latent nodes – nodes not directly connected to the output node. Usually, latent nodes are used to represent non-observational variables. Figure C.3 presents a graphical example of those three types of structure.

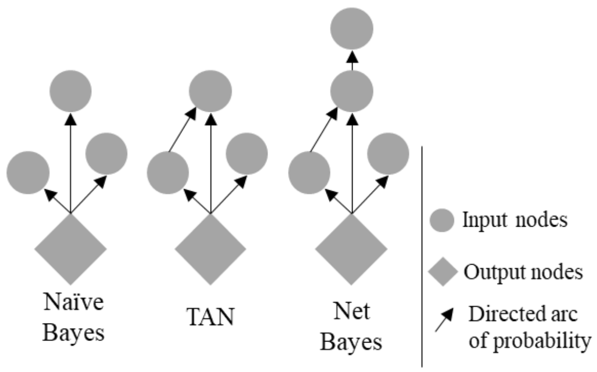


Figure C.3 – Differences among Bayesian Network structures.

Therefore, three types of networks were developed each one combining three different discretization approaches for continuous variables, resulting in nine networks.

To use the network, one must settle the class in all input nodes regarding to its school information according to the intervals defined in the discretization. The output node was the energy use intensity, and, despite this node was denoted by a discrete node, the output is a continuum value because the Bayesian Network can be used as a predictor by multiplying the output probabilities of each output class by their average value. The predicted energy use intensity can be estimated by means of Equation C.5.

$$EUI = \Sigma(p_i \text{ x } a_i) \qquad \text{(C.5)}$$

Where *EUI* is the predicted energy use intensity (output of the Bayesian network); p_i is the probability outputted for each class; and a_i is the average value of energy intensity for each interval class of the EUI node.

The standard deviation of the predicted energy use intensity was also calculated, using the same mathematical structure of Equation 5 but considering the standard deviation instead of the average value of each interval class of the EUI node. Considering a distribution of Student, the final predicted EUI value was shown with a confidence interval, i.e., predicted EUI + or –confidence interval. In the first attempts, the total consumption was used as output node, but it was found that using EUI as output node the network achieved more reliable results.

Two types of EUI were used to test the network performance. The first EUI was based on the rate between energy consumption per month and floor-plan area, used by many authors to measure performance (Chung 2011). The second was based on energy consumption per month and number of students, as suggested by Dias Pereira et al. (2014) to assess performance of school buildings.

Performance analysis

The performance analysis measured the capacity of each network to predict reliable results.

A dataset containing known-output values (real values) were inputted in the network and the outputs predicted by the network were compared to those already acknowledged. This process was performed using a bootstrap routine which resamples the dataset that was used to train the network.

A first analysis compared the predicted output values with the known-output values by verifying if the known-output values were fitted inside the confidence interval outputted by the network. If so, the network was considered able to predict monthly EUI, considering the confidence interval. This analysis compared the correct and the non-correct results grouping them in a bar chart.

To determine the network that had the best performance, a numerical approach was used. To assess the performance, the NRMSE (Normalized Root Mean Square Error) was adopted as an indicator, which can be calculated according to Equation C.6.

$$NRMSE = 100 \times [\Sigma(y'_t - y_t)]^{1/2} / (y_{max} - y_{min}) \quad (C.6)$$

Where *NRMSE* is the Normalized Root Mean Square Error (indicator of performance); y'_t is the predicted EUI (network output) corresponding to the case *t*; y_t is the real EUI corresponding to the case *t*; *t* is the number of cases; y_{max} is the maximum value of real EUI; and y_{min} is the minimum value of real EUI.

In summary, the square difference of the predicted output energy use intensity and the real energy use intensity was computed for each case of the bootstrapping sample, divided by the number of cases in the sample and then the square root was taken. Then, the indicator was normalized to exclude the influence of the scale on the result. This indicator expresses a reliable network performance measure because it gives the idea of the potential global fitness (Hyndman and Koehler, 2006). Thus, the lower the NRMSE the stronger the network for predicting energy intensity.

The NRMSE was calculated using the bootstrapping for each network combination, i.e, three discretization methods times three structures equals nine networks. Since two EUI indicators were used as output node, the NRMSE was calculated for the networks that use EUI as a function of floor-plan area and as a function of number of students, totalizing eighteen networks.

A final performance analysis used the best network selected from the previous analysis (smaller NRMSE) to predict the EUI over a year for a sample of schools (monthly). This result was compared to the real EUI to evidence the Bayesian Network behaviour in practice.

Results

The Bayesian Network

Eighteen Bayesian Networks were built. An example of a Naïve Bayes Network is shown in Figure C.4. Each square represents a node, and their classes are displayed by bars with the probabilities *a priori*. Those probabilities *a priori* were calculated using the dataset to train the network. The trained network can be used to insert a case by setting the states on classes of each node according to the classes of the case analysed.

Then, the output node gives the predicted EUI by calculating the probabilities *a posteriori* multiplied by the average values of the classes of the output node.

The NRMSE was calculated for each combination of discretization method and structure types used to build the networks. The networks were identified by means of an id number, followed by the discretization method and followed by the structure.

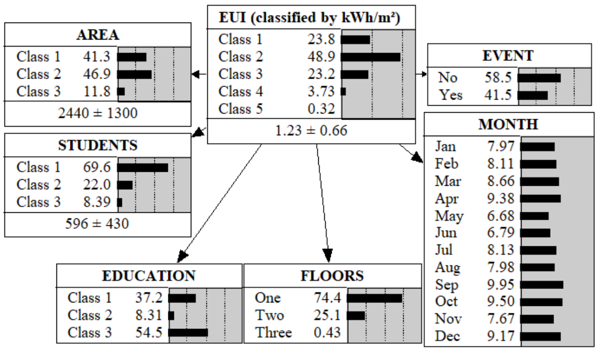


Figure C.4 – Bayesian Network.

A first analysis compared a resampled dataset with real output values with those predicted by the network. If the real value was within the confidence interval, the result was considered a correct prediction; otherwise, it was considered an incorrect prediction. Figure C.5 shows the result of this analysis.

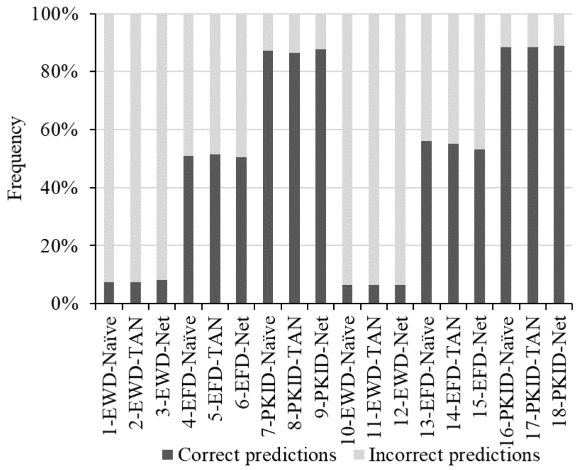


Figure C.5 – Correct and incorrect predictions.

The variation in results due to using different structures was very low. The major variation was due to the utilization of different discretization methods.

The discretization method that led to the best result – higher correct predictions – was the EWD. Both EFD and PKID methods led to higher inaccuracy predictions. This could be explained because both EFD and PKID methods considered low variance among bins, what does not represent the dataset.

In this analysis, it was not possible to define which output node was the best (EUI rated by floor-plan area or by number of students).

Performance analysis

To compare the representation capacity of the output node two indicators were used: EUI based on kWh/m².month and EUI based on kWh/student.month. Figures C.6 shows the NRMSE for the networks 1 to 9, which used kWh/m².month, and Figure C.7 shows the NRMSE for the networks 10 to 18 which used kWh/student.month. The NRMSE analysis assessed the numerical difference between the predicted and the real values. So, it was an analysis with more accuracy.

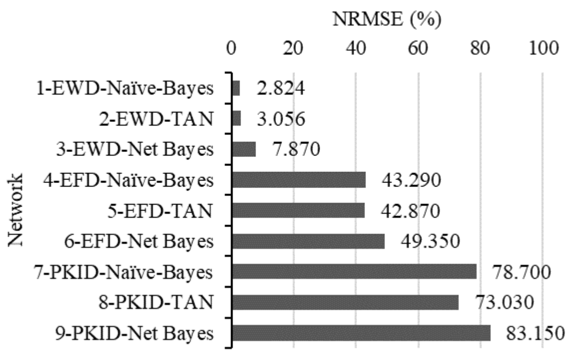


Figure C.6 – NRMSE for energy use intensity based on floor-plan area (kWh/m².month).

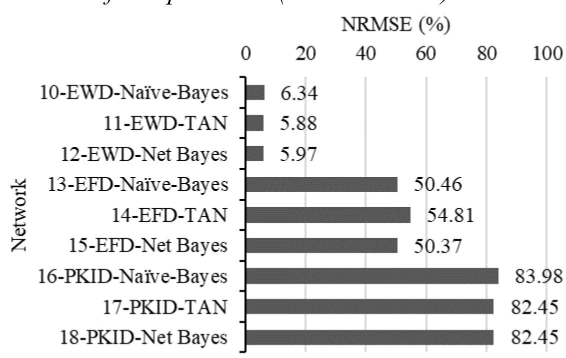


Figure C.7 – NRMSE for energy use intensity based on number of students (kWh/student.month).

Assessing the NRMSE, the best discretization method was the EWD. This is due to the nature of the continuum variables that are best categorized using a simple binning method that led to more representative bins. Indeed, the data showed that same-sized bins (as created by EFD and PKID methods) do not represent the actual data behaviour observed in the dataset. For example, for the variable EUI, the majority of the data (90%) ranged from 0.3 to 6.0 kWh/m².month, while 10% ranged from 6.0 to 16.0 kWh/m².month. For the nodes “Area” and “Students”, the trend is more linear.

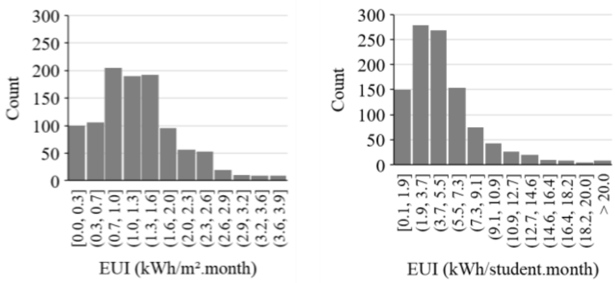
This could be explained because school buildings in general have a very constant pattern of consumption despite a few outlier values as observed. In addition, PKID method cuts the dataset into a lot of bins, what might make the network performance decrease due to the increase of the bias. This method leads to a better performance for small datasets (Yang and Webb, 2002), so it did not fit well on this dataset.

