Correlation and sensitivity of building economy and energy consumption to design parameters

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ABSTRACT

On the **Correlation and sensitivity of building economy and energy consumption to design parameters**

Rafaela Orenga Panizza

With the growth in the criticality of buildings' lifecycle performance, building performance simulation (BPS) is becoming a more prominent step in the building design process. BPS's ability to approximate the performance of a building in the real world enables BPS to be used for ensuring compliance and trade-off of design parameters at a late period of design. The quantitative information provided by BPS, if applied at an earlier period of design, has the potential to assist in more impactful decisions (which are currently being based on rules of thumb). The problem, however, is that the lack of details set at such early design translates to a very large number of scenarios to be simulated, requiring extensive time and computational power that is not available to designers during that phase.

To try limiting the number of scenarios to be simulated, the main goal of this study is to provide a deeper understanding of the impact caused by building design parameters and building characteristics. To accomplish that, data analyses were performed on a database of representative building models to investigate the sensitivity of outputs (Energy use intensity – EUI and net present worth of cost – NPW) to design parameters (architectural, electrical and mechanical systems) and the sensitivity of parameters' impact to building models. For each building model, energy simulations were performed based on a one-parameter-at-a-time (OAT) sampling, and the costs were evaluated through developed cost models.

The results of this study show that wall and roof insulation, window type, window-to-wall ratio, and lighting efficiency parameters are sensitive to the analyzed model. When analyzing different building groups (e.g. low- and high-rise) separately, it was found that parameters' significance is correlated to building characteristics (e.g. building height). This can be particularly of extreme importance for limiting design alternatives at the early stage of design when the multiplicity of design scenarios is currently limiting the applicability of BPS in the early-stage decision-making for building designs. In the future, the use of more advanced data

analysis tools will help improve the accuracy of the observed results as well as provide an inclusive classification for the level of impact of various design parameters in different building types.

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Chapter 1 – Introduction

1.1) Motivation and background

The building sector is a significant player when discussing worldwide energy use. When considering both the construction and operation phases, as of 2017, the industry was responsible for 36% of the total energy use in the world and, consequently, also responsible for 39% of the worldwide energy-related carbon emissions when considering upstream power generation [1]. Buildings (ranging from industrial to office buildings), according to standards, should be designed for a life that ranges from 25 to 99 years [2], which means that their operating performance will impact the world's energy consumption for decades to come. Buildings in their operation phase alone are responsible for 30% of the world's energy use [1].

The development of sustainable practices has begun in the building design industry back in 1993 with the development of LEED [3], which has been gaining popularity ever since. However, it was not until 2015, when the Paris Agreement [4] was signed, that the entire world started to prioritize such practices. In addition to the significant share of energy use that the building sector has been responsible for, the Paris Agreement [4] shifted the world's attention to the building sector for three other reasons. Firstly, the available technologies make it more cost-effective to reduce emissions in the building sector rather than in the industrial and transportation sectors (the two other major sectors in terms of energy use). Secondly, due to the continuing increase in energy demand in buildings caused by the increasing comfort standards [1], and lastly, because of the long-term impact that the building sector has. The higher the introduction of energy efficiency measures to the building sector today, the more savings will be compounded in the decades to come.

In response to the achievement of the Paris Agreement, in 2017 and 2018, a wide range of building energy policies were introduced or improved across the world. One of the most practical and cost-effective steps taken by government policy sectors is the development and introduction of building energy codes to be followed by new buildings [5] [6]. These building codes typically set standards for the performance of a few critical elements of the buildings:

building envelope; lighting, heating, ventilating and air conditioning systems (HVAC); service water heating; and electrical power systems and motors [5].

In Canada, the first application of a national standard for building energy performance occurred in 1997, with the name of Model National Code for Buildings (MNECB). Fourteen years later, in 2011, the code was updated with a 25% average improvement in the code's performance, and a new name, National Energy Code for Buildings (NECB). The standard was then updated for the last time in December of 2015 to ensure higher levels of energy efficiency in new buildings [5]. Since the application of the MNECB (which became NECB in 2011), the energy use intensity (unit of energy per area of the building) of new buildings has declined over the years [7]. Nevertheless, this decrease has not yet offset the increase in floor area built during the same period [8].

With the growth of the energy-efficient building design domain, the term building performance simulation (BPS) became popular among designers. BPS is a potent multi-disciplinary analysis method. It uses numerical methods to approximate the performance of a building model in the real world. BPS software generally receives two main inputs: a building model file and a weather file. The building model file contains, but is not limited to, the building envelope characteristics, electrical and mechanical system details, occupancy, and operation schedules. The weather file contains detailed information about the weather in the location where the construction of the building will take place. Based on these given details, the BPS tool can estimate indicators of building performance, such as the energy consumption of the building and thermal comfort of occupants, among other outputs [9].

There are several applications for building performance simulation tools. The most common uses include (*i*) building performance ratings, which is used to ensure code compliance and energy certifications; and (*ii*) architectural design, to be able to quantitatively inform the trade-offs between constructions and to estimate operational costs when designing energy-efficient buildings [9]. In the design phase, both mentioned applications are applied during a late phase (after the detailed design stage) and are used to help the building sector scenario in terms of energy consumption [10].

1.2) Problem statement

After the detailed design phase, when designers usually use BPS as a design tool, the majority of building components and attributes have already been defined. Though it is still possible, at that point, to make changes to the model if necessary, all the components and attribute details selected in earlier phases were decided by the designer without the influence of BPS. The process of taking decisions starts from the very start of the design process and, the earlier they are made (during the conceptual phase, for example), more impact in building's life cycle they will have [10]. And yet, knowing the importance of the decisions taken at such an early phase, today's design practices still rely on rules of thumb and engineering judgment for making those decisions.

BPS, as previously mentioned, can simulate the performance of building design, and quantitatively evaluate its energy consumption performance, utility cost data, as well as construction cost data. Based on its capacity to analyze building designs in terms of energy and cost, BPS has the potential to provide designers with quantitative energy and cost information that can help in the decision-making of building parameters. With the ability to make more informed decisions, designers would then be able to optimize their designs based on energy performance and lifecycle costs. Consequentially being able to design more energy-efficient buildings. However, to have the greatest design impact, the use of BPS for decision-making needs to occur during the early stages of building design, when most impactful decisions are made.

During such an early phase (post-conceptual phase), however, no existing cost models have the capability of providing cost details necessary to the decision-making for energy performance-related parameters. There are existing cost models that can suit both conceptual and detailed phases of design; however, existing limitations do not let them support the proposed solution of using BPS for decision-making during the early design development. Current cost models for the early design development phase do not take into consideration any energy performance-related parameters, and cost models used during the detailed design phase need more input details than the early phase can supply them.

On the energy performance side, BPS does not present substantial limitations when it comes to performing the simulation of early design models. The use of BPS for decision-making of parameters, however, would require the simulation of a large number of building scenarios (containing all possible combinations of parameter alternatives). Since, at such an early stage, many parameter details are not yet finalized, and various alternatives are still being studied for them; the combinations of possible building parameters' alternatives (i.e. design scenarios) are enormous.

To better illustrate this problem let's assume that, while designing a building, the designer would like to test four different alternatives for four different design parameters (roof insulation, window-to-wall ratio (WWR), overhang and HVAC system). In this example, the number of possible design scenarios, considering that the selections for WWR and overhangs are made per façade (south, north, east, and west), goes above 1 million (1,048,576 scenarios). The simulation of a single scenario (based on a building model of 10,821 ft^2 floor area) on the Cloud (one worker of c3.xlarge type) takes about 1 minute and 50 seconds to be completed [11]. With that in mind, if one could extrapolate to find the time needed for simulating 1 million scenarios, the calculated time would be of great magnitude. Thus, simulating all possible scenarios would require very extensive time and computational power, which is not available during the design process.

1.3) Objectives

To take a step forward with using BPS during the early-stage decision-making for parameters of energy-efficient buildings, this research is an attempt to provide the relevant attributes for the development of a recommender system that will be capable of rapidly limiting the number of building design scenarios during early phases of design. The ultimate goal is not only to limit the number of design alternatives for those parameters which do not have a significant contribution to the energy performance; but also to limit the scenarios to those with better energy and cost performance than the baseline (i.e. the design that follows recommendations of building energy code of performance). By limiting the number of possible scenarios to only the relevant ones, the time and computational power needed for implementing

BPS to help with decision-making at this stage will decrease. This decrease would then make it possible and worthwhile for designers to implement BPS during early design phases.

With that in mind, the main goal of this research is to provide a deeper look at correlation and dependencies within the building and design parameters. These correlations and dependencies can help to understand what parameters are worth investigating, depending on the analyzed building model, therefore limit the number of scenarios being simulated.

To achieve this overarching goal, the Research Objectives (RO) of this study are defined as:

- *Research Objective #1 (RO 1):* Setting the scope of the parametric analysis of this study by screening the energy-influential parameters through the evaluation of the sensitivity of building energy performance to variations of their values;
- *Research Objective #2 (RO 2):* Developing a cost model, capable of estimating construction and operation costs of building components based on their energy performance related attributes. To be useful during the early design phase, such cost models must follow what is known as 'semi-detailed' or 'parametric' cost estimation;
- *Research Objective #3 (RO 3):* Investigating how building energy and cost performances (possible through the developed cost models – RO 2) are sensitive to design parameters, and how the entire parametric behavior is sensitive to building model;
- *Research Objective #4 (RO 4):* Hypothesizing the possible cause roots of such differences in behavior;
- *Research Objective #5 (RO 5):* Testing the developed hypotheses and recommending important attributes to the development of a recommender system.

1.4) Organization of the thesis

After providing an overview of the research's motivation, existing problems and the list of objectives in the current chapter, the remainder of this document is organized as follows: the literature review is presented in chapter 2; methods are introduced and explained in chapter 3; implementation is presented and hypotheses were developed in chapter 4; evaluation and discussion in chapter 5; and finally, concluding remarks are provided in chapter 6.

Chapter 2 – Literature Review

2.1) Building performance simulation systems

Since the scope of this research mainly entails the BPS environment, the study of the available performance analysis tools (of both energy and lifecycle cost) was an important step. This section shows this step's findings by dividing it between construction cost assessment tools, lifecycle cost assessment tools, and energy simulation systems.

(2.1.1) Construction cost assessment tools

To begin this research work, previous works in the design cost estimation field were investigated. The analyzed literature shows the evolution in early design construction cost estimation methods that happened over the past years. Before building information modeling (BIM) started to be widely used 2-dimensional CAD drawings were used for cost estimation purposes. Until the early 2000s, commonly used methods counted on Quantity Takeoff (QT) model (based on the information provided by the drawing). QT models mainly include the number of items and materials needed for the given project as well as the defined dimensions [12]. This method is limited by the use of detailed information about the quantity and material of items used in a building when estimating cost. Other QT methods, such as constructed area method; quantity of work and elementary price; construction cost index and complex nature; estimation based on work breakdown structure [13]; and others were under a questionable linear relationship [14]. Another major limitation of these methods was the fact that their whole process was done manually, so not only errors were frequent, but it was also very time consuming [12].