The best structure method was the Naïve-Bayes which was also the simplest one used. This could be explained because there was no conditional relation among the variables used to describe the consumption. Despite the attempts to link the nodes and create statistical relations, a more effective statistical test must be performed to find real relationships among the input variables.

Comparing the output unit used, either relative to the floor-plan area or to the number of students, the best network performance (lower NRMSE) was observed using the EUI rated by floor-plan area.

This could be explained because the appliances used in schools in Brazil are usually HVAC for cooling, lights and computers for employees, as observed *in situ*. This makes the consumption somehow independent from the number of students and more dependent from the size of the school. For example, if the lights and HVAC were turned on in a classroom, they would consume very similar energy either for ten or thirty students.

In fact, if one takes the EUI rating by floor-plan area or number of students, it is possible to observe the differences, as shown in Figure C.8.



(a) *(b)*

Figure C.8 – Histogram of EUI rated in relation to (a) floor-plan area and (b) number of students.

The kurtosis of the histogram (a) was 0.9 and for the histogram (b) was 14.0, which indicates that the peak of the frequency-distribution curve of (b) was sharper than (a). In other words, the histogram of EUI rated by floor-plan area presented more similarity to the normal distribution if compared to EUI rated by number of students. Despite the impossibility to determine a cause-effect model as shown in Figure C.2, the relationship between energy consumption and floor-plan area was very strong, since the observations were more equally distributed among the bins.

To analyse the network usage in practice, each one of the 90 schools were inserted in the network to predict their EUI throughout the year. The best performance network structure combination was used: Naïve-Bayes constructed with EWD that outputs EUI rated by floor-plan area (network #1). Figure C.9 shows the real and predicted EUI for a single school as example.

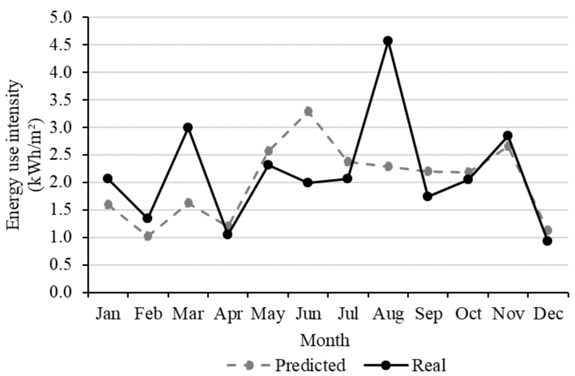


Figure C.9 – Real vs predicted EUI for a single school throughout the year (real data over 2016).

In general, the predicted values overlapped on real values, but this case was chosen to illustrate some interesting observations, such as noted in other cases.

From Figure C.9 one can observe that the predicted values were very similar to the real values despite some outlier points as in March, June and August. In March and August, there were indications of some peak consumptions, probably due to the educational schedule variation from one year to another (sometimes school year starts in February and sometimes in March, depending on holidays, and returns from winter break either in July or in August). Since the dataset used was composed of three years, an improvement in the network could be made by using larger dataset, contemplating several years.

In June, the energy usage was lower than the predicted also probably due to the schedule variation (holidays in June) or because most of the schools had events in June that are not common on that school.

In fact, the network was a more stable predictor, i.e, the predicting throughout the year followed a steady trending but not accomplished peaks or outlier values. This is also concluded by other authors (Borunda et al., 2016; Sokol et al., 2017), who recommended the Bayesian Network as a robust technique for classification, but not so robust to be used in regression analysis, as predicting energy consumption requires.

Another possible explanation for these inaccuracies can be found in a limitation of the network: the incapacity of differentiation year to year. The network always predicts for an undefined year and it is not possible to predict for 2019 or 2020 differently, for example. However, the purpose behind the Bayesian Network is retro-feeding, i.e., the possibility of inserting new information successively. Therefore, while more information is added to the network more possibilities to predict specific events can be built. Some examples of improvement are the addition of specific information as weather data (e.g., average monthly temperature), or rearrangement of the network structure due to newly found relationships.

Conclusion

This paper presented a Bayesian Network constructed to predict energy consumption in schools in Brazil. The database of 90 schools was used. This study analysed the performance of eighteen networks built using different structures and discretization methods. This study addresses the noteworthy findings as follows:

(a) The type of discretization method expressively impacted on the network performance, and the EWD was the most suitable method for discretizing the continuum variables considered in the network construction of this study;

(b) EUI rated by floor-plan area led to better predictions instead of EUI rated by number of students due to the relationship between appliances and building sizes found in schools;

(c) The network with the best performance could lead to a proper accuracy, but it failed to predict peak values or to distinguish one year from another;

(d) Some limitations of this method could be drawn, such as the need of a greater dataset and the incapacity to predict peak or outlier values. However, if the limitations are solved, the Bayesian Network will be useful in contexts where there is limited information available, such as developing countries like Brazil.

The detailed reasons for the aforementioned findings will be investigated in future studies. For example, the improvement of the database with more characteristics and enlargement of the actual data. Furthermore, the use of Bayesian Networks for classifying energy performance instead of predicting energy consumption would be explored.

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Appendix D – Protocol for energy audit in low-complex buildings

Introduction and context

Energy audit is a useful strategy to study the energy usage of buildings. It allows to identify opportunities for improving the energy performance, reducing their energy consumption and enhancing environmental comfort for occupants (WILDE, 2018). Energy audits are a procedure to measure the energy used in a building according to their systems, aiming to propose strategies for energy efficiency (GERALDI; GHISI, 2020a).

Obtaining the energy consumption breakdown – i.e. identifying the energy consumed according to each end use – enables the deep understanding of the building operation; hence, it supports the straightforward analysis of technical and economic strategies according to the specific building needs. Energy audits are standardised by the ISO 50002/2014 (ISO, 2014), which provides general guidelines. However, this standard does not provide any specific calculation method of energy breakdown or energy analysis. In summary, the ISO explains the steps for energy audit process, dividing into: planning; opening meeting, data collecting, measurement plan, conducting the site visit, analysis, energy audit reporting, closing meeting. Thumann et al. (2013) classify the energy audits in four types (Table D.1).

Table D.1 – Energy audits classification according to Thumann et al. (2013).

Level	Name	Description
Type 0	Benchmark Audit	Preliminary analysis of energy usage and bills. Determination of the benchmark indicators, e.g., Energy Use Intensity (EUI). The audit determines whether the future investments produce significant energy savings.
Type I	Walk-Through Audit	Basic evaluation of the target building. Utility bills are analysed and an inspection through the building is conducted to identify and to examine the actual systems. Simple recommendations are indicated to the occupants.
Type II	Standard Audit	Deep evaluation of the systems and equipment in the building to quantify the energy use and losses. It can include site measurements, mid-term monitoring and recommendations for energy savings.
Type III	Computer Simulation	A digital model of the building based on actual data is developed. The computer simulation includes more details of the energy usage and the climate conditions. The aim of the simulation is to obtain a baseline to compare simulated and actual building performance. It allows scenario evaluation for advanced strategies. This analysis demands more effort but it provides accurate and high-resolution outcomes.

The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE, 2011) provides an orientation for energy audits and classify them into:

- Level 1 (Walk-through Survey): a brief visit to the building analysed is carried out to recommend basic energy efficiency measures (EEMs) to potential savings for the facility. It is the most basic assessment of a building's performance and similar to Type I described previously.
- Level 2 (Energy Survey and Analysis): this type of survey leads to deeper recommendations of EEMs, including operation and maintenance procedures and cost analysis. The operator will be able to choose modifications to reach his cost-effectiveness expectations.
- Level 3 (Detailed Analysis of Capital-intensive Modifications): it can include equipment monitoring and more detailed site inspection. Energy simulation is a common tool used to respond to the rigorous economic-engineering analysis, which elevates the level of confidence reached by the final report.

Energy audits are employed to understand the energy usage in buildings, once some important information for building performance assessment, such as construction characteristics, equipment type and efficiency, and operation monitoring can only be obtained through in-situ inspections. Attia et al. (2020) conducted energy audits in high performance schools to create two reference buildings of Nearly Zero Energy Buildings in Belgium. Brás et al. (2015) presented an integrative approach to refurbish primary schools in Portugal. The authors visited one school and carried out survey with the occupants, teachers and pupils. Also, invasive and non-invasive tests and equipment monitoring were used. Five different refurbishment scenarios were studied, considering the cost-effectiveness targets.

Along these lines, this paper aims to present a method of energy audit adapted to the context of low-complex and non-residential buildings in Brazil. The method presented herein was based on current existing methods with some specific modifications to simplify the process and allow extensive application. An example of one actual case that was performed is presented. Although energy audits usually comprise strategies for energy reduction in their final step, in this method we are limited to identify target end uses for further economic studies.

Method

This short-paper aims to present a method to perform simplified energy audits in low-complex buildings. First, the planning process will establish the walkthrough plan. Then, a site inspection in the building raises all equipment and their power density. An interview with occupants' (or occupant representation) provides the patterns of use of the equipment and systems. Finally, all information acquired is input in a spreadsheet, which calculates the energy use in the audited buildings, presenting also the breakdown of energy consumption by end use and by month. Figure D.1 shows the flowchart of the method.

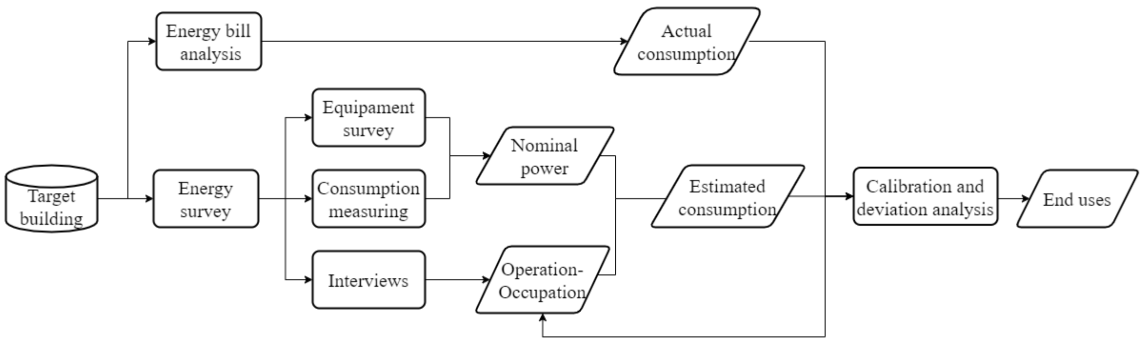


Figure D.1 – Flowchart of the method.