Starting in the early 2000s, with the rise of artificial intelligence (AI) and machine learning algorithms, neural network approaches were then promising for cost estimation in the construction business because of its ability to deal with multiple parameters [15] [16] [14]. By using artificial neural networks (ANN), building cost estimates began to show great accuracy thanks to its ability to investigate non-linear and multilinear relationships between building cost parameters [14] [16]. ANN also showed promise in selecting the key building parameters to be investigated in the data analysis section [16]. A great downside to this method, however, is its dependency on a large quantity of quality data. The method requires a great selection of data points to train the network algorithm, and a different selection to go through the testing phase [15] [16] [14].

Later, when building information modeling started to gain strength in the market, new methods for calculating construction cost using BIM started to merge [17]. Thanks to BIM's capacity to store information about multiple aspects of building parameters, the integration of BIM and cost evaluation tools can lead to more precision and both cost and time efficiencies during early-stage design projects [12]. One of the first examples of BIM tools for cost evaluation was developed as a plug-in to the 3D design tool SketchUp [17]. Within this module, the cost of a design alternative can be continuously updated as the designer moves forward with making design changes. This tool takes into consideration five major groups of elements for cost estimation purposes: substructure, superstructure, finishes, fitting/furnishing, and services [17]. Another example of BIM tools for cost estimation is the Autodesk Revit Architecture plug-in developed by Jalaei and Jrade (2015), this tool links the building model with "Sage Timberline" cost database [18]. This link can estimate construction costs by examining structural components of the building as it is designed in BIM. The use of a database, in this case, enables the components to be matched to the most relevant cost item in a cost database to find the building's construction cost. This tool's product database contains a limited variety of components based on their physical structure, with no emphasis on their performance [18].

(2.1.2) Lifecycle cost assessment tools

Along with the rise of BIM use in the market and the use of building performance simulation engines, a new kind of tool began to be introduced, tools that combine both construction and operation cost estimation for building design phases. Several working systems can integrate lifecycle cost assessment of building designs with design authoring tools for early design phases. One example was developed by Basbagill et al. (2013) at Stanford University. This semi-automated process evaluates the lifecycle impact of design alternatives during early design phases by connecting 'DProfiler' (design authoring tool) to energy simulation software eQUESt and lifecycle impact assessment software tools, SimaPro and Athena EcoCalculator; and also the CostLab online facility operation database for operation and maintenance (O&M) costs [19]. One very helpful aspect of this system is the integration of 3D models with cost estimating databases such as RSMeans and Timberline [19].

On the conceptual phase of design, previous projects have combined low LOD (Level of Development) BIM models, which are available in early design phases, with lifecycle impact estimator tools such as SimaPro [20] [21]; independent databases [22] [23]; or lifecycle cost databases in combination with energy simulation software tools [24]. Tools available for such an early phase of design mainly focus on evaluating embodied energy or CO2 emission during the lifecycle. Even though it was found that parameters in the LEED's (leadership in energy and environmental design) energy and atmosphere category are highly influential in the cost estimation process of a sustainable building [15], the analyzed literature does not show details concerning cost estimation of energy conservation attributes based on their performances.

(2.1.3) Energy simulation system

Most existing cost evaluation tools make the use of vendor proprietary software for the simulation of a building's performance for calculation of lifecycle (i.e. energy consumption) cost. However, with the growth in demand for such tools, there has also been a growth in the development of validated open-source simulation engines, such as EnergyPlus [25] (for energy simulation); Radiance [26] (for lighting simulation); Therm [27] and Window [28] (for heat-transfer analysis and window thermal performance modeling). The open-source aspects of these simulation engines have provided them with the possibility of development for a variety of validated open access software tools that can work around them. The EnergyPlus plug-in OpenSudio, for example, which was developed by the US Department of Energy – National Renewable Energy Laboratory (NREL) is one of the best-known examples of such tools. OpenStudio uses EnergyPlus for whole-building energy modeling and HVAC sizing; and Radiance for daylight analysis [29]. The vendor neutrality of such tools has made them ideal candidates for integration with other design authoring tools, and this has given rise to new cross-platform applications (such as [30] and [31] among others).

Apart from its open-source nature, the OpenStudio plug-in provides the ability to use 'measures'. Measures are programs that can access and make changes to a building model automatically (rather than manually). This feature has made OpenStudio an ideal tool for building parameter investigations that can take into consideration energy performance and lifecycle costs.

2.2) Data mining applications in the design of energy-efficient buildings

The process of limiting the number of design scenarios relies on the analysis of BPS data to achieve the goal of this research. A variety of data analysis techniques have been used in the design of energy-efficient buildings. This section highlights the methods found in the literature.

(2.2.1) Sensitivity analysis of building parameters

In the field of building energy analysis, the use of sensitivity analysis for studying energy influential parameters is very common. The investigated literature showed a variation between screening, local and global methods for sensitivity analysis of parameters in the building energy modeling field. Screening methods have shown the capability of ranking parameters based on their impact on the output with a relatively low computational cost [32] [33] [34] [35] however, with a large number of parameters, this type of analysis becomes time-intensive [36]. Global sensitivity analysis methods, on the other hand, can provide very advanced results but always will require a very costly computation effort [37] [38] [39]. The Morris Method, however, is an intermediate method due to its cooperation between the quality of results and computational cost [37] thanks to its one-parameter-at-a-time (OAT) sampling method (same as screening and local methods).

Screening is known to have lower computational cost and, while widely used in the domain of building energy, it has shown to be successful in identifying and ranking parameters that affect the output, though qualitatively [40] [41] [42]. This is a very common method for complex situations as it performs well with the management of computational complexities involved in sensitivity studies that involve multiple parameters ([34] [43] [35] [44] among several other examples). Screening is considered an OAT method, where parameters are evaluated in turn and normally being deviated to the two extreme values [40]. Similarly, the local method for sensitivity also uses an OAT style. In this case, however, the input-output relationship is assumed to be linear, which is not necessarily the case in the building energy analysis field. OAT methods, though they are economical (in terms of number of simulations needed), have their limitations (compared to global sensitivity analysis methods), a major one being the disregard of interactions among various parameters [41]. Global sensitivity methods, on the other hand, do consider the interactions between parameters. That is done by varying all design parameters when analyzing the impact of a single one. This method is known to provide more trustworthy results at a much larger computational cost [40] [11].

The reviewed papers have investigated a pool of different cases such as single-zoned rooms to office buildings, townhouses, residential buildings, etc. as well as generic buildings [45] [46] [33]. All of these case studies were modeled in different locations (represented by the weather files used for simulation) such as Hong Kong [46], Portugal [32] and Denmark [47] [40]. These studies that test the sensitivity of building performance to the input parameters have shown a large range of tested variables. It was noticed that variables related to envelope insulation, window sizes, and mechanical systems were chosen to be investigated in the majority of the analyzed literature, and they showed to be parameters of great importance in the building energy field.

Regardless of the method used, the reviewed literature reports success in analyzing the energy influential parameters of their case studies. However, all of these studies only analyze one building model (mostly with numerical inputs), which makes their results "case-dependent".

Table 2.1: Sampling methods used by analyzed literature

Authors (year)	**Sampling method**	**Number of case studies**	**Case study details**
Tavares & Martins (2007) [32]	OAT	1	Townhall building
Petersen & Svendsen (2010) [48]	OAT	1	Two-person office
Smith et al. (2012) [43]	OAT	1	House
Nembrini et al. (2014) [49]	OAT	1	5 level housing
Dreau & Heiselberg (2014) [47]	OAT	1	Office room
Sun (2015) [35]	OAT	1	N/A
Heiselberg et al. (2009) [40]	OAT	1	7 story office building
Corrado & Mechri (2008) [50]	OAT	1	Dwelling
Ourghi et al. (2007) [34]	OAT	1	Office building
Pushkar et al. (2005) [33]	OAT	1	Office building
Aksoy & Inalli (2006) [51]	OAT	1	Intermediate floor
Ostergard & Jensen (2015) [52]	OAT	1	Office building
Olivero et al. (2015) [53]	OAT	2	Library and office buildings
Ostergard & Jensen (2016) [54]	OAT and Global	1	Residential building
Sanchez et al. (2014) [37]	OAT and Global	1	Apartment building
Attia et al. (2012) [55]	Global	1	Apartment
Mora & Tarantola (2008) [39]	Global	1	N/A
Mechri et al. (2010) [56]	Global	1	Intermediate floor in a multi-story office building
Mostrucci et al. (2017) [57]	Global	1	Residential building
Gagnon et al. (2018) [58]	Global	1	LEED silver building in Canada
Hopfe & Hensen (2011) [59]	Global	1	Office building
Capozzoli et al. (2009) [38]	Global	1	Intermediate floor of a multi-story office building

(2.2.2) Machine learning models for building energy prediction

Nowadays, building performance analysis methods through simulation are known to have high accuracy when predicting the performance of a building. It is no secret, however, that performing such analyses is a very time-consuming task [60]. With the development of data analytics tools, researchers in the building energy field have worked on a variety of machine learning approaches to be applied in the building energy management field. Existing studies on the topic are categorized based on their objectives, the most relevant ones including energy consumption prediction, and economic analysis methods [61].

Given the objectives of this study and the reviewed data science techniques, classification appeared to be the more appropriate model for the present study [61] [60]. Classification is a supervised learning technique where the algorithm is capable of classifying outputs into discrete categories [62]. Amongst the existing classification methods, the most common algorithm tackling energy consumption and economic analysis in the building energy industry is decision tree [61].

Decision tree is a logical model in the form of a flowchart that is used to segregate a set of data points into predefined classes given a set of attributes [63]. Though the selection of the used set of attributes is an important step for the use of classifiers, the analyzed literature did not show in-depth analyses for the proper selection of input attributes. Similar to any other machine learning techniques, the generation of a decision tree relies on two steps: training phase and classification phase. These require a very large amount of data but, according to the reviewed studies, generated decision trees for energy and cost prediction have shown high levels of accuracy [60] [61] [63] [64].

2.3) Gaps in the literature

Based on the topics discussed during this chapter, gaps in the literature can be classified under technical and research gaps. Technical gaps include the shortcomings in the existing lifecycle analysis field, and research gaps include the shortcomings in the parametric analysis field.

(2.3.1) Technical gaps

Even though there was great progress in the field of energy analysis and lifecycle cost estimations, the objectives of most existing tools are either detailed cost estimates (which apply to high LOD models at the late phases of design) or conceptual cost estimates (applicable to schematic designs which are composed of solid forms without many details). Conceptual cost models are tools used to forecast what the project cost will be before the detailed information of the building is available [65]. At the early design development phase, when the spaces and basic properties are known and decisions are being made on further details of building systems, it is important to include the parameters that greatly impact energy consumption in the cost estimation process. Therefore, not enough lifecycle cost tools are available for aiding designers during decision making of those parameters. Existing tools that do provide this kind of information are tools developed for semi-detailed cost estimation tools (require models with a higher level of detail). Furthermore, most of the available tools for the early design development phase do not consider one key element: the lifecycle cost of the energy-efficient measures.

(2.3.2) Research gaps

The reviewed literature has shown a variety of works done in the building energy analytics field. Sensitivity analysis, for instance, has been used to study many different building models from many different locations. The gap found in the pool of reviewed studies, however, includes the focus on a single building when performing the sensitivity analysis, therefore the sensitivity of the parameter impacts to the building type, size, volume, etc. are unknown. Also, due to the existing limitations on the existing cost estimators, no previous studies have focused on the sensitivity of economy measures to design parameters. On the machine learning side, not a lot of emphasis has been put into the selection of the attributes used in the dataset, even though that dictates how the classifier performs.