Applicability

This method is suitable to perform energy audits in low-complex and non-residential buildings. By low complex we assume that the building:

- Is supplied in low voltage.
- If there is an air-conditioning system, it is by means of single-units (not central units such as Chillers or Cooling towers);
- Does not have high-demand or specific loads.

Furthermore, it covers electrical energy usage. Therefore, this method is adapted and suitable for the following building typologies: small and average offices; Schools; Nurseries; Small retails; Small grocery stores; Small hotels and alike.

Step 1 – Energy audit plan

In this method we assume that a certain building was selected to receive an energy audit and there is a channel of communication between the energy audit team and the responsible staff of the building.

The first step is to plan the site visit. A first data collecting is necessary to primarily understand the building architecture and context. Thus, the drawings of the building, their location and a brief description is necessary to plan the visit. Floor-plan area for each environment and window specifications are essential. Additionally, it is important to obtain at least 2 years of energy consumption from utility bills, to establish a solid use pattern. The actual energy consumption is then compared with the energy end use estimated.

It is important to study the floor-plan layout and prepare a clear version of the drawings. Rooms can be numbered and a roadmap can be included in the drawings to facilitate the walkthrough during the inspection. At this point, it is important to underline the equipment that need to be measured and to register all questions that were not clear in the drawings. All the information important to perform the posterior research should be noted in an organized way.

The material necessary to perform the site inspection includes:

- Spreadsheets to collect data;
- Energy monitoring equipment;
- Measuring tape and similar equipment;
- Equipment for image registration (smartphone, cameras, etc).

The site inspection should be previously scheduled and confirmed with the building administration.

Step 2 – Site inspection

A comprehensive site inspection is performed to collect information about all systems and equipment that consumes energy in the building. It is mandatory that the site inspection is accompanied by a building manager. Ideally, this person (or people) should be a staff of the building – who knows operation details and occupation dynamics.

During the previous step (Energy audit plan), we recommend to arrange a roadmap to guide inspection throughout the building. In this step, we recommend to begin by visiting each room in the building and to classify them according to space types. Also, it is possible to register their floor-plan area, their window-to-wall ratio and the orientation of the window. Space type is the nomenclature given to spaces of the building that share similar characteristics, considering their occupation and operation. For example, for school buildings, we defined three space types: classrooms, transitional spaces (such as halls and aisles) and offices rooms. Each building has its own space types classification, so this step it is hard to generalise. We suggest to use Table D.2 to help characterise the spaces.

Table D.2 – Classification of the building spaces.

Space	**Space type**	**Floor-plan area (m^2)**	**Window orientation**	**Window-to-Wall Ratio (%)**
Example 1	Space type i			
Example 2	Space type ii			
		...		
Example N	Space type N			

Meanwhile visiting each space to classify their type, a careful observation of the space can be carried out. We recommend a top-to-bottom observation, starting by identifying the lighting system in the space, then going through the systems installed in the wall – generally fans and air-conditioning – and finally registering other equipment present in the space. Regarding the lighting system, we suggest to register their type, the number of light bulbs and their corresponding power. Usually, a space shares the same type and power of lighting systems, but several types of lightings can be found in different spaces. We recommend to use Table D.3 to register lighting data.

Table D.3 – Lighting data collecting table.

Space	**Lighting type 1**		**Lighting type 2**		**Lighting type N**	
	Power (W)	**Quantity**	**Power (W)**	**Quantity**	**Power (W)**	**Quantity**
Example 1						
Example 2						
			...			
Example N						

After collecting lighting data in the space, it is possible to register the information of equipment. In this stage, a careful observation of the equipment, their names, their nominal power and their daily usage – the daily usage can be informed by the building manager that accompanies the site inspection. Some electronic equipment will need a special attention regarding their coefficient of performance – such as air-conditioning and refrigerators, because this kind of equipment does not operate always consuming the same nominal power.

Thus, the nominal power indicated by the label might not match with the actual energy usage. For this kind of equipment, the coefficient of performance is available in the energy label. Otherwise, a simple measurement can be performed using an energy monitoring equipment (a 24 hours monitoring is recommended). Other different equipment that works in cycles, such as washing machines and clothes drier can be measured as well. In this case, the monitoring can be performed according to one cycle of the equipment, and it is possible to ask the building manager how many cycles a day is usually done. In the building's typologies eligible for this type of energy audit, reactive power is usually not an issue, once the power factor is commonly observed as higher than 0.95. If the utility bill informs a power factor lower than 0.95, we suggest to perform a monitoring test in all equipment to measure the reactive power usage. We recommend to use Table D.4 to help collect the equipment data.

Table D.4 – Equipment data collecting table.

End use type	**Equipment name**	**Equipment Power (W)**	**Quantity of equipment**	**Typical daily usage (h)**	**Usage factor (W/W)**	**Space**
End use A	Example 1					
End use B	Example 2					
			…			
End use Z	Example N					

Additionally, it is highly recommended to take pictures of all spaces during the site inspection. Register the spaces, the equipment and the moment in general can be handy in the moment of tabulating data or to solve possible later queries.

According to the building typology, end-uses should be categorised in this step: Air-conditioning; space heating; fans; water heating; plug loads; data processing; lighting; water pumps; specific loads; refrigerators; Laundry (washing machine and clothes dryer).

Step 3 – Interview with the building manager

After the inspection of each space of the building and the raise of all equipment information, an interview with the building manager can be conducted. This interview is a survey to characterise the building occupation and the systems' operation.

The literature supports that the role of the occupant behaviour in the energy consumption is sometimes a cause for performance gap. Often, the occupant behaviour is a key information that determines the energy usage. Thus, to address this important issue, this method intends to ask directly to an effective occupant how the occupation and operation of the building occurs. The advantage of this method is that the occupation is characterised according to the space types, while the operation of the systems is characterised according to the end use. Grouping those issues in this way (in general aspects) facilitates for the building manager to remember the answer, making the question easier to answer. This approach is useful for non-complex and non-residential buildings because this kind of building often operates their systems in a very similar way.

In order to make this interview more applicable, we recommend to split the question in two parts. First, the characterisation of the occupation can be performed according to the space type throughout the year by asking the building manager the percentage of occupation of the certain space type in every month. The characterisation of the occupation according to space types can be very effective, and people usually have a good discernment of the information in terms of percentage. We recommend the use of Table D.5 for this assessment.

Table D.5 – Occupation of the environment types.

Space type	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Space type i												
Space type ii												
					…							
Space type N												

Next, a similar approach can be performed to register the operation of the equipment throughout the year according to the end use listed in the building. For each end use identified in the building, it can be asked to the building manager the percentage of usage in every month. We advise the use of Table D.6 for such data collecting.

Table D.6 – Operation of the equipment.

End use	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
End use A												
End use B												
						…						
End use Z												

Since this energy audit is adapted for non-complex buildings, usually a building manager is eligible to provide such information regarding occupation and operation.

Finally, it is possible to ask about the working days. It can be different according to each building typology, so it is important to obtain this information in a reliable way. We recommend the use of Table D.7 for such data gathering.

Table D.7– Useful working days of the building.

Month	Workdays*
January	22
February	20
March	20
April	21
May	22
June	20
July	23
August	22
September	21
October	23
November	20
December	21

* In this case, we present the standard workdays in Brazil.

Step 4 – Energy use estimation

After the site inspection, it is possible to organise and tabulate the collected data into spreadsheets to estimate the energy use. Since every equipment was collected and their use estimated by the building manager, it is possible to estimate the monthly energy usage of all equipment. Also, every equipment was assigned with their end use and space type, which allows to group the energy use by end use and by space type.

We programmed a dynamic and standard spreadsheet to facilitate this process. Also, this standard spreadsheet facilitates the use of Tables D.2 to D.6 for data collecting. Table D.8 shows the spreadsheet structure and explains each sheet contents.

Table D.8 – Spreadsheet structure.

Sheet	Description
(1) Information	This sheet is used to register the building main information, such as the building name, their ownership, the name and contact of the building manager, its typology and a brief description of the building features and usage.
(2) Spaces and lighting	In this sheet, it must be registered data regarding the spaces of the building (Table 2) including their space types registration. Also, it is possible to register the lighting information (Table 3) according to each space. The spreadsheet automatically calculates the total energy usage for lighting for each space at the end of the rows, after the matrix of operation and occupation is done.
(3) Equipment	In this sheet, all the equipment in the building is registered according to Table 4, i.e. the registration of the nominal power, daily operation hours, and location.
(4) Occupation and Operation Matrices	This sheet is used to specify the occupation and operation estimation for each month, according to Tables 5 and 6, collected in the interview with the building manager. The occupation is divided by space type and the operation by end uses. The results are assigned in percentage.
(5) Experiments	This sheet registers data collected from the experiments measured during the site inspection. Usually, monitoring is used to assess energy consumption of freezers, refrigerators, washing machines, dryers and air-conditioning systems.
(6) Results	This sheet presents the outcomes of the energy use estimation. The formulas on this sheet use the information from sheets (2), (3), (4) and (5). The estimated monthly energy consumption is presented according to each end use, each space type and for the whole-building. Additionally, it is possible to compare the predicted and the actual energy monthly consumption in order to calibrate the estimation for a realistic outcome.

Figure D.2 shows the integration between data into the spreadsheet through a visual schema. It is possible to see how the calculations are performed.

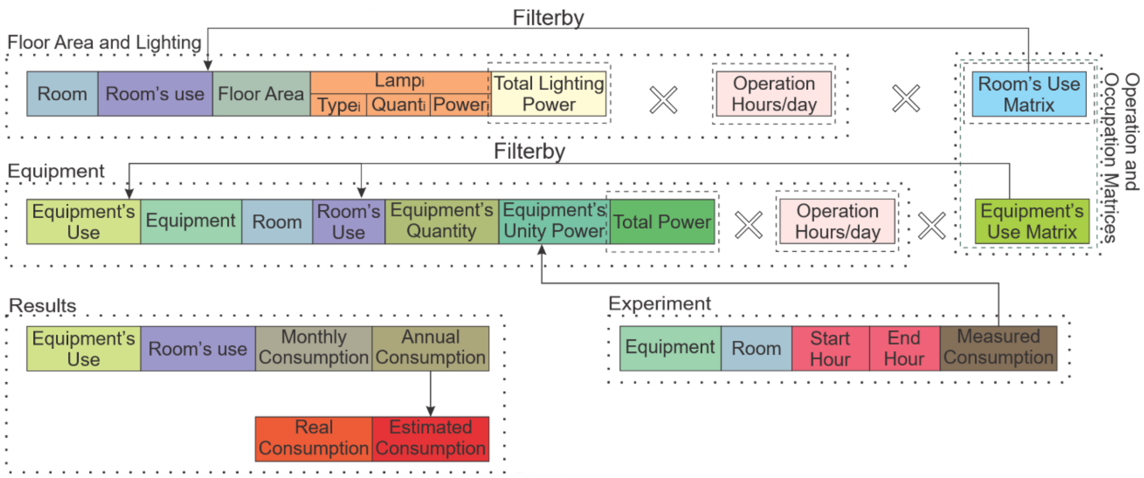


Figure D.2 – Schema of the spreadsheet workflow.

The energy consumption estimation is performed through a calculation considering the nominal power of each equipment or lighting, their hour of operation, their days of operation and a coefficient considering the operation and the occupation of the space where the equipment or lighting is. Equation 1 demonstrates this calculation (we use equipment to demonstrate the formulas but the same calculation is valid for energy consumption estimation of the lighting).

$$E_{e,s}^{m} = \frac{P_e}{1000} \times h_e \times d_e^{m} \times \frac{1}{f} \times c_{e,s}^{m} \quad (1)$$

where: E is the monthly energy consumption of an equipment "e", in a space type "s", for a month "m" (kWh/month); P is the nominal power of the equipment "e" (W); h is the daily operation hours of the equipment "e" (hours/day); d is the number of workdays of the month "m" (day/month); f is the coefficient of performance (W/W); and c is the coefficient of occupation-operation for the correspondent end use of the equipment "e" and the space type "s", for a month "m" (%).

All information necessary for Equation 1 is collected during site inspection. The nominal power, the usage factor and the daily operation hours are collected through Table D.4, while the number of workdays through Table D.7. The coefficient of occupation-operation is obtained through Equation 2.

$$c_{e,s}^{m} = Ope_e^{m} \times Occ_s^{m} \quad (2)$$

where: c is the coefficient of occupation-operation for the correspondent end use of the equipment "e" and the space type "s" (%); Ope is the operation ratio of an end use "e" for a month "m" (%); Occ is the occupation ratio of a space type "s" for a month "m".

Both operation ratio and occupation ratio were reported by the building manager through Tables D.6 and D.5, respectively.

For example, in January in Brazil, a school's operation is very low due to the holidays. However, there is a small administrative work shift during this period. Then, the occupation of office rooms of a given school was estimated as 25% (two out of eight administrative staff work in this period during half day shift). In the same school, the occupation of computer lab was set as 0% in January (because there are no classes). The operation for computer end use was 100%. According to Equation 2, the coefficient of occupation-operation is 25% for computers in office spaces in January, while it is 0% for computer in computer labs. From that, it is easy to calculate the energy consumption in January for office rooms, considering the nominal power of the computer raised during site inspection (200 W), their daily operation (four hours a day – half shift), the number of workdays in January (22 days), the coefficient of performance (in this case, one); and applying the 25% coefficient of occupation-operation, resulting in 4.4 kWh/month.

Then, it is possible to determine the total energy consumption for each end use by summing all equipment energy consumption assigned as a given end use "e", for all months (Equation 3).

$$U_e = \sum_{i=0}^{m} \quad \sum_{i=0}^{e} \quad E_{k,s}^{m} \tag{3}$$

where: U is the total energy consumption of an end use "e" (kWh/year); E is the monthly energy consumption of an equipment "k" assigned as end use "e", in a space type "s", for a month "m" (kWh/month).

It is handy to represent the end use analysis in a percentage perspective. Thus, it is possible to view accurately the impact of each end use on the annual energy consumption of the building. Similarly, it is possible to determine the total energy consumption for each space type by summing all equipment energy consumption assigned in a given space type "s" (Equation 4).

$$T_s^m = \sum_{i=0}^{s} \quad E_{e,s}^{m} \tag{4}$$

where: T is the total energy consumption of a space type "s" (kWh/month); E is the monthly energy consumption of an equipment "k" assigned as end use "e", in a space type "s", for a month "m" (kWh/month).

Finally, the total monthly energy consumption can the obtained by summing all equipment energy consumption according to their month (Equation 5).

$$M_m = \sum_{i=0}^{m} \quad E_{e,s}^{m} \tag{5}$$

where: M is the total energy consumption of a month "m" (kWh/month); E is the monthly energy consumption of an equipment "k" assigned as end use "e", in a space type "s", for a month "m" (kWh/month).

The monthly whole-building energy consumption can be used to calibrate the estimation, as shown in Section 5. Also, the monthly whole-building energy consumption can be used to determine the whole-building annual energy consumption. For further analysis, the whole-building annual energy consumption can be used to determine the Energy Use Intensity in terms of floor-plan area (kWh/m^2.year) and occupation (kWh/person.year). For high air-conditioned buildings, it can be useful to analyse the EUI in terms of the volume (kWh/m^3.year) using the building height collected initially.

Therefore, by completing the spreadsheet it is expected that it will be possible to understand better the building operation and occupation, as well as the energy usage in practice. Thus, Energy Efficiency Measures (EEMs) can be proposed in a more specific way, considering specific conditions identified during the energy audit process.

Step 5 – Calibration of the estimated energy use

Calibrating the estimated energy consumption is an important step to provide reliable results. In this method, the calibration was performed considering the Annual Percentage Difference (APD) and Monthly Percentual Difference (MPD). We used the difference between the monthly energy consumption registered by the utility bill and the monthly energy consumption estimated according to the energy audit process to determine the APD (Equation 6) and the MPD (Equation 7).

$$APD = (A_p - A_a)/A_a \tag{6}$$

Where: APD is the annual percentual difference of energy consumption (%); A_p is the predicted annual energy consumption (kWh/year); A_a is the actual annual energy consumption (kWh/year).

$$MPD = (M_p - M_a)/M_a \quad (7)$$

Where: MPD is the monthly percentual difference of energy consumption (%); M_p is the predicted monthly energy consumption (kWh/month); M_a is the actual monthly energy consumption (kWh/month).

In our experience, APDs around 10% provide good approximations with the actual energy consumption pattern. The calibration consists of an iterative process to both reduce the APD and MPD between predicted and actual energy consumption. We recommend to perform the calibration according to the following orderly steps.

1. We recommend to begin the calibration process by reviewing all information on the energy audit. Attentively interpret the results and make sure that the they converge with what was observed during the site inspection.
2. Identify the most impactful end use (with major percentage in the annual energy consumption).
3. Adjust the operation values in "Operation-Occupation Sheet" of this most impactful end use by increasing or decreasing the values in 5% of the months with MPC higher than 20% (increase for negative percentage or decrease for positive percentage).
4. Check the APD. If it continues to be higher than 10%, repeat steps 1 and 2 by adjusting values in 10%.
5. If the APD continues to be higher than 10%, identify the most important space type and adjust its occupation values in "Operation-Occupation Sheet" by increasing or decreasing the values in 5% of the months with MPC higher than 20% (increase for negative percentage or decrease for positive percentage).
6. Check the APD. If it continues to be higher than 10%, repeat step 4 by adjusting values in 10%.
7. If the APD continues to be higher than 10%, consider adjusting the second most impactful end use by the same way of steps 2 to 5, and so on. The lower the impact of an end use on the total energy consumption the lower the impact of this adjustment on the calibration.

8. If the APD continues to be higher than 10%, we recommend to carefully review the energy audit information:
    a. Check if the most impactful end use identified on this energy audit make sense for this typology;
    b. Check if the workdays make sense for this typology;
    c. Double-check the nominal power information and hours of operation of the equipment.

Appendix E – Energy audit reports

This appendix presents the report of the energy audit results performed in three schools in Florianópolis.

Energy Audit Report 01

EBM Almirante Carvalhal
Address: R. Bento Góia 113, Coqueiros, Florianópolis

Floor plan area:	1,283.08 m²
Number of Students:	537 students
Number of employees:	21 employees
Date of inspection:	August 28, 2020
Actual EUI:	28.9 kWh/m².year
EUI predicted with the energy audit:	27.5 kWh/m².year

Figure E.1 – Building location

1. Building floor-plan

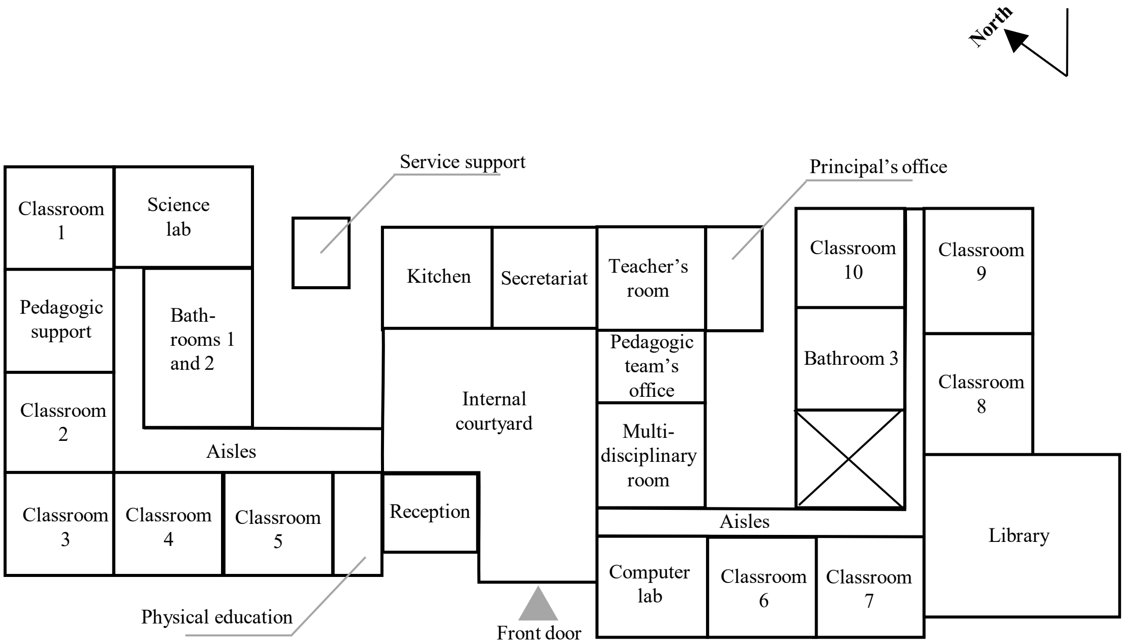


Figure E. 2 – Schematic representation of the building floor-plan (no scale)

2. List of spaces and lighting

Table E.1– List of spaces and lighting characterisation

Space	Space type	Area (m²)	Total lighting power (W)
Aisles	Transitory	128.3	100
Bathroom 1	Transitory	15.6	50

Table E.1 – List of spaces and lighting characterisation (continuation).