Chapter 3 – Methods

This chapter focuses on the adopted methods that made the development of this study possible. Before moving on to the details of this research, an illustration of the high-level methodology is presented in Figure 3.1 to enable an understanding of the overall process of this work. The start point of this entire process is the input with two main parts: energy influential building parameters that are normally set at the early stages of design development, and building energy codes that exist to set a minimum standard performance for new (and sometimes existing) buildings. Influential parameters going through decision-making steps at this stage include aspects of building envelope, mechanical and electrical systems.

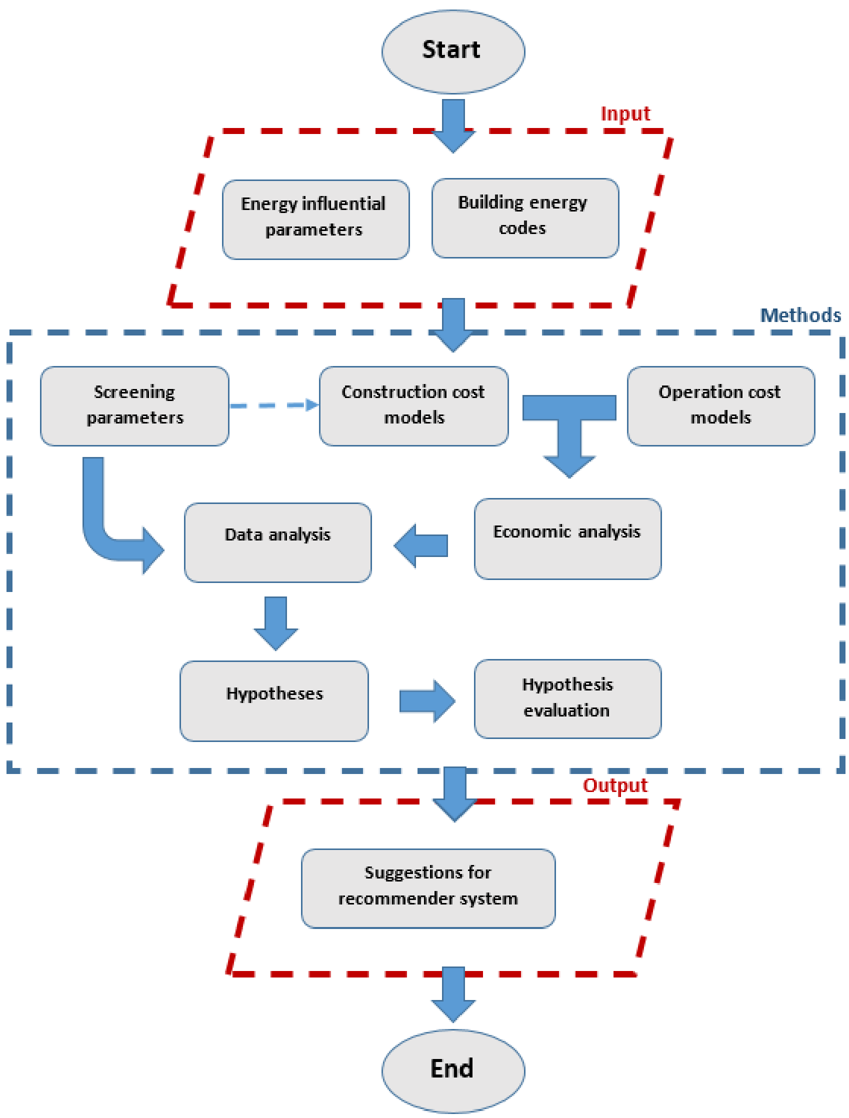


Figure 3.1: High-level methodology of this study

To set the scope of this study (and complete RO1), the pool of recommended energy influential architectural parameters went through a screening process ("Screening parameters"). This process was in place to ensure that all chosen parameters had a significant enough impact on the building performance, which makes it worthwhile to be included in the data analysis section. When the greatest difficulty of running BPS for early-stage decision-making is the computational effort required, setting aside low-significance parameters is a crucial step. Once the scope of the study was set, the following steps were executed.

Given the importance of the economic aspect of decision-making (due to its ability to provide quantitative information on the trade-off between construction/installation cost and energy savings), the step following the screening of building parameters was the evaluation of construction/operation costs for the influential parameters ("Cost models development"). The parameters that remained part of this study's scope are the significant architectural (from "Screening parameters"), and the suggested mechanical and electrical systems parameters. The parametric construction cost models developed in this research take the energy performance of building design parameters as input for estimation of construction/installation costs. In addition to the construction cost models, the development of an operation cost model was also part of this study. Since this work focuses on the province of Québec, Canada, it was necessary to develop a cost model capable of applying appropriate rates/policies. The combination of both construction and operation costs will then accomplish RO2 and contribute to the development of a cost model that can analyze the lifecycle cost of building models during the early design development stage. The cost model excludes the end of lifecycle demolition costs.

Next, with the parameters defined as this study's scope and their respective cost models, a meta-level analysis (in terms of both energy and cost) was possible ("Data analysis"). This step of the methodology is in place to analyze what design parameters are significant enough (in terms of both energy and cost), and to investigate how sensitive building parameters' behaviors are to the different building models (RO3). With the help of the above-mentioned early design development cost model, the BPS outputs (energy performance and lifecycle cost) and a set of data mining techniques, made the analysis of design parameters' behavior possible. Then the results of this meta-level analysis enabled the development of hypotheses comprised of building characteristics that appear to be the cause of the variation of impact behaviors throughout different building models (RO 4). Finally, also with the help of data mining techniques, the developed hypotheses were evaluated, and the final suggestion of important building aspects was made (output of this study and RO 5).

3.1) Inputs

(3.1.1) Energy influential parameters

Parameters focused on by this study are the ones decided during the early design development phase. In consultation with an energy consulting firm, a set of design parameters (decided during the early stages of design) were suggested to this research as common energy influential parameters. Akonovia is an energy consulting firm situated in the province of Québec. The suggested parameters cover architectural aspects of a building; lighting; and HVAC systems. Architectural parameters that are taken into consideration are the following: building orientation; window-to-wall ratio (WWR); overhangs (OH); wall, roof, and window insulation; and solar heat gain coefficient (SHGC) of windows. The lighting parameter includes its efficiency and the HVAC parameter includes system type.

The selected simulation engine to analyze the suggested parameters is EnergyPlus. The main reason for such selection is due to OpenStudio's (EnergyPlus interface) existing ability to automatically manipulate building design parameters, through what they call OpenStudio measures. Due to the structure of the measures used for manipulating the suggested parameters, the appropriate inputs to be investigated for each parameter were selected. The variation of WWR and OH through the OpenStudio measures only allow the variation of one façade at a time (south, north, east or west), which turns them into eight separate parameters in this research (WWR South, WWR North, WWR East, WWR West, OH South, OH North, OH East, and OH West). Window insulation and SHGC parameters, on the other hand, are applied together through the selection of window glazing types. The summary of all building parameters investigated along with the OpenStudio measures responsible for their application and expected inputs can be seen in Table 3.1.

Table 3.1. Summary of design parameters, inputs, and implementation for creating design alternatives

Category	Parameter	Inputs	Implementation (OpenStudio Measure)
Architectural	Orientation	Degrees of rotation clockwise (^{0})	*Rotate Building Relative to Current Orientation*
	WWR (S, N, E, W)*	Ratio	*Set Window to Wall Ratio by Façade*
	Overhang (S, N, E, W)*	Projection factor (overhang depth/window height)	*Add Overhangs by Projection Factor*
	R-value	R-value (ft^2*h*R/Btu)	*Set R-value of Insulation for Roofs to Specific Value* *Set R-value of Insulation for Exterior Wall to Specific Value*
	U-factor & SHGC	Set window type from the product library	*Replace Exterior Window Constructions At Different Orientations With Another Construction*
Lighting Power	LPD	LPD reduction (%)	*Set Lighting Loads by LPD* *Reduce Lighting Power Loads by Percentage*
HVAC	System type	The type(s) to be included will be selected by the user	Each system type has its measure (see Figure 3)

*S: South, N: North, E: East, W: West

(3.1.2) Building energy standard requirements

In North America, there are two major standards for building energy performance: NECB [66] and ASHRAE 90.1 [67]. Both standards are relatively similar in terms of requirements for the parameters being focused on by this research. Nonetheless, the focus of this study was turned to ASHRAE 90.1 2007 because it is the standard that is most frequently used by Akonovia.

The building energy standard sets minimum performance requirements for a variety of building components. These requirements vary from place to place depending on their climatic zone. The climate zone profile of the province of Québec varies from zones 6, 7 and 8 of ASHRAE 90.1 (Figure 3.2). Based on the appropriate climate zone standards and recommendations from Akonovia, the minimum requirements for the energy influential parameters being analyzed in this study are shown in Table 3.2.

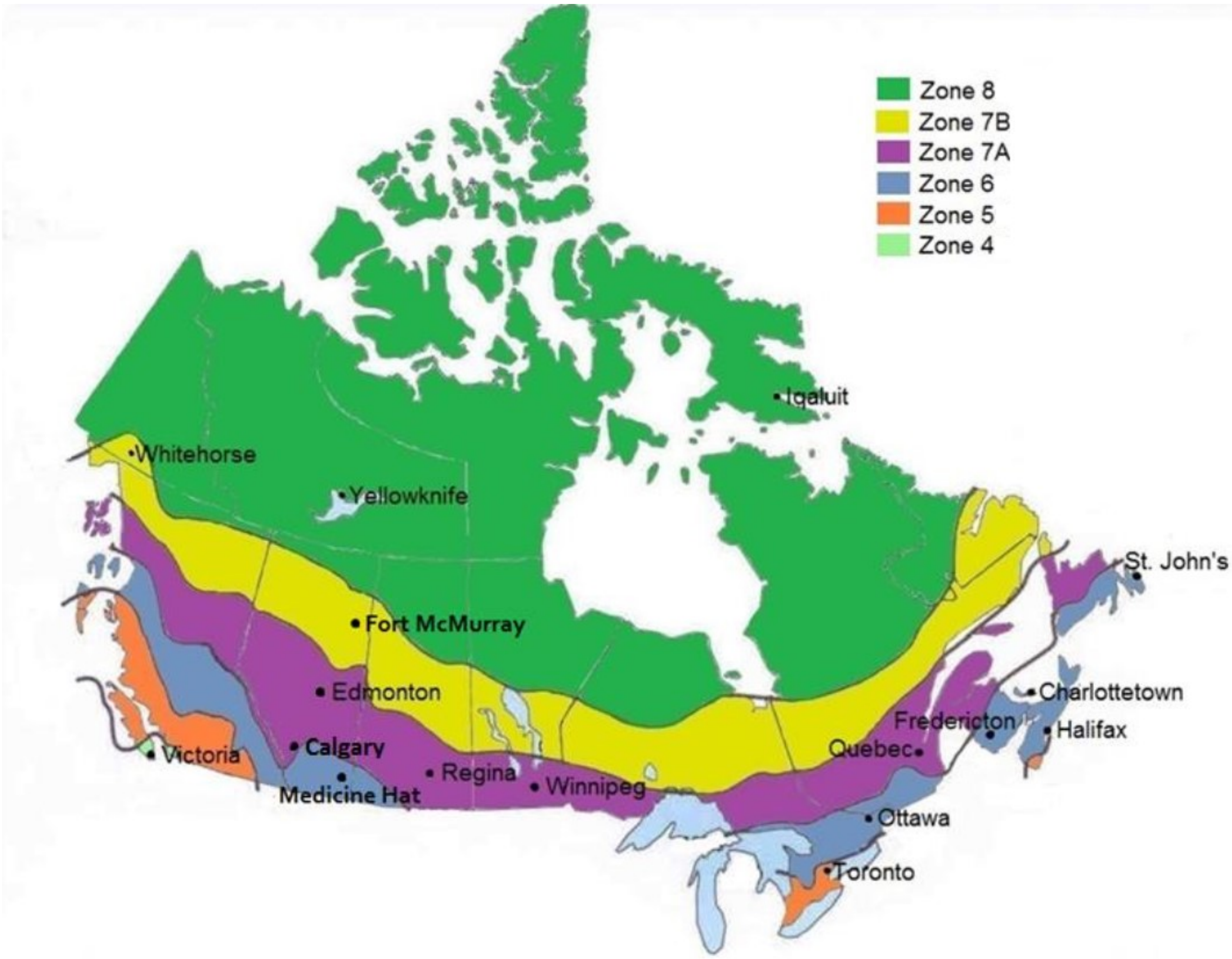


Figure 3.2: Climate zones as set by ASHRAE 90.1 [68]