Space	Space type	Area (m²)	Total lighting power (W)
Bathroom 2	Transitory	40.2	50
Bathroom 3	Transitory	158.3	50
Classroom 2	Classroom	51.2	220
Classroom 3	Classroom	39	290
Classroom 4	Classroom	49.2	215
Classroom 5	Classroom	35.7	120
Classroom 6	Classroom	47.7	340
Classroom 7	Classroom	49.2	230
Classroom 8	Classroom	48.4	250
Classroom 10	Classroom	51.2	245
Classroom 11	Classroom	51.2	235
Computer lab	Classroom	35.7	160
External Courtyard	Transitory	47.5	0
Intern courtyard	Transitory	160.9	245
Kitchen	Transitory	35.7	50
Library	Classroom	89.8	490
Multidisciplinary room	Classroom	24.2	90
Pedagogic team’s office	Office	24.2	90
Pedagogic support	Classroom	49	215
Physical education	Transitory	7.6	15
Principal’s office	Classroom	16.9	100
Reception	Office	47.3	50
Science lab	Classroom	51.2	300
Secretariat	Office	24	100
Service support	Transitory	19.7	75
Teacher’s office	Office	29.6	90

3. List of equipment in each space and their features

Table E.2 – List of equipment and their characterisation

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
HVAC unlabelled	HVAC	Secretariat	1	7500.0	7500.0	8.0
HVAC Label A	HVAC	Principal's office	1	3514.8	12000.0	8.0
HVAC Label B	HVAC	Classroom 4	1	6443.8	22000.0	4.0
HVAC Label B	HVAC	Classroom 5	1	6443.8	22000.0	4.0
HVAC Label B	HVAC	Classroom 6	1	6443.8	22000.0	4.0
HVAC Label B	HVAC	Classroom 7	1	6443.8	22000.0	4.0
HVAC Label B	HVAC	Classroom 8	1	6443.8	22000.0	4.0
HVAC Label C	HVAC	Library	1	7029.6	24000.0	4.0
HVAC Label A	HVAC	Pedagogic team’s office	1	7029.6	24000.0	8.0
HVAC Label A	HVAC	Teacher’s office	1	7029.6	24000.0	8.0
HVAC Label A	HVAC	Science lab	1	7029.6	24000.0	4.0

Table E.2 – List of equipment and their characterisation (continuation).

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
HVAC Label A	HVAC	Multidisciplinary room	1	7029.6	24000.0	4.0
HVAC Label A	HVAC	Classroom 1	1	8787.0	30000.0	4.0
HVAC Label A	HVAC	Classroom 10	1	8787.0	30000.0	4.0
HVAC Label A	HVAC	Classroom 2	1	8787.0	30000.0	4.0
HVAC Label A	HVAC	Classroom 3	1	8787.0	30000.0	4.0
HVAC Label A	HVAC	Computer lab	1	8787.0	30000.0	4.0
Fan 200W	Fans	Pedagogic support	1	200.0	200.0	8.0
Fan 200W	Fans	Pedagogic support	1	200.0	200.0	8.0
Electric shower	Hot water	Bathroom	1	5500.0	5500.0	1.0
Fan 200W	Fans	Physical education	1	200.0	200.0	8.0
Drinking fountain	Other equipment	Internal Courtyard	2	145.0	290.0	24.0
Drinking fountain	Other equipment	External Courtyard	2	125.0	250.0	24.0
Fan 200W	Fans	Reception	1	200.0	200.0	6.0
Electric shower	Hot water	Kitchen	2	5500.0	11000.0	1.5
Electric oven	Electric oven	Kitchen	1	1750.0	1750.0	2.0
Fan 160W	Fans	Teacher's office	1	160.0	160.0	6.0
Fan 160W	Fans	Classroom 3	1	160.0	160.0	6.0
Fan 160W	Fans	Classroom 4	1	160.0	160.0	6.0
Fan 160W	Fans	Classroom 5	1	160.0	160.0	6.0
Fan 160W	Fans	Secretariat	1	160.0	160.0	6.0
Fan 160W	Fans	Library	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 11	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 10	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 2	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 6	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 8	2	160.0	320.0	6.0
Fan 160W	Fans	Science lab	2	160.0	320.0	6.0
Fan 160W	Fans	Multidisciplinary room	2	160.0	320.0	6.0
Fan 160W	Fans	Classroom 7	3	160.0	480.0	6.0
Computer	Computer	Principal's office	2	150.0	300.0	8.0
Computer	Computer	Secretariat	2	150.0	300.0	8.0
Computer	Computer	Pedagogic team's office	3	150.0	450.0	8.0
Computer	Computer	Multidisciplinary room	3	150.0	450.0	8.0
Computer	Computer	Computer lab	20	150.0	3000.0	0.2
TV	Other equipment	Pedagogic team's office	1	300.0	300.0	0.2
TV	Other equipment	Library	1	300.0	300.0	0.2
Projector	Other equipment	Pedagogic support	1	326.0	326.0	0.2
Printer	Other equipment	Reception	1	45.0	45.0	8.0
Printer	Other equipment	Secretariat	1	45.0	45.0	8.0
Rack	Other equipment	Computer lab	1	3000.0	3000.0	24.0
Refrigerators 1	Refrigerators	Kitchen	1	39.0	39.0	24.0
Refrigerators 2	Refrigerators	Kitchen	1	40.0	40.0	24.0

Table E.2 – List of equipment and their characterisation (continuation).

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
Refrigerators 3	Refrigerators	Kitchen	1	48.0	48.0	24.0
Freezer 1	Refrigerators	Kitchen	1	46.3	46.3	24.0
Freezer 2	Refrigerators	Kitchen	1	84.0	84.0	24.0
Freezer 3	Refrigerators	Kitchen	1	41.0	41.0	24.0

4. Operation and Occupation Schedules

Table E.3 – Schedules of operation for each end use.

End use	Operation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
HVAC	1.00	0.50	0.75	0.75	0.75	0.50	0.25	0.25	0.25	0.50	0.50	1.00
Hot water	0.00	0.50	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Lighting	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fans	1.00	0.50	0.75	0.75	1.00	0.50	0.25	0.25	0.25	0.50	0.50	1.00
Computer	0.50	1.00	1.00	1.00	1.00	0.50	0.50	1.00	1.00	1.00	1.00	0.50
Other	0.00	1.00	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Refrigerators	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Electric Oven	0.25	1.00	1.00	1.00	1.00	0.25	0.25	1.00	1.00	1.00	1.00	0.50

Table E.4– Schedules of occupation for each space type.

Space type	Occupation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Office	0.25	0.50	0.75	1.00	1.00	0.75	0.75	1.00	1.00	1.00	0.75	0.75
Classroom	0.10	0.25	1.00	1.00	1.00	0.50	0.75	1.00	1.00	1.00	1.00	0.75
Transitory	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

5. Predicted and actual monthly energy consumption

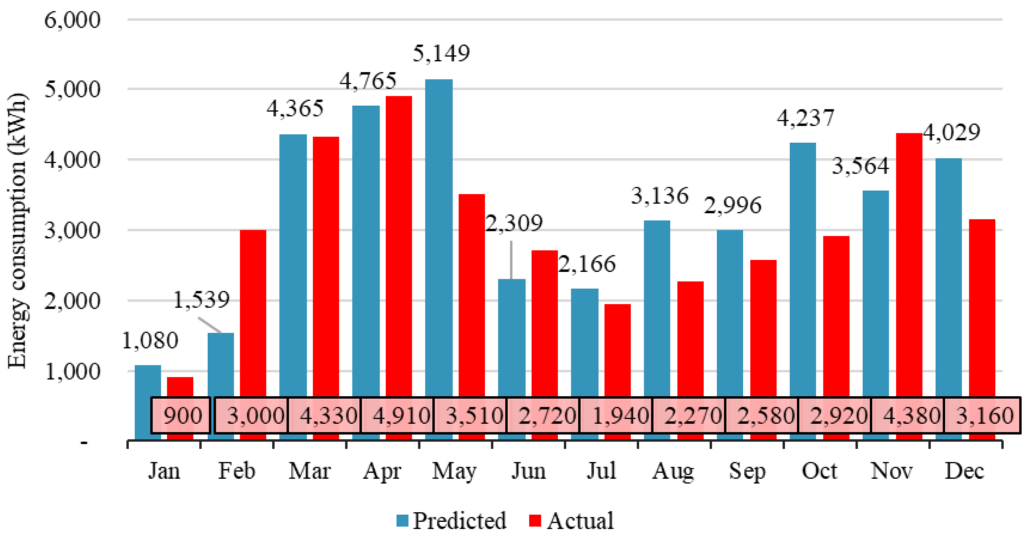


Figure E.3 – Predicted and actual monthly energy consumption. Estimation was performed through the energy audit method presented in Appendix D.

6. Annual end-use proportions

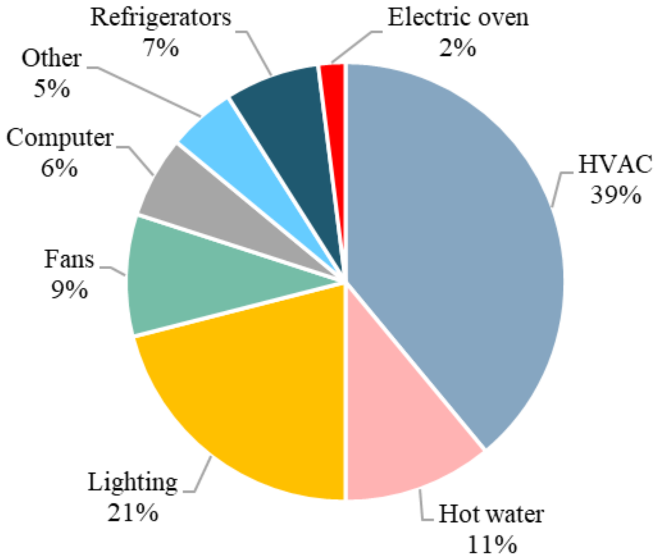
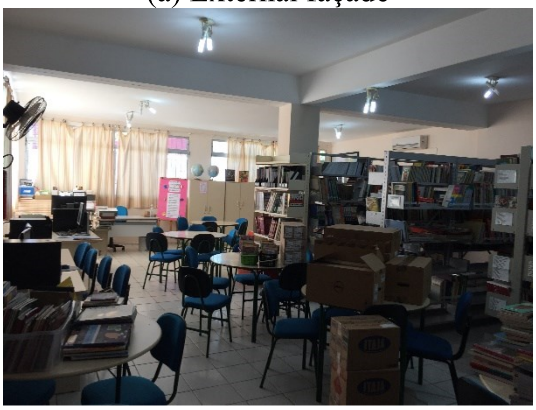


Figure E.4 – Annual end use estimations. Estimation was performed through the energy audit method presented in Appendix D.

7. Photographic record

(a) External façade

(b) Typical classroom



(c) Library overview

(d) Computerlab overview

Figure E.5 – Photographic record of the energy audit inspection in the school Almirante Carvalhal.

(e) Detail: refrigerators

(f) Detail: water heater in the kitchen

Figure E.5 – Photographic record of the energy audit inspection in the school Almirante Carvalhal (continuation).

Energy Audit Report 02

EBM Beatriz de Souza Brito
Address: R João Evangelista da Costa 455, Pantanal, Florianópolis

Floor plan area:	2.183 m²
Number of Students:	531 students
Number of employees:	24 employees
Date of inspection:	October 1st, 2020
Actual EUI:	26.9 kWh/m².year
EUI predicted with the energy audit:	23.5 kWh/m².year

Figure E.6 – Building location

1. Building floor-plan

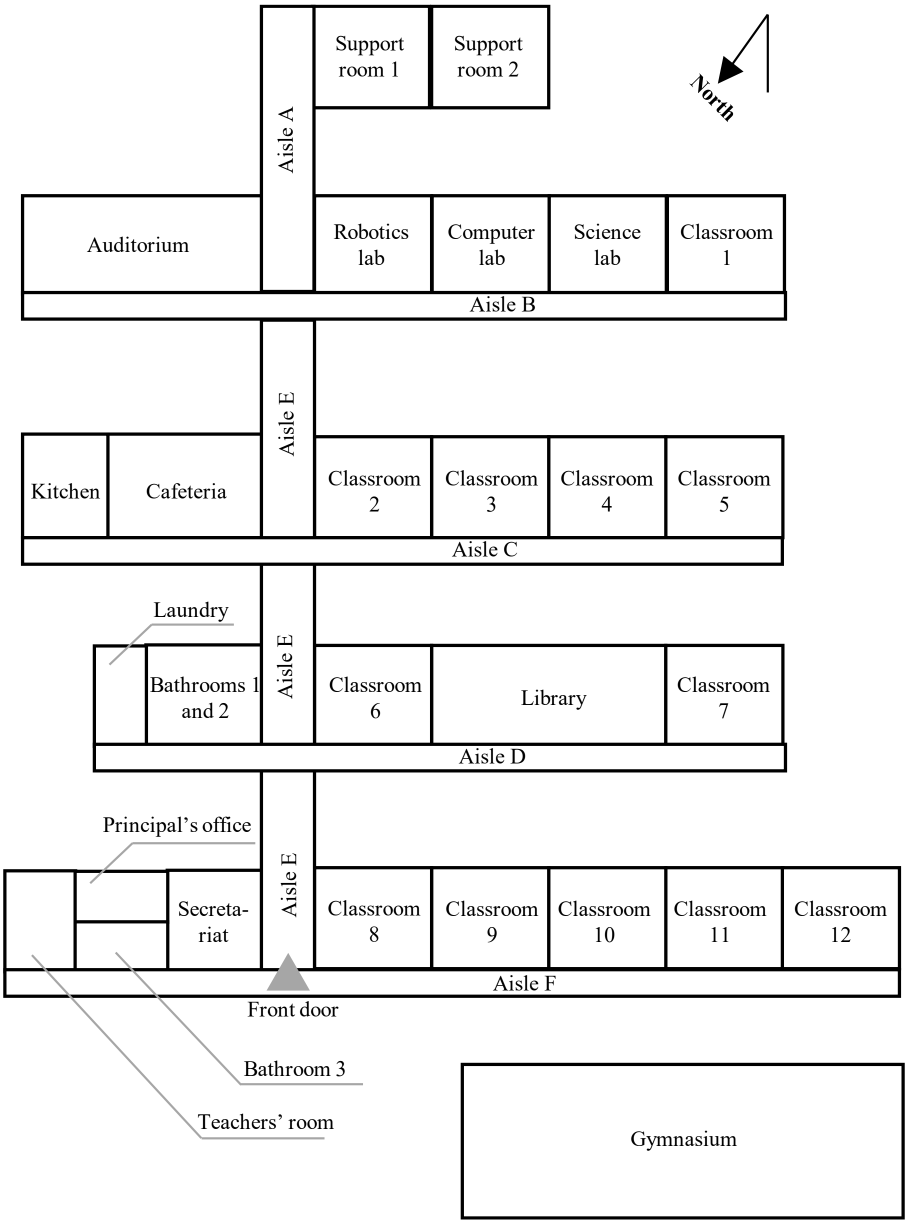


Figure E.7 – Schematic representation of the building floor-plan (no scale)

2. List of spaces and lighting

Table E.5 – List of spaces and lighting characterisation

Space	Space type	Area (m²)	Total lighting power (W)
Cafeteria	Transitory	14.15	288
Kitchen	Transitory	28.3	288
Cafeteria	Transitory	97.9	864
Aisles A	Transitory	25	2652
Support room 1	Transitory	37.72	432
Support room 2	Transitory	8.05	72
Auditorium	Classroom	117.28	894
Science lab	Classroom	47.65	432
Classroom 1	Classroom	24.65	144
Robotics lab	Classroom	48.45	432
Classroom 2	Classroom	95.9	432
Aisles C	Transitory	25	432
Classroom 3	Classroom	48.24	216
Classroom 4	Classroom	48.24	216
Classroom 5	Classroom	48.24	216
Classroom 6	Classroom	48.24	216
Aisles D	Transitory	25	281
Computer lab	Classroom	48.64	216
Library	Classroom	147.14	648
Bathroom 1	Transitory	22.18	144
Bathroom 2	Transitory	24.01	144
Laundry	Transitory	6.4	144
Classroom 7	Transitory	5.64	144
Aisles E	Transitory	25	338
Classroom 8	Classroom	48.55	216
Classroom 9	Classroom	48.55	216
Classroom 10	Classroom	48.55	216
Classroom 11	Classroom	48.55	216
Classroom 12	Classroom	48.55	216
Aisles F	Transitory	25	1000
Gymnasium	Classroom	200	6000
Bathroom 3	Transitory	9.75	50
Bathroom 4	Transitory	9.75	25
Security cabin	Office	6	45
Secretariat	Office	42.12	180
Principal's office	Office	12.16	180
Bathroom 5	Transitory	7.5	54
Teacher's room	Office	60.9	360
Aisles B	Transitory	25	1500

3. List of equipment in each space and their features

Table E.6 – List of equipment and their characterisation

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
Elevator	Other equipment	Gymnasium	1	2000	2000	0.02
Drinking fountain	Other equipment	Gymnasium	2	75	150	24
Electric shower	Hot water	Gymnasium	2	5500	11000	2
Fan	Fans	Security cabin	1	160	160	8
Microwave	Other equipment	Security cabin	1	10	10	2
Refrigerator	Refrigerators	Security cabin	1	60	60	24
Printer	Other equipment	Secretariat	1	45	45	8
Fan	Fans	Secretariat	1	200	200	4
Computer	Computer	Secretariat	2	150	300	8
Computer	Computer	Principal's office	1	150	150	8
Fan	Fans	Principal's office	1	100	100	8
Computer	Computer	Teacher's room	1	150	150	8
Electric oven	Electric oven	Teacher's room	1	1750	1750	0.5
Microwave	Other equipment	Teacher's room	1	10	10	24
Drinking fountain	Other equipment	Teacher's room	1	75	75	24
Refrigerator	Refrigerators	Teacher's room	1	136	136	24
Refrigerator	Refrigerators	Cafeteria	1	45	45	24
Refrigerator	Refrigerators	Cafeteria	1	52	52	24
Freezer	Refrigerators	Cafeteria	1	123	123	24
Freezer	Refrigerators	Cafeteria	1	67	67	24
Microwave	Other equipment	Kitchen	1	10	10	
Washing machine	Other equipment	Kitchen	1	9	9	1
Electric oven	Electric oven	Kitchen	1	6000	6000	1
Fan	Fans	Cafeteria	1	160	160	4
Fan	Fans	Cafeteria	1	200	200	4
Drinking fountain	Other equipment	Aisles A	3	75	225	24
Microwave	Other equipment	Classroom 1	1	10	10	24
Refrigerator	Refrigerators	Classroom 2	1	60	60	24
HVAC	HVAC	Auditorium	2	24000	48000	1
Fan	Fans	Science lab	1	200	200	4
Projector	Other equipment	Science lab	1	326	326	2
TV	Other equipment	Science lab	1	300	300	1
Fan	Fans	Science lab	1	200	200	4
Fan	Fans	Tech lab	1	200	200	6
Computer	Computer	Tech lab	6	150	900	8
Fan	Computer	Classroom 3	2	160	320	6
Projector	Other equipment	Classroom 3	1	326	326	2
TV	Other equipment	Classroom 4	1	300	300	2
Fan	Fans	Classroom 4	2	160	320	6
Projector	Other equipment	Classroom 5	1	326	326	2
Fan	Fans	Classroom 6	2	160	320	6
Projector	Other equipment	Classroom 7	1	326	326	2

Table E.6 – List of equipment and their characterisation (continuation).