Table 3.2: Baseline settings as defined by ASHRAE 90.1 2007 and the industry partner

Parameter	**Standard performance**
Roof R-value	20.83 $ft^2 \cdot °F \cdot h/Btu$
Ext. Wall R-Value	15.625 $ft^2 \cdot °F \cdot h/Btu$
SHGC	0.45
U-value	2.2698 $W/(m^2K)$
Lighting efficiency	Depends on building (see Table 3.7)
HVAC Type	ASHRAE 90.1-2007 Sys 7 Baseline Measure

3.2) Initial parameter screening

As previously mentioned, limiting the number of building scenarios during the early phases of design is among the main goals of this research. The first step towards achieving this goal is to narrow the scope of the study to parameters that impact energy performance significantly. This research step was achieved by analyzing nine real-world projects (received from Akonovia) with the help of a screening OAT method. It must be noticed here, that while prioritization of design parameters' impact on energy performance can be perceived from more comprehensive/ complex sensitivity analysis methods (e.g. global methods); the simplified technique along with the available pool of building models used in this study can sufficiently address the above-mentioned needs [36] [37].

The suggested electrical and mechanical system parameters are known to have a significant impact on the energy performance of a building. Differently from the architectural parameters, these directly impact a building's energy consumption. Therefore, they will be set aside during this screening investigation.

(3.2.1) Output generation

When comparing the energy performance of different buildings, analysis outputs must be normalized to enable their comparison. The appropriate output (target) variable selected for the screening of parameters is the energy use intensity (EUI - kBtu/ft^2-yr). EUI is the measurement of a building's annual energy consumption relative to its gross area [69]. To investigate the impact of parameters' variation on the energy performance of buildings, energy simulations were performed using the EnergyPlus simulation engine, via OpenStudio software. The variation of parameters was automated with the help of OpenStudio measures (details on the measures used for each parameter can be found in Table 3.1). During this study, simulations of all available models were performed in their baseline form (for more details see section (3.1.2) Building energy standard requirements), as well as with the manipulation of selected parameters through an OAT sampling method [70].

(3.2.2) Analyzed case studies

To cover a wide range of designs from the province of Québec, this screening process is taking into consideration nine (9) building models based on real-world projects designed for the cold climate of the province of Québec. The models were provided to this research by the energy consultant, Akonovia. The goal was to cover a wide range of building types (excluding low-rise residential buildings) with different sizes and uses. The database of building models, though limited, can address the needs of this research step. Information on each case study used for the initial screening analysis can be found in Table 3.3.

Table 3.3: Model details (modified from [70])

BUILDING MODEL NAME	NUMBER OF FLOORS	FLOOR AREA (FT^2)	RISE	BUILDING TYPE(S)
Clinique Dentaire	2	10,821.5	Low-rise	Healthcare Clinic
Poly St	10	177,607.4	High-rise	School
Capwood	18	429,725	High-rise	Restaurant, Healthcare Clinic, Office, Residential, Parking
Arch TP	8	8,355.9	High-rise	Office
Arch Vit	8	8,355.9	High-rise	Office
Arch VRF	8	8,355.9	High-rise	Office
Copie 25	8	64,013.2	High-rise	Gymnasium, Dining
Copie 27	8	64,069	High-rise	Gymnasium, Dining
Islo 5	2	72,012	Low-rise	Exercise Center, Healthcare Clinic

(3.2.3) Input parameters' ranges

When selecting input ranges to be tested (through OpenStudio measures), a set of factors were taken into consideration. The selected inputs were based on a combination of building standards, literature and common inputs found in projects from Québec (provided by Akonovia). In the case of parameters with inputs of a continuous nature with minimum performance requirements set by building codes (e.g. R-values), the lower bound range of input was set as so (standard requirements can be found in Table 3.2). The remaining values for design parameters with continuous nature (i.e. OH and WWR) were set based on the literature and the acceptable/ common ranges found in actual projects, respectively. The same procedure was performed for finding maximum values for building code parameters of continuous nature. For parameters with discrete nature such as orientation and window type (U-factor & SHGC), the market availability was taken into consideration.

Normally, the screening method uses OAT to manipulate the parameters to their two extreme values [55]; however in the current study, since there are some essentially discrete parameters (such as window type), more than two extreme input values were tested [11]. Thus, for the purpose of this sensitivity analysis, probability distributions had to be defined for all input parameters. Both discrete and continuous nature parameters were defined with a uniform distribution. Discrete parameters were represented by the available alternatives of each parameter, and the continuous ones were represented by 5 discrete values, which were selected based on the previously selected ranges. All ranges of input values tested for each parameter can be found in Table 3.4.

Table 3.4: Summary of sensitivity analysis inputs

Parameter	Range of input
Orientation (Rotation)	0°, 90°, 180°, 270°
Ext. Wall R-Value	15.625 ~ 41.2 $ft^2 \cdot °F \cdot h/Btu$
Roof R-value	20.83 ~ 66.3 $ft^2 \cdot °F \cdot h/Btu$
Window Type	1 - 9 types (Table 3.5)
WWR South	0 ~ 0.8
WWR South	0 ~ 0.8
WWR South	0 ~ 0.8
WWR South	0 ~ 0.8
Overhang North	0 ~ 1.6
Overhang South	0 ~ 1.6
Overhang East	0 ~ 1.6
Overhang West	0 ~ 1.6

Table 3.5: Window glazing types

#	Glazing	Thickness	Gas filling	U-value ($W/(m^2K)$)	SHGC
1	Double Clear	3mm/6mm	Air	3.122	0.762
2	Double Clear	6mm/13mm	Air	2.67	0.703
3	Double Clear	6mm/13mm	Argon	2.511	0.704
4	Double Grey	3mm/6mm	Air	3.122	0.614
5	Double Grey	6mm/13mm	Air	2.67	0.479
6	Double Grey	6mm/13mm	Argon	2.511	0.476
7	Triple Clear	3mm/6mm	Air	2.143	0.682
8	Triple Clear	3mm/13mm	Air	1.765	0.684
9	Triple Clear	3mm/13mm	Argon	1.624	0.685

All tested parameters are analyzed one at a time since there are no co-dependencies between them (i.e. changing the input to one parameter will not impact other parameter's input). This study, however, does not take into consideration the compound effect of co-variation of multiple parameters. Overhang size is applied based on the projection factor (overhang depth/window height) however, even though it is calculated based on the height of the existing windows, a modification on window size does not automatically modify the existing overhangs. The U-value and SHGC, on the other hand, are applied through the modification of a window type. Different window types bring different U-values and SHGC. These two values, however, are not necessarily dependent on one another [70].

(3.2.4) Scope of study

In each case study, inputs of the twelve parameters were deviated (within their appropriate ranges) in each building model (using OpenStudio measures). Each parameter was evaluated in every different model separately based on the percentage change in the response variable (EUI). The impact caused by each parameter was represented by the percentage increase in EUI from the minimum to maximum output values. Each parameter was evaluated in each building and their averages were used to create an overall ranking of parameters [11]. Details of the ranking are shown in Table 3.6.

Table 3.6: Summary of sensitivity analysis results

	Percentage increase from lowest to highest energy consumption (distribution among nine case study projects)					
Parameter	**Min**	**Max**	**Average**	**St dev**	**t-test (3% threshold)**	**Rank**
WWR West	4.37%	32.05%	12.49%	9.63%	S.	1
WWR North	5.85%	17.39%	11.38%	3.57%	S.	2
WWR East	7.44%	16.59%	11.36%	3.88%	S.	3
Ext. Wall R-Value	1.31%	15.16%	6.98%	4.10%	S.	4
Window Type	0.24%	14.97%	5.96%	4.71%	S.	5
WWR South	0.00%	18.20%	5.67%	5.75%	N.S.	6
Roof R-value	1.44%	10.99%	5.53%	3.12%	S.	7
Orientation (Rotation)	0.23%	6.16%	2.92%	2.06%	N.S.	8
Overhang North	0.00%	5.41%	1.94%	2.52%	N.S.	9
Overhang South	0.03%	4.52%	0.84%	1.48%	N.S.	10
Overhang East	0.07%	4.09%	0.78%	1.28%	N.S.	11
Overhang West	0.04%	1.39%	0.41%	0.45%	N.S.	12

To investigate the statistical significance of these parameters' impact on the EUI, a t-test was performed (an upper tailed test with 95% confidence level) on the percentage of increase in EUI (from minimum to maximum) as the input parameters deviate within their ranges. For each parameter, the percentage increase in EUI was investigated to see whether it is significantly greater than a threshold. Based on Beguery et al. (2015), the minimum energy consumption increases to be considered significant is 3% [71]. Thus, along with the rank of parameters, the t-test results show that not only the length of overhang in all faces is always at the lowest ranks of impact, but also the associated changes are insignificant at the evaluated threshold (Table 3.6). Based on the results of sensitivity analysis two major decisions were made. Both the overhang (in all the four sides) and the orientation parameters have shown a nonsignificant impact on energy consumption. For that reason, it was decided that the overhang and orientation parameters will be set aside and will not be further analyzed in this study. Finally, as a result of the screening process, the architectural parameters to remain as part of the scope of this project are the first seven ranked parameters shown in Table 3.6: WWR (all facades), insulation of wall and roof, and window type.

3.3) Construction cost models

As shown in the high-level methodology (Figure 3.1), the next step involves the development of construction cost models for parameters selected to be a part of this study. The main contribution of these models is their ability to estimate the cost of a building's energy influential components at an early stage of design (post-conceptual). The presented method aims to provide models that are not only easy to implement during BPS analysis, but also can be easily updated (since the cost of products is frequently changing).

The models presented in this section will focus on three main areas of energy conservation: architectural, lighting, and HVAC. In the previous section (section 3.1), it was mentioned that electrical and mechanical systems are known to have a great impact on the energy consumption of a building in comparison to other parameters (architectural parameters). For that reason, lighting and HVAC systems were the first two parameters to be considered for the cost model development. Architectural parameters that were included in the scope of this project, along with lighting and HVAC systems, are windows (type and size) and insulation (wall and roof). Therefore, construction cost models were developed for these elements as well.

Based on lessons learned from the reviewed literature, this study decided to use a database to assist with the application of cost models. The database was developed to record prices and/or unit costs for various building elements. Databases, apart from helping with model implementation, allow for updating the components without having to modify the developed models.

(3.3.1) Lighting system

In the case of the building's lighting system, the main design parameters for energy simulation are lighting power density (LPD) and LPD reduction (representing the use of energy-efficient lighting systems). LPD is a metric used to measure lighting energy use and is defined as watts per floor area. Thus, the purpose of this cost model was to estimate the cost, based on LPD and LPD reduction inputs. There are two measures responsible for setting the cost of lighting systems in OpenStudio. One which sets the baseline cost (conventional fluorescent lights) and one which changes that cost accordingly when implementing energy conservative lighting systems such as light-emitting diode - LED (same measures that set the desired performance inputs). To implement lighting installation costs to BPS, the cost database stores the information required to calculate measure inputs for both conventional and LED lighting systems. The measure that applies the baseline lighting load (named "Set Lighting Loads by LPD") is responsible for setting the appropriate LPD for a building (as defined by the building code – see Table 3.7) based on its building type (ASHRAE 90.1 2007) and its respective cost.

Table 3.7: Norm Power allowance for different building types according to ASHRAE (W/m2)

Building Type	ASHRAE 2007
Automotive Facility	9.7
Convention Centre	12.9
Courthouse	12.9
Dining: bar lounge/leisure	14.0
Dining: cafeteria/fast food	15.1
Dining: family	17.2
Dormitory	10.8
Exercise Centre	10.8
Fire Station	10.8
Gymnasium	11.8
Health care clinic	10.8
Hospital	12.9
Hotel/Motel	10.8
Library	14.0
Manufacturing facility	14.0
Motion picture theater	12.9
Multi-unit residential building	7.5
Museum	11.8
Office	10.8
Penitentiary	10.8
Performing arts theatre	17.2
Police station	10.8
Post Office	11.8
Religious building	14.0
Retail area	16.1
School/university	12.9
Sports arena	11.8
Storage garage	3.2
Townhall	11.8
Transportation facility	10.8
Warehouse	8.6
Workshop	15.1

The main challenge here was the fact that the same level of LPD (and accordingly, LPD reduction) can be virtually attainable by a wide range of different lighting technologies, each of which is associated with a different level of initial and life cycle costs. Based on the research performed during this study, the cost of lighting systems can depend on factors such as technology (fluorescent, LED, etc.), type (troffers, surface ambient, high-bay, etc.), model, brand, store location, and other specifications. To keep the database complete yet consistent, the database is limited to the most common and available lighting technologies and types. In consultation with building energy consultants, a basic/common set of fluorescent lighting system types (that use either T8 or T5 bulbs) was selected as the main source of lighting for baseline buildings. Models of each technology in the market were matched to find the closest equivalent model while keeping brand, store, and location consistent.

Lighting system types considered in this model are troffers, surface ambient, and high-bay/low-bay. To support the measure that sets lighting loads, a few tables were added to the database which entails frame cost data, light bulb cost, and useful life data for the baseline fluorescent systems. Frame and light bulb costs were extracted from the Home Depot [72] product database and the useful life data for the bulbs come from the manufacturer specifications [73] [74].

The second aspect of building lighting is to reduce the lighting load, by using energy conservative lighting technologies. This is applied in OpenStudio via the measure called "Reduce Lighting Loads by Percentage" which is responsible for the efficiency increase from the previously set lighting system (baseline), as well as to add its respective cost increase. The increase in efficiency of lighting load in this measure is implemented as LPD reduction percentage, which represents the process of replacing one type of lamp for a similar one that consumes less energy (with the assumption that the same lighting comfort is maintained for the building user). The required cost model must link each percent of LPD reduction into the expenses associated with it. Table 3.8 shows the performance and unit cost data used in the cost calculations for all three previously mentioned lighting types for both fluorescent and LED technologies. In addition to the cost of implementing such systems, there is also another important positive aspect to more energy-efficient lighting systems, which is their longer expected life.

Table 3.8: Summary of lighting system details (modified from [75])

Lighting type	**Technology**	**Watt**	**Are light bulbs included?**	**Bulb type (quantity)**	**Expected life (hours)**	**Unit cost (CAD/W)**
Troffers	Fluorescent	96	No	T8 (3)	24,000	0.91
Surface Ambient	Fluorescent	64	No	T8 (2)	24,000	0.66
High-Bay/ Low-Bay	Fluorescent	216	No	T8 (4)	24,000	0.90
Troffers	LED	59	Yes	-	60,000	2.53
Surface Ambient	LED	35	Yes	-	50,000	4.83
High-Bay/ Low-Bay	LED	112	Yes	-	100,000	2.94

The baseline lighting cost of a building is then calculated by multiplying the unit cost (CAD/W) of the fluorescent light (frame plus bulb) with standard LPD (W/ft^2). This cost (CAD/ft^2) is used in the first OpenStudio measure (i.e. Set Lighting Loads). After that, the premium cost for adding the energy-efficient system increase is calculated by Equation 1, to be introduced to the simulation, through the second measure (Reduce Lighting Loads), for evaluating the final system's cost.

[1] $Iuc = \frac{UCred}{UCn}(1 - reduction) - 1$ [75]

In the equation, Iuc is the percentage increase in unit cost, UCred is the unit cost of the reduced design, UCn is the unit cost of standard lighting and reduction is the desired percentage reduction in LPD that is manually entered to the measure.

(3.3.2) HVAC system

When it comes to the HVAC system components, the application of associated costs to energy simulations works differently than all the other components. For HVAC, instead of introducing costs (or unit costs) as an input through the OpenStudio measure (prior to the simulation); they must be calculated after the simulation is completed, and based on the specifications (i.e. count and capacity) of different components of the system. In terms of varying system types, HVAC also works differently than the other components; instead of being able to input a variable through one or two measures, the variable inputs to a model are the measures themselves. Each HVAC measure represents a different type of system (e.g. rooftop package, water source heat pump, etc.). These measures add to the model a set of components that are characteristic of the selected system (details of measures and its components can be seen in Table 3.9); however, the quantity and capacity of each type of component will be an output of the energy simulation and will depend on the characteristics of the building being analyzed. Based on RSMeans data [76], the costs of studied systems are calculated as the summation of partial costs of existing components in the system. The cost of each of those components will vary mainly depending on their capacity. Both the unknown quantity and capacity of components make the costing procedure impossible to happen before the building simulation. Once the building simulation is finished, its output must be parsed and matched with the components from RSMeans.

Table 3.9: HVAC types and cost components

#	HVAC Type	HVAC Measures	RSMeans Cost Components (*not from RSMeans)
1	Dual duct	AEDG K12Dual Duct DOAS	Variable DOAS, baseboard, pump, chiller, boiler
2	Fan coil	AEDG K12 HVAC Fan Coil DOAS	Pump, chiller, boiler, heat exchanger, variable DOAS, fan coil
3	Heat pump	AEDG K12 HVAC GSHP DOAS	Heat exchanger, pump, chiller, boiler, water-source heat pump, variable DOAS, geothermal system*
4	Heat pump	AEDG Office HVAC ASHP DOAS	Heat exchanger, air-source heat pump, constant DOAS
5	Fan coil	AEDG Office HVAC Fan Coil DOAS	Pump, chiller, boiler, heat exchanger, constant DOAS, fan coil
6	Rooftop unit with variable air volume (VAV) boxes	AEDG Office HVAC VAV Chilled Water	Heat exchanger, rooftop package, VAV terminals, pump, chiller, boiler
7	Rooftop unit with variable air volume (VAV) boxes	AEDG Office HVAC VAV DX Coil	Heat exchanger, rooftop package, VAV terminals, pump, boiler
8	Heat pump	AEDG Office HVAC WSHP DOAS	Heat exchanger, boiler, pump, water source heat pump, cooling tower, constant DOAS

To support the costing procedure for HVAC systems, links to the RSMeans cost database [76] were provided for all components used by the OpenStudio measures. All varieties of capacities available in the RSMeans items were targeted so that the post-processing for evaluating components' costs can find the cost for the closest capacity to the design output. The components modeled in our database are divided into 6 main groups (one table created for each): HVAC packages; geothermal; terminal units; fan coil; heating and cooling; and pumps and heat exchangers. Also, each table is further divided into the subcomponents, e.g. heating and cooling table encompasses chillers, boilers, cooling towers and radiant heaters of different types and capacities.

(3.3.3) Architectural parameters

Following the HVAC system are the architectural parameters, window, and insulation. To be able to calculate the construction cost of all parameters that were selected to be further analyzed, cost models will also be needed for these parameters. For the completion of a cost model that is capable of calculating the construction costs of all selected energy influential parameters, the developed models for lighting and HVAC systems were matched with available cost models for windows and insulation (as reported in paper [75]).

(3.3.4) Cost models output

The developed conceptual cost models were applied via a cost database. The product database was divided into four major categories of products: window, insulation, lighting, and HVAC. Each of these sections has its own specific set of tables, format, and relations. The lighting system itself has separated two main sections, the fluorescent lighting data, and energy-efficient lighting data. Both sections have information on three lighting types, these types are then compared based on their performance and unit costs to enable the calculations of the cost increase of energy-efficient systems. The section of HVAC components, in this database, are divided into the 6 categories mentioned earlier. The cost of an entire system is calculated based on the sum of all components existing in the given system. The Entity-Relationship (ER) diagram of the database is represented in Figure 3.3.

Insulation, as a major category, supports two different types: insulation for wall and roof. Both types of insulation use a different material but, to calculate the unit cost to be added through measures, the method is the same. A regression is derived from the table of available products. When it comes to windows, the data is divided into window glazing, framing, as well as additional coefficients. To provide the appropriate measure with the unit cost of a window, all window parts are taken into consideration. The inter-relation between window parts and insulation materials can be visualized in the database ER diagram in Figure 3.3.