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
Fan	Fans	Classroom 8	2	160	320	6
Projector	Other equipment	Classroom 9	1	326	326	2
HVAC	HVAC	Computer lab	1	18000	18000	4
TV	Other equipment	Computer lab	2	300	600	2
Rack	Other equipment	Computer lab	1	3000	3000	24
Computer	Computer	Computer lab	20	150	3000	8
HVAC	HVAC	Library	1	18000	18000	4
Computer	Computer	Library	6	150	900	8
Fan	Fans	Library	2	160	320	4
Washing machine	Other equipment	Laundry	1	31	31	0.2
Fan	Fans	Classroom 10	2	160	320	6
Projector	Other equipment	Classroom 10	1	326	326	2
Fan	Fans	Classroom 11	2	160	320	6
Projector	Other equipment	Classroom 11	1	326	326	2
Fan	Fans	Classroom 12	2	160	320	6
Projector	Other equipment	Classroom 12	1	326	326	2
Fan	Fans	Classroom 13	2	160	320	6
Projector	Other equipment	Classroom 13	1	326	326	2
Fan	Fans	Classroom 14	2	160	320	6
Projector	Other equipment	Classroom 14	1	326	326	2

4. Operation and Occupation Schedules

Table E.7 – Schedules of operation for each end use.

End use	Operation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
HVAC	1.00	1.00	1.00	1.00	0.75	0.50	0.25	0.25	0.25	0.50	1.00	1.00
Hot water	0.00	0.50	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Lighting	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fans	1.00	1.00	1.00	1.00	1.00	0.50	0.25	0.25	0.25	0.50	1.00	1.00
Computer	0.50	1.00	1.00	1.00	1.00	0.50	0.50	1.00	1.00	1.00	1.00	0.50
Other equipment	0.00	1.00	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Refrigerators	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Electric oven	0.25	1.00	1.00	1.00	1.00	0.25	0.25	1.00	1.00	1.00	1.00	0.50

Table E.8 – Schedules of occupation for each space type.

Space type	Occupation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Office	0.25	0.50	0.75	1.00	1.00	0.75	0.75	1.00	1.00	1.00	0.75	0.75
Classroom	0.10	0.25	1.00	1.00	1.00	0.75	0.75	1.00	1.00	1.00	1.00	0.75
Transitory	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

5. Predicted and actual monthly energy consumption

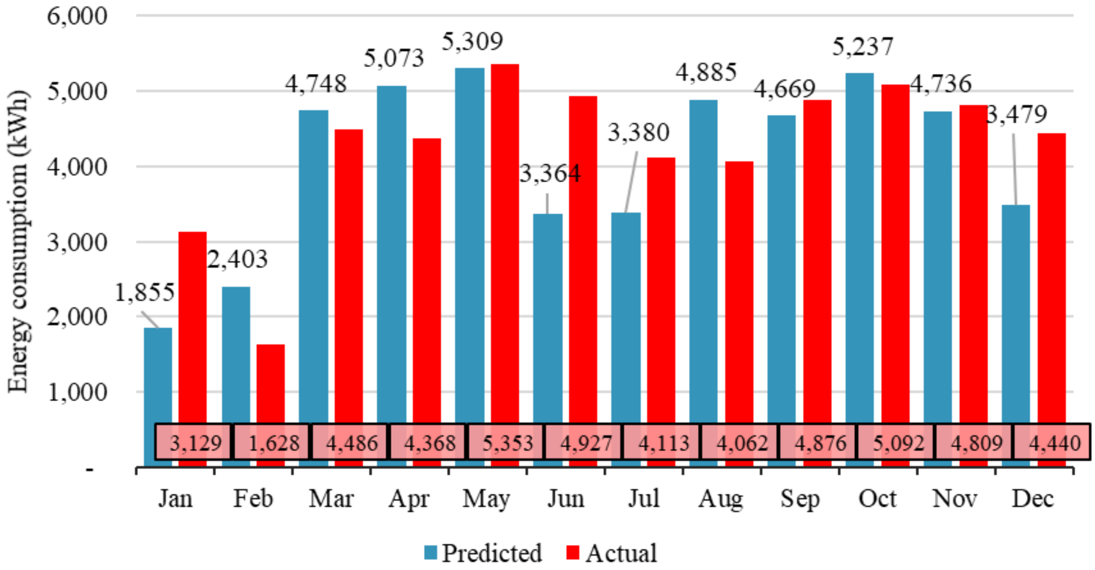


Figure E.8 – Predicted and actual monthly energy consumption. Estimation was performed through the energy audit method presented in Appendix D.

6. Annual end-use proportions

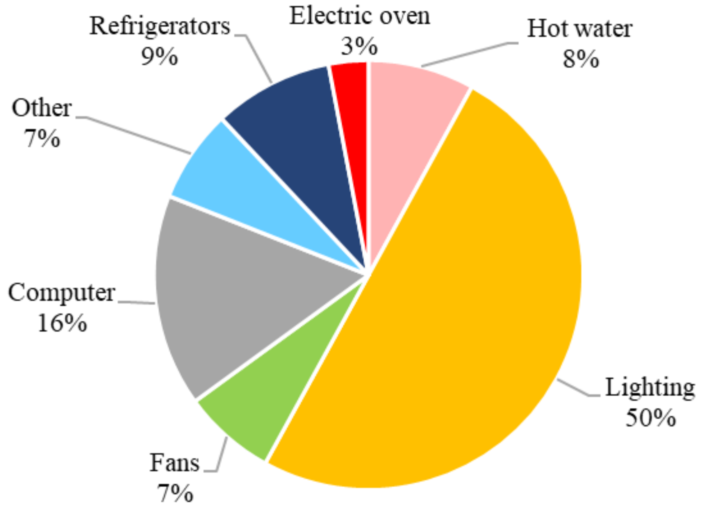


Figure E.9 – Annual end use estimations. Estimation was performed through the energy audit method presented in Appendix D.

7. Photographic record

(a) External façade of classrooms

(b) Typical classrooms. Note that there are windows in two opposite façades and no HVAC.

(c) Computer lab overview

(d) Principal's office overview

(e) Auditorium overview

(f) Ailes are opened spaces.

Figure E.10 – Photographic record of the energy audit inspection in the school Beatriz de Souza Brito

Energy Audit Report 03

EBM João Alfredo Rohr
Address: R João Pio Duarte Silva 1123, Córrego Grande, Florianópolis

Floor plan area:	1,111 m²
Number of Students:	379 students
Number of employees:	14 employees
Date of inspection:	October 1st, 2020
Actual EUI:	22.8 kWh/m².year
EUI predicted with the energy audit:	23.8 kWh/m².year

Figure E.11 – Building location

1. Building floor-plan

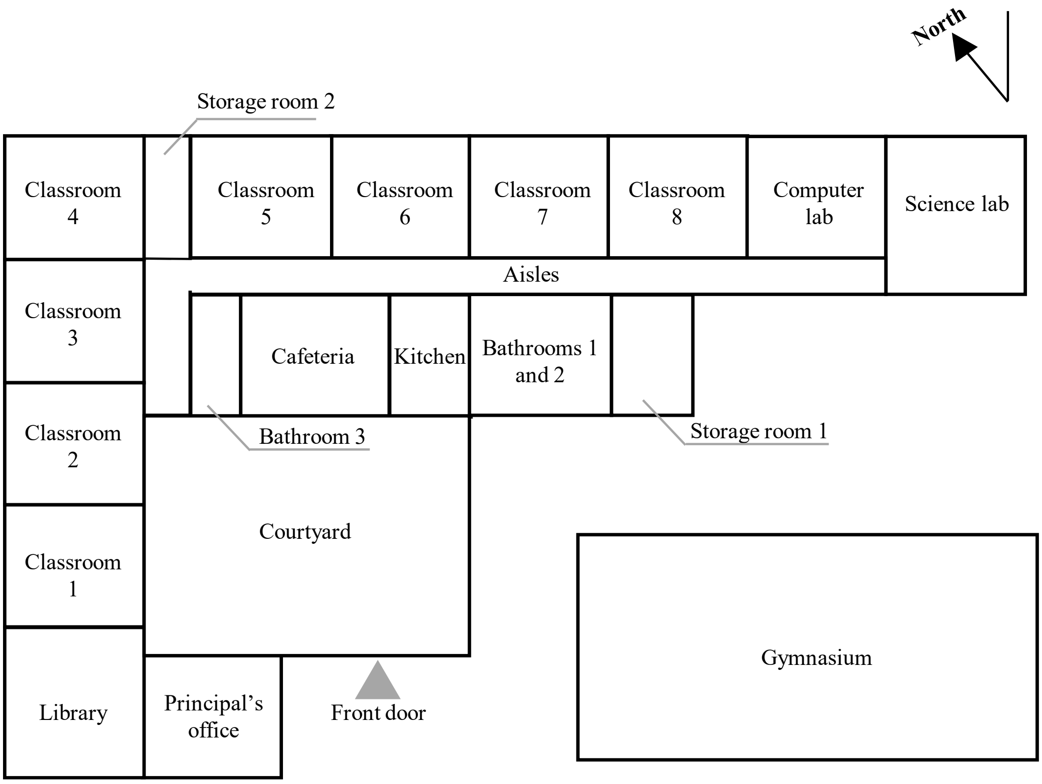


Figure E.12 – Schematic representation of the building floor-plan (no scale)

2. List of spaces and lighting

Table E.9– List of spaces and lighting characterisation

Space	Space type	Area (m²)	Total lighting power (W)
Library	Classroom	46.41	260
Classroom 2	Classroom	46.06	476
Classroom 3	Classroom	46.26	180

Table E.9 – List of spaces and lighting characterisation (continuation).