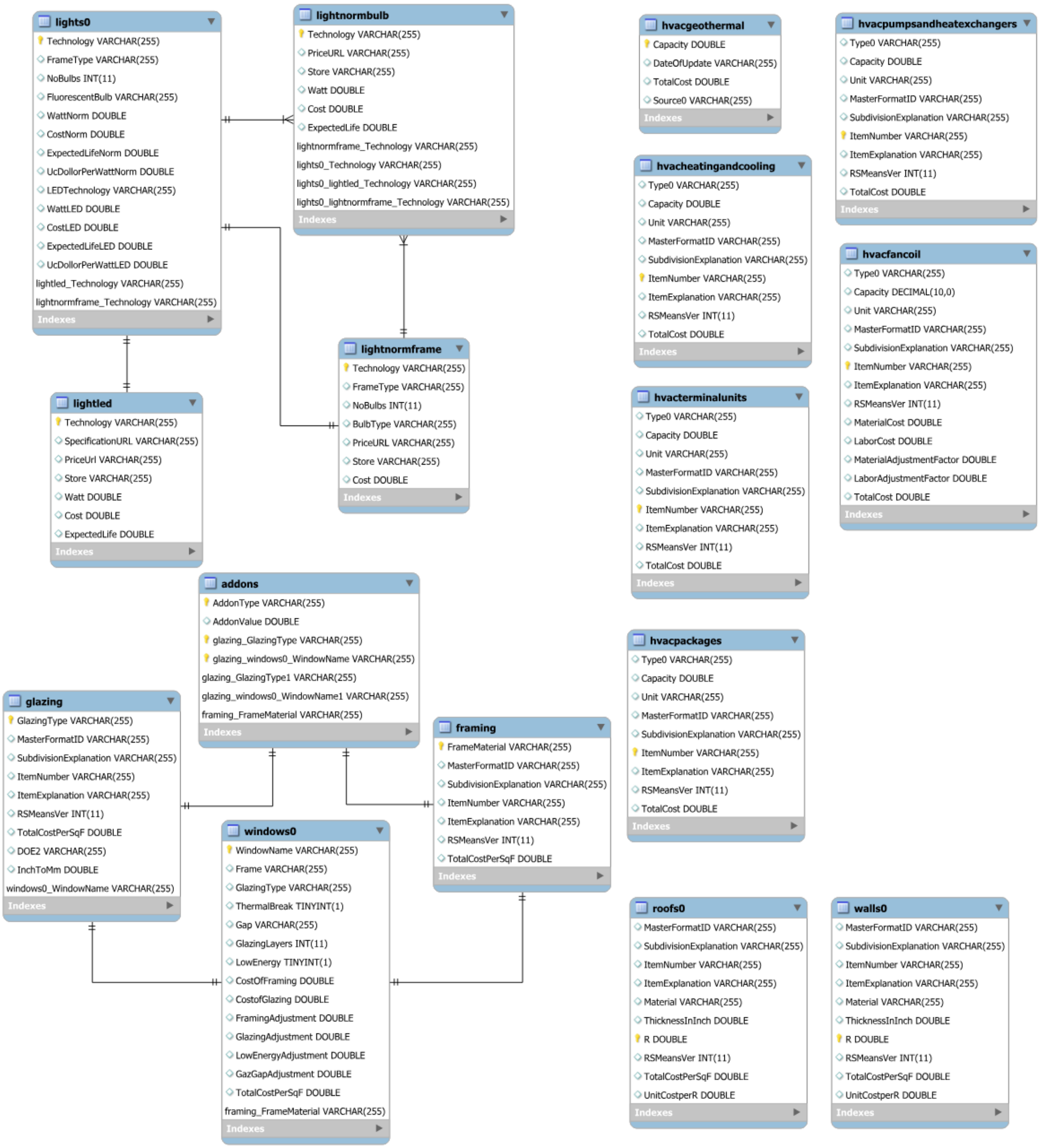
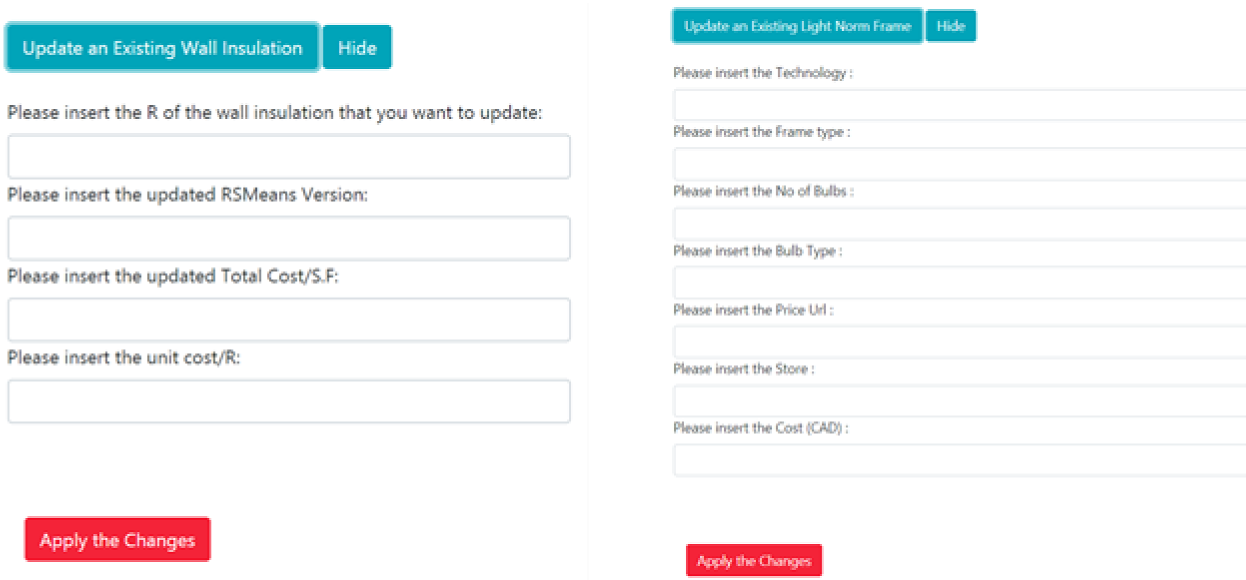


Figure 3.3: Entity Relationship diagram of the developed product database [75]

This database was developed to be linked with applications running through OpenStudio so that they can automatically pull the cost information from the database. To keep the cost information up-to-dated or adding new items (as required) an admin interface was developed. Items taken from RSMeans are identified through their code (MasterFormat) as the key. After updating (or adding new) cost information, the updated information is stored back in the database through the key and overrides the older version. Figure 3.4(a) provides a sample snapshot of the admin interface.



(a) Updating wall insulation cost (b) Updating lighting frame cost

Figure 3.4: Sample screenshots of the user interface developed for the management of the created cost database [75]

In items that use non-RSMeans sources, such as lighting system components, the key to keeping them updated in the database is to include their source web address and the store location to which the price was found.

3.4) Operation cost models

Unlike the construction cost models, operation costs do not directly depend on building components. Operation cost models include utility rates of the location where the buildings are located. For this study, since the focus is on the province of Québec, the two pricing policies considered are Hydro-Québec [77] and Energir [78] for electricity gas respectively.

(3.4.1) Electricity rates

The main non-governmental rates set by Hydro-Québec are divided into four different building categories: domestic, small power, medium power, and large power. They are mainly divided based on their energy demand and consumption. The "domestic" category aggregates buildings that use energy for domestic use only (e.g. single-family houses). This group does not generally include establishments such as hotels, motels, etc. or hospitals, clinics, etc. The three other building categories include other types of buildings, which are then separated based on their energy use. The "small power buildings" category includes buildings with a minimum power demand of 50 kilowatts. The next category, "medium power", includes buildings with power demands lower than 5,000 kilowatts; and "large power" covers the buildings with a power demand of 5,000 kilowatts or more. With the help of the industry partner, three different building categories were selected to be focused on in this model: domestic, small power and medium power.

Electricity Rates Details

While researching the appropriate rates for each building category, a set of electricity rates were found to be available. The domestic section has four subcategories (D, DP, DM, DT) which are mainly divided based on energy consumptions (kWh), the maximum power demand (kW), time of the day, the season, and the outside temperature. The selection of the residential building rate contract is based on a series of eligibility requirements, such as installed equipment and previous consumption history.

The small power rate category, on the other hand, has only one available rate which is known as Rate G. This rate bases the utility bill on demand as well as total energy usage and fixed service charge. To be eligible for this rate, the building demand must exceed 50 kilowatts. The medium power category has four main rates. Two of them (M and G-9) depend on the previous 12 months' maximum power demand; one (GD) applies to independent energy producers, and lastly, an experimental rate applies to the purpose of electric vehicle charging (BR). The structure of these rates mainly depends on the billing demand and energy consumption (could be different during summer and winter periods); however, a minimum billing is also applied to some rates depending on the type of the electricity delivered (single-phase or three-phase).

At the early design stage, it is known in what category the building fits into. However, at this phase, normally not many details of the building model are yet set, which means that the required information for the eligibility of different rates may not be available. Based on common rates applied in Québec (according to Akonovia's experience), three main rates were selected: D, G, and M. Details of the rate application and structure for charging clients can be found in Table 3.10.

Table 3.10: Electricity rate application and structure details as defined by Hydro Québec [77]

	Application	Structure
Rate D	Domestic Rate D applies to a contract for domestic use in a dwelling whose electricity is metered separately and whose maximum power demand was less than 65 kilowatts during the 12 consecutive monthly periods ending at the end of the consumption period in question.	40.64¢ fixed charge for each day in the consumption period, plus, 5.91¢ per kilowatt-hour for energy consumed, up to the product of 36 kilowatt-hours and the number of days in the consumption period, and 9.12¢ per kilowatt-hour for the remaining consumption
Rate G	General Rate G applies to a small-power contract whose minimum billing demand is less than 65 kilowatts. Rate G does not apply to electricity delivered to supply a direct-current electric vehicle charging station rated 400 volts or more.	\$12.33 fixed charge, plus \$17.49 per kilowatt of billing demand above 50 kilowatts, plus 9.81¢ per kilowatt-hour for the first 15,090 kilowatt-hours, and 7.20¢ per kilowatt-hour for the remaining consumption. The minimum monthly bill is \$12.33 when single-phase electricity is delivered or \$36.99 when three-phase electricity is delivered
Rate M	General Rate M applies to a medium-power contract whose maximum power demand has been at least 50 kilowatts during a consumption period included in the 12 consecutive monthly periods ending at the end of the consumption period in question.	\$14.46 per kilowatt of billing demand, plus 4.99¢ per kilowatt-hour for the first 210,000 kilowatt-hours, and 3.70¢ per kilowatt-hour for the remaining consumption. The minimum monthly bill is \$12.33 when single-phase electricity is delivered or \$36.99 when three-phase electricity is delivered.

Implementation

Comparably to the OpenStudio measures used to change building parameters in a model, there are also measures capable of applying tariff, but they are EnergyPlus measures. EnergyPlus measures are like OpenStudio measures, the only difference is that they are applied directly to the EnergyPlus simulation (while running it), as it needs inputs from the results of the simulation itself. Meanwhile, OpenStudio measures are applied directly to the model itself. The existing EnergyPlus tariff measure, "Tariff selection generic" (available in the BCL Library [79]), allows for a selection of different formats to calculate the utility rate within one measure. For applying Hydro-Québec policy rates, the existing rates will need to be adjusted. This can be done through the development of IDFs (EnergyPlus input data files) to reflect Québec rates.

The existing Tariff selection generic measure enables the user to input the desired gas and electricity rates from a selection of different rate structures. These rates are organized and stored in the measure's 'resources' folder, and their structures are saved as EnergyPlus IDF files. From a technical point of view, an IDF is a type of data file that lets OpenStudio users change the parameters of a measure without directly accessing the measure script (a piece of code in Ruby language). By the aid of these files, parameters of the measure can be assigned and modified without getting involved with the sophisticated Ruby measures. As depicted in Figure 3.5, these files are composed of a set of arguments and their values. The already existing IDF files can be edited as needed through its text file, or by the IDF Editor (the editor that reads EnergyPlus Data Dictionary), which is supplied with EnergyPlus installation. This editor also enables the creation of new IDFs that can be added to the rates library in the measure folder and be used as wished when running an Open Studio simulation. To apply the electricity rates, 3 IDF files were developed with the appropriate specifications for Hydro-Québec rates D, G and M (details included in the IDF files can be seen in Appendix 1).

```
UtilityCost:Tariff,
  ExampleC,                        ! Name
    ElectricityPurchased:Facility,   !- Output Meter Name
  KWh;                             ! Conversion Factor Choice


UtilityCost:Charge:Block,
  BlockEnergyCharge,               ! Charge Variable Name
  ExampleC,                        ! Tariff Name
  totalEnergy,                     ! Source Variable
  Annual,                          ! Season
  EnergyCharges,                   ! Category Variable Name
  ,                                ! Remaining Into Variable
  ,                                ! Block Size Multiplier Value or Variable Name
  20000,                           ! Block Size 1 Value or Variable Name
  0.0474,                          ! Block 1 Cost per Unit Value or Variable Name
  180000,                          ! Block Size 2 Value or Variable Name
  0.0424,                          ! Block 2 Cost per Unit Value or Variable Name
  remaining,                       ! Block Size 3 Value or Variable Name
  0.0383;                          ! Block 3 Cost per Unit Value or Variable Name


UtilityCost:Charge:Block,
  BlockDemandCharge,               ! Charge Variable Name
  ExampleC,                        ! Tariff Name
  totalDemand,                     ! Source Variable
  Annual,                          ! Season
  DemandCharges,                   ! Category Variable Name
  ,                                ! Remaining Into Variable
  ,                                ! Block Size Multiplier Value or Variable Name
  20,                              ! Block Size 1 Value or Variable Name
  5.38,                            ! Block 1 Cost per Unit Value or Variable Name
  80,                              ! Block Size 2 Value or Variable Name
  4.23,                            ! Block 2 Cost per Unit Value or Variable Name
  remaining,                       ! Block Size 3 Value or Variable Name
  3.60;                            ! Block 3 Cost per Unit Value or Variable Name
```

Figure 3.5: Example of an IDF snippet developed for Block Energy and Demand Charges

(3.4.2) Gas rates

Like in the electricity policies section, the selection of an appropriate gas policy rate also depends on a set of criteria. These rates depend mostly on the type of load (‘general’; ‘stable’; or ‘interruptible’). “General” load customers are the ones that do not consume enough natural gas per day to reach a stable load. “Stable” load is the definition used by Energir to characterize the customers whose subscribed volume is at least 333 m^3/day. The last load profile is “interruptible”, for which the minimum volume required per day is at 3,200 m^3 [78].

Gas Rate Details

Similar to the procedure used for electricity rates, the selected load type to be focused on in this research was based on the experience of Akonovia. The selected rate was the distribution rate D1. Rate D1 consists of a basic fee as well as a unit cost for the volume withdrawn. The basic fee is charged per meter device every day and its value depends on the annual volume withdrawn (details of the pricing for the basic fee can be found in Table 3.11). The second part of the gas utility rate is the price paid per unit volume, the unit cost applied in this section depends on the volume withdrawn per day (details of unit cost can be found in

Table 3.12).

Table 3.11: Distribution rate D1 - Basic fee [78]

Volume withdrawn (m^3/Year)				Price (¢/Metering device/Day)
From	0	To	10,950	51.247
From	10,950	To	36,500	104.416
From	36,500	To	109,500	124.546
From	109,500	To	365,000	131.437
From	365,000	To	1,095,000	172.393
From	1,095,000	To	3,650,000	227.157
	3,650,000		And over	565.045

Table 3.12: Distribution rate D1 - Unit prices for the volume withdrawn [78]

Volume withdrawn (m^3/Day)				Price (¢/m^3)
From	0	To	30	25.657
From	30	To	100	17.519
From	100	To	300	15.159
From	300	To	1,000	11.483
From	1,000	To	3,000	8.497
From	3,000	To	10,000	5.969
From	10,000	To	30,000	4.802
From	30,000	To	100,000	3.981
	100,000		And over	3.301

Implementation

Just like the electricity rates, gas rates are also applied through the measure "Tariff selection generic" with the help of IDFs. The gas rate IDF can calculate the unit price for volume withdrawn (Table 3.12). The gas rates, however, also have a basic fee, which is normally applied every day, and its price depends on the building's annual volume withdrawn. The problem is that this annual volume is not known until the entire building simulation is complete, which makes it impossible for the current versions of tariff measures to use in the utility rate calculations. For that reason, the basic fee section of the gas rate is calculated post-simulation.

When an EnergyPlus simulation is complete, an HTML file is generated. Based on the annual volume of natural gas withdrawn(reported by EnergyPlus); the structure of utility calculations (monthly instead of daily),; and assuming that the building withdraws natural gas every day of the year, the basic fee for the selected rate was converted to GJ/year and CAD/month (Table 3.13). The desired output can be found in the EnergyPlus HTML file in a table called "Source Energy End Use Source Summary". An example of this output table can be found in Figure 3.6.

Table 3.13: Basic fees converted into appropriate units for post-simulation utility cost estimation

Volume withdrawn (GJ/Year)				**Price (CAD/Metering device/Month)**
From	0	To	414.8955	15.579
From	414.8955	To	1382.985	31.742
From	1382.985	To	4148.955	37.862
From	4148.955	To	13829.85	39.957
From	13829.85	To	41489.55	52.407
From	41489.55	To	138298.5	69.056
	138298.5		And over	171.774

Source Energy End Use Components Summary

	Source Electricity [GJ]	Source Natural Gas [GJ]	Source Additional Fuel [GJ]	Source District Cooling [GJ]	Source District Heating [GJ]
Heating	0.00	329.24	0.00	0.00	0.00
Cooling	226.29	0.00	0.00	0.00	0.00
Interior Lighting	476.78	0.00	0.00	0.00	0.00
Exterior Lighting	0.00	0.00	0.00	0.00	0.00
Interior Equipment	1322.45	0.00	0.00	0.00	0.00
Exterior Equipment	0.00	0.00	0.00	0.00	0.00
Fans	97.79	0.00	0.00	0.00	0.00
Pumps	94.75	0.00	0.00	0.00	0.00
Heat Rejection	0.00	0.00	0.00	0.00	0.00
Humidification	0.00	0.00	0.00	0.00	0.00
Heat Recovery	0.00	0.00	0.00	0.00	0.00
Water Systems	0.00	0.00	0.00	0.00	0.00
Refrigeration	0.00	0.00	0.00	0.00	0.00
Generators	0.00	0.00	0.00	0.00	0.00
Total Source Energy End Use Components	2218.05	329.24	0.00	0.00	0.00

Figure 3.6: Screenshot of EnergyPlus output table (Source Energy End Use Source Summary)

3.5) Economic analysis

To be able to analyze the lifecycle cost of a building model due to the adoption of energy-efficient components, while including both construction and operation costs, the net present worth (NPW) had to be calculated. NPW allows for the trade-off analysis between investment and savings. To calculate the NPW, an analysis period of 25 years was considered with an annual interest rate of 3%. During this period, the analyzed cash flow includes installation costs of considered building components, identical replacements, and utility costs. More details about the used economic analysis can be found in [11].

3.6) Data analysis

The last step of the methodology uses all the processes and components developed to answer the research questions of the study. Based on the parameters selected as well as the knowledge gained through the process of analyzing parameters' sensitivity during the first step, along with the implementation of the developed cost models, a meta-level analysis of building parameters became possible. The expected outcome of this analysis is the set of relevant parameters that should be considered by the recommender system.

(3.6.1) Model preparation

To prepare for simulations in general, all OpenStudio model (OSM) files (i.e. building models) must have their complete geometry and non-geometry data. The non-geometry data include thermal zone breakdown; the construction and schedule sets; occupancy loads, and operation schedules for lighting and electric equipment; assignment of loads to their respective space types; and cooling/heating thermostat schedules.

For sensitivity analysis, models must be set to a baseline setting (mostly according to minimum requirements set by ANSI/ ASHRAE/ IES Standard 90.1 – see section 3.1.2). The baseline settings include the addition of HVAC system type ASHRAE 90.1-2007 Sys 7 Baseline; R-values for roof and walls equal to 20.83 $ft^2·°F·h/Btu$ and 15.625 $ft^2·°F·h/Btu$ respectively; lighting system type as surface ambient; and window glazing type as Dbl Ref-D Clr 6mm/13mm. Parameters that do not have a minimum or maximum requirement, (such as window to wall ratio), were kept as is (in the design shipped from the architect). Lastly, the final step of preparation for the sensitivity analysis is loading window glazing types into the model library. This step is only required for windows since for new windows to be added to a model (when creating scenarios) they must be loaded to the OSM file before proceeding to the BPS process.

(3.6.2) Parameters and input values

Based on the pool of energy influential parameters within the scope of this study, and their respective cost components, the selected parameters for this analysis were chosen (parameters and respective inputs can be seen in Table 3.14). Similar to section 3.2, parameter input ranges were based on building codes, literature, and common values (for more information refer to section 3.2.3). For each of the parameters, the range of values was discretized to 5 discrete values (if they were not already of a discrete nature). The appropriate cost input for each selected parameter alternative was calculated based on the procedure explained in section 3.3. By applying the desired parameter inputs through a system that integrates energy simulation with the developed cost model (described in sections 3.2 and 3.3), the cost inputs needed are automatically applied.

Table 3.14: Parameters and discrete inputs

Parameter	Unit	Discrete inputs
WWR	n/a (ratio)	0, 0.2, 0.4, 0.6, 0.8
Roof R-value	$ft^2·°F·h/Btu$	29.294, 39.018, 48.112, 57.206, 66.3
External Wall R-value	$ft^2·°F·h/Btu$	29.294, 39.018, 48.112, 57.206, 66.3
Window Type	n/a (type)	1, 2, 3, 4, 5, 6, 7, 8, 9 (see Table 3.5 for types)
Lighting Efficiency	% reduction	45.3
Lighting Type	n/a (type)	Troffer, High-Bay/Low-Bay
HVAC	n/a (type)	1, 2, 3, 4, 5, 6, 7, 8 (see Table 3.9 for types)

(3.6.3) Output generation

Figure 3.7 shows the output generation process. The BPS process begins with the generation of building design scenarios for each seed model used. In this analysis, the scenarios were generated based on an OAT sampling method, so for each scenario, only one parameter was varied, while all other parameters were fixed at their baseline settings. Once the scenarios are generated, they all go through the energy simulation stage. Since the focus of this study is to provide suggestions for the development of a recommender system that bases analysis on both energy and cost, the selected outputs for this method were EUI and NPW. EUI because it represents the energy performance, and NPW because it provides the trade-off between investment and savings. The simulation stage alone (with the help of applied input measures) can generate the EUI results for each scenario, as well as the output files that provide all the necessary inputs for calculation of NPW of the model [11]. A software system developed by Nik-Bakht et al. (2020) integrates and automates the energy simulations, cost application and economics analysis processes [11]. That system was used to evaluate both the energy (EUI) and cost (NPW) aspects of each scenario.