Space	Space type	Area (m²)	Total lighting power (W)
Classroom 4	Classroom	46.03	364
Classroom 5	Classroom	46.34	332
Bathroom 1	Transitory	20	36
Aisles	Transitory	98.99	507
Internal Courtyard	Transitory	80	544
Cafeteria	Transitory	63.49	216
Kitchen	Transitory	20	210
Storage room 1	Transitory	11.54	55
Classroom 6	Classroom	45.74	348
Classroom 7	Classroom	46.79	392
Classroom 8	Classroom	46.65	436
Classroom 9	Classroom	46.83	348
Computer lab	Classroom	46.7	436
Science lab	Classroom	46.13	436
Bathroom 2	Transitory	20	177
Storage room 2	Transitory	5.98	100
Courtyard	Transitory	-	255
Bathroom 3	Transitory	25.5	50
Gymnasium	Transitory	200	2500
Principal's Office	Office	42.07	718

3. List of equipment in each space and their features

Table E.10 – List of equipment and their characterisation

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
HVAC	HVAC	Library	1	18000	18000	4
Fan	Fans	Library	2	160	320	4
Computer	Computer	Library	2	150	300	4
TV	Other equipment	Library	1	300	300	2
Microwave	Other equipment	Classroom 1	1	1400	1400	0
Computer	Computer	Classroom 1	2	150	300	4
HVAC	HVAC	Classroom 1	1	12000	12000	4
Refrigerator	Refrigerators	Classroom 1	1	60	60	24
HVAC	HVAC	Classroom 2	1	30000	30000	6
Fan	Fans	Classroom 2	1	160	160	4
Projector	Other equipment	Classroom 2	1	326	326	
Computer	Computer	Classroom 2	3	150	450	4
HVAC	HVAC	Classroom 3	1	30000	30000	6
Fan	Fans	Classroom 3	1	160	160	4
Projector	Other equipment	Classroom 3	1	326	326	2
HVAC	HVAC	Classroom 4	1	30000	30000	6
Fan	Fans	Classroom 4	1	160	160	4
Projector	Other equipment	Classroom 4	1	326	326	2
Drinking fountain	Other equipment	Internal Courtyard	2	76	152	24

Table E.10 – List of equipment and their characterisation (continuation).

Equipment	End-use	Space	Quant.	Unitary Power (W)	Total Power (W)	Daily Operation (h)
Fan	Fans	Internal Courtyard	4	16	64	2
Fan	Fans	Cafeteria	2	160	320	2
Drinking fountain	Other equipment	Cafeteria	1	75	75	24
Water heater	Hot water	Cafeteria	1	5500	5500	1
Microwave	Other equipment	Cafeteria	1	1400	1400	0
Water heater	Hot water	Kitchen	1	5500	5500	1
HVAC	HVAC	Classroom 5	1	30000	30000	6
Projector	Other equipment	Classroom 5	1	326	326	2
HVAC	HVAC	Classroom 6	1	30000	30000	6
Projector	Other equipment	Classroom 6	1	326	326	2
HVAC	HVAC	Classroom 7	1	30000	30000	6
Projector	Other equipment	Classroom 7	1	326	326	2
Fan	Fans	Classroom 7	1	160	160	4
HVAC	HVAC	Classroom 8	1	30000	30000	6
Projector	Other equipment	Classroom 8	1	326	326	2
Fan	Fans	Classroom 8	1	160	160	4
Computer	Computer	Computer lab	20	150	3000	8
Rack	Other equipment	Computer lab	1	3000	3000	24
HVAC	HVAC	Computer lab	2	7500	15000	6
Printer	Other equipment	Computer lab	1	45	45	8
HVAC	HVAC	Science lab	1	18000	18000	4
Fan	Fans	Science lab	2	160	320	4
Electric shower	Hot water	Bathroom 2	1	5500	5500	0
Refrigerator	Refrigerator	Cafeteria	1	75	75	24
Refrigerator	Refrigerator	Kitchen	1	99	99	24
Refrigerator	Refrigerator	Kitchen	1	68	68	24
Freezer	Refrigerator	Kitchen	1	149	149	24

4. Operation and Occupation Schedules

Table E.11 – Schedules of operation for each end use.

End use	Operation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
HVAC	1.00	1.00	1.00	1.00	0.75	0.50	0.25	0.25	0.25	0.50	1.00	1.00
Hot water	0.00	0.50	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Lighting	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fans	1.00	1.00	1.00	1.00	1.00	0.50	0.25	0.25	0.25	0.50	1.00	1.00
Computer	0.50	1.00	1.00	1.00	1.00	0.50	0.50	1.00	1.00	1.00	1.00	0.50

Table E.11 – Schedules of operation for each end use (continuation).

End use	Operation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Other equipment	0.00	1.00	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	1.00	0.50
Refrigerators	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Electric oven	0.25	1.00	1.00	1.00	1.00	0.25	0.25	1.00	1.00	1.00	1.00	0.50

Table E.12 – Schedules of occupation for each space type.

Space type	Occupation											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Office	0.25	0.50	0.75	1.00	1.00	0.75	0.75	1.00	1.00	1.00	0.75	0.75
Classroom	0.10	0.25	1.00	1.00	1.00	0.75	0.75	1.00	1.00	1.00	1.00	0.75
Transitory	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

5. Predicted and actual monthly energy consumption

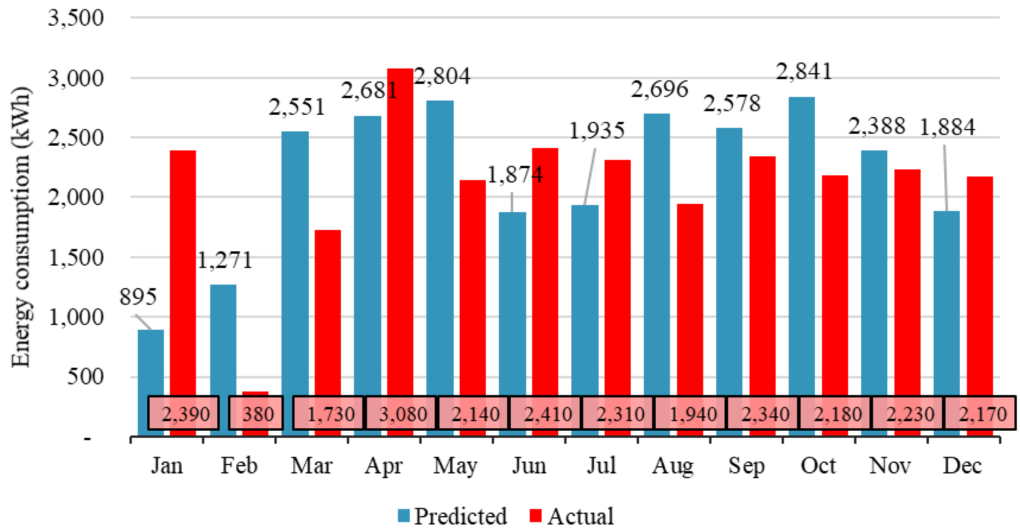


Figure E.13 – Predicted and actual monthly energy consumption. Estimation was performed through the energy audit method presented in Appendix D.

6. Annual end-use proportions

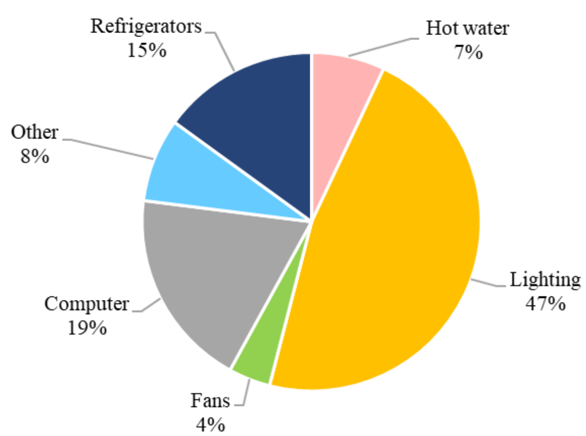


Figure E.14 – Annual end use estimations. Estimation was performed through the energy audit method presented in Appendix D.

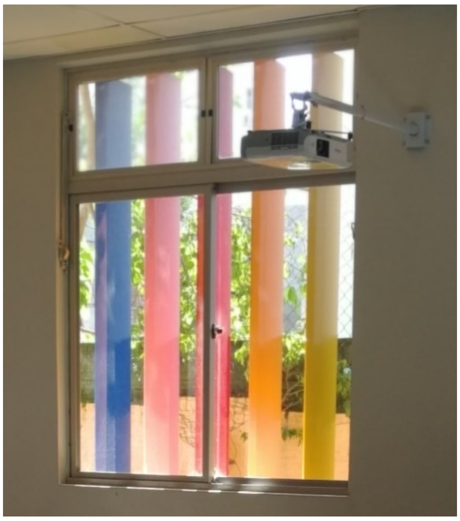
Photographic record

(a) External façade
(Source: Google Maps)

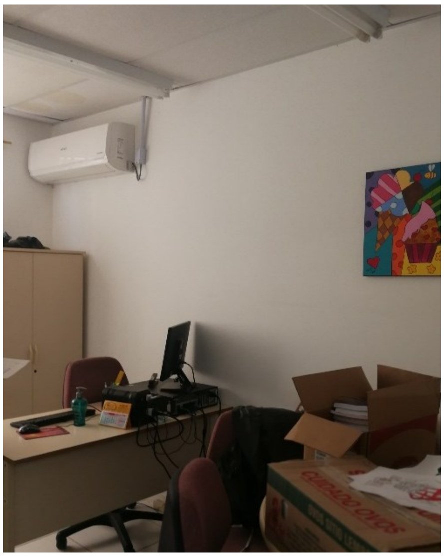
(b) Typical classroom

(c) Detail: Type of the predominant lighting system. A double LED T5 18W.

(d) Detail: radiant barrier above the roofing



(e) Detail: Brises-soleil outside the some windows



(f) Overiew of the Principal's office.

Figure E.15 – Photographic record of the energy audit inspection in the school João Alfredo Rohr

Appendix F – Shared authorship agreement of Chapter 6

Termo de concordância para utilização de artigo

Este documento atesta que os coautores do artigo intitulado **Impact of implementing air-conditioning systems on the school building stock in Brazil considering climate change effects: a bottom-up benchmarking** de autoria de Matheus Soares Geraldi, Mateus Vinicius Bavaresco, Veronica Gnecco Martins, Enedir Ghisi and Michele Fossati, nesta ordem, e publicado nos **Anais do Congresso Building Simulation 2021**, **CONCORDAM** com o uso do artigo aqui especificado para utilização na tese de **doutorado** do aluno **Matheus Soares Geraldi** (primeiro autor do artigo), orientado pelo **Professor Enedir Ghisi**, do Programa de Pós-Graduação em Engenharia Civil (PPGEC) da Universidade Federal de Santa Catarina (UFSC).

Florianópolis, 16 de julho de 2021

Co-autores:

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