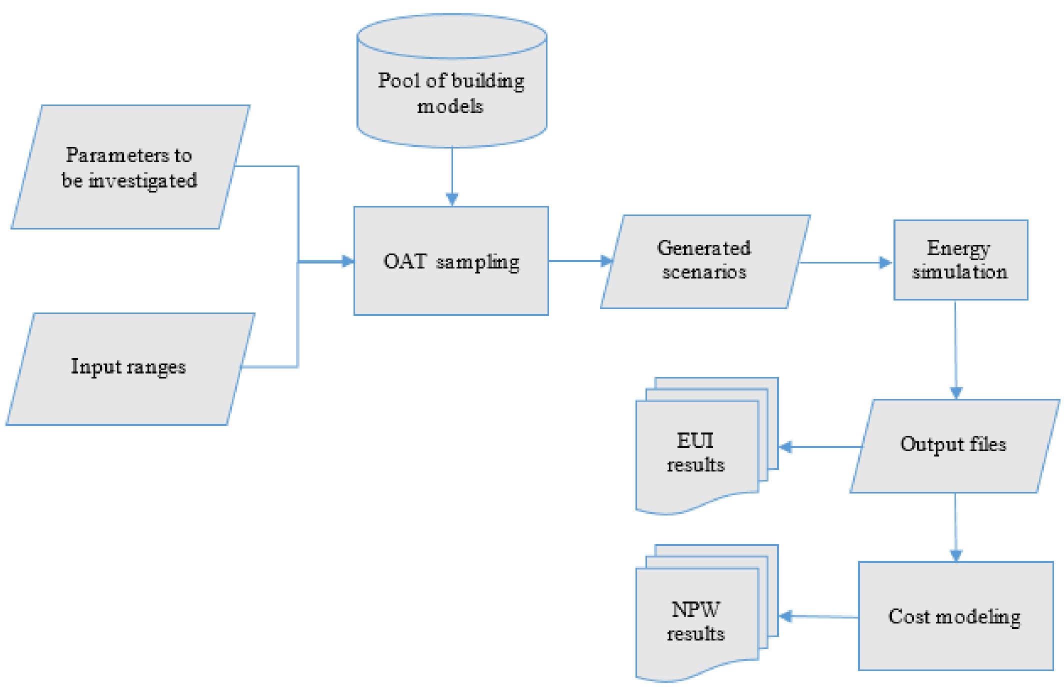


Figure 3.7: Output generation flow chart

(3.6.4) Output analysis

The two main contributions of this section are the selection of the significant parameters, in terms of both EUI and NPW, as well as the creation of hypotheses that explain the cause root of parameters' sensitivity to the building model. To achieve these, the previously generated output dataset must go through two analyses: evaluation of the sensitivity of building performance (energy and cost) to the previously selected design parameters, including lighting and HVAC systems (a method similar to RO1); and the sensitivity of parameters' impact to the analyzed model. The process of analyzing outputs is shown in Figure 3.8.

As seen in the flowchart, the first step (Figure 3.8 a) is to run both the EUI and NPW outputs through a significance test. Parameters that show to be nonsignificant in both analyses (EUI and NPW) are then set aside for the next step (Figure 3.8 b). Significant parameters are then classified (as "low impact"; "medium-low impact"; "medium-high impact"; or "high impact") based on their impact rankings in each case study models. That enables the investigation of the stability of such results in various building models (RO 3). In other words, the sensitivity of the findings (in terms of high/low impact parameters) to the building models is evaluated based on their respective models. For this purpose, those parameters that steadily appear in the same class are considered non-sensitive to the building model; and should be set aside. To then investigate the cause root of parameters' sensitivity to the models, the entire two-step analysis is performed by dividing the analyzed buildings into groups with different characteristics (e.g. low- and high-rise buildings).

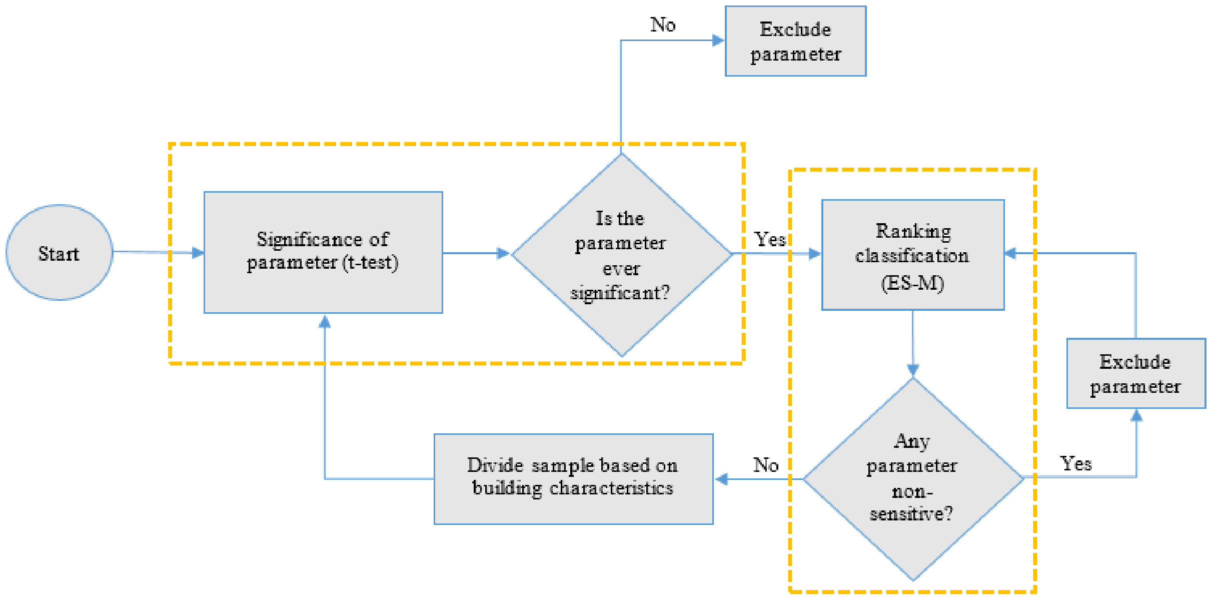


Figure 3.8: Output analysis flowchart (a: sensitivity of building performance to the design parameters; b: sensitivity of parameters' impact on the building model)

Significance of Parameters

To test the significance of the impact for each design parameter, t-tests were conducted (considering both energy and cost outputs separately). Each test analyzes one parameter at a time. The method used to perform the t-test was a single sample upper-tailed test with a 95% confidence level, where the null hypothesis is Ho: $\mu \leq x$ (i.e. the true mean 'μ' of the sample is less than or equal to the comparison value 'x') and the alternative hypothesis is Ha: $\mu > x$ (i.e. the true mean 'μ' of the sample is greater than the comparison value 'x'). In this study, 'x' is the necessary variation in EUI that a parameter needs to cause to be considered to have a significant impact. Based on Beguery et al. (2015), the minimum energy consumption increase to be considered to have a significant impact is 3% [71]. On the cost side, however, no representative values were found in the literature. Thus, a set of 'x' values (0.5% to 10% in 0.5 intervals) were tested to find the appropriate threshold to be used in the analysis of NPW. The selected threshold must have the same level of significant parameters as the EUI t-test. This range remains within the conservative bound of Class 1 estimate, introduced by AACEI, and is taken as a notion of the desired level bound of confidence on cost estimates [80]. The null hypothesis must be rejected to say that the parameter has a statistically significant impact on the output. Parameters that show to be nonsignificant to both energy and cost performances are excluded for the remainder of this analysis.

Ranking Classification

The remaining parameters were then ranked based on the range existing between their minimum and maximum values (percentage increase from the minimum to maximum). Their normalized ranges for each model were graphed versus their respective rankings, and that allowed for the proper and proportional classification between the four different levels of impact (the four classes introduced earlier). This classification was done through the Extended Swanson-Megill (ES-M) discretization method [81], which is a 3-point discretization method that weights the 10th, 50th, and 90th percentiles of a continuous distribution function (in this case ranking vs. normalized impact). The different levels of impact were quantitatively set as high impact (parameters found to be above 0.9 percentile), medium-high impact (parameters located in between 0.5 and 0.9 percentiles), medium-low impact (parameters located in between 0.1 and 0.5 percentiles), and low impact (parameters found to be below 0.1 percentile).

The sensitivity of parameter impact on the investigated models was evaluated based on the frequency distribution of impact groups for each parameter. If a parameter was always found to be in one impact group, that parameter is considered non-sensitive to the building model. If the parameter ranges between two different levels, it is considered to be slightly sensitive to the analyzed case. And, if they range from three or four different levels, they are considered sensitive and very sensitive, respectively.

3.7) Hypothesis evaluation

To verify the previously developed hypotheses, linear correlation analyses (through Pearson correlation [82]) were performed. The objective of this analysis was to see if there is an existing correlation between the hypothesized attributes and the impact of design parameters. This hypotheses investigation analysis is being done in two parts, the first part uses OAT sampling and the second uses Monte Carlo sampling (global method). The OAT correlation analysis (using OAT sampling) utilizes the output data from the previous data analysis, while the global correlation analysis (using Monte Carlo sampling) required the development of a new dataset of building scenarios.

In Pearson correlation analysis, values ranging from 0 to ±0.2 are usually considered to not show any correlation; ±0.2 to ±0.4 to have weak correlation, ±0.4 to ±0.6 some correlation, ±0.6 to ±0.8 strong correlation, and ±0.8 to ±1 are considered to have a very strong correlation.

In this analysis, however, the conclusion will be drawn based on three main levels of correlation: no correlation (0 to ±0.4), some correlation (±0.4 to ±0.6), and strong correlation (±0.8 to ±1).

(5.7.1) Global sampling

Based on the design parameters found to have a significant impact on the building models' performance (EUI and NPW) as well as the ones found to be sensitive to the building models, a new dataset of scenarios was generated through Monte Carlo sampling [83]. Monte Carlo sampling method, differently from OAT, varies all analyzed parameters when creating a new scenario. The variation of each input parameter is based on random sampling of a uniform distribution.

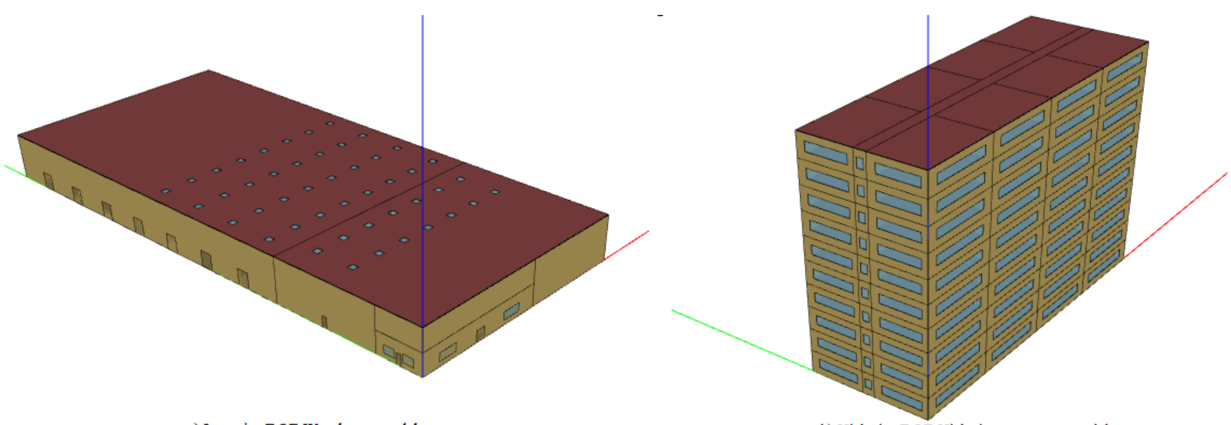
During this study, the scenarios for global analysis were generated through a system developed by [11]. In this system, the user inputs different alternatives to each design parameter, and the scenarios are automatically generated based on every possible combination of design alternatives. Since the system does not support a random scenario generation feature, the values inputted to the system were selected in random form.

Chapter 4 – Implementation

This chapter focuses on the implementation of the methods presented in the previous chapter, their results, and discussion. The start of the chapter will provide details on the case studies analyzed, followed by the results and a discussion on the sensitivity of EUI and NPW to energy influential design parameters. Then, the level of sensitivity of those parameters to the case studies used is examined (as the original contribution of this study). And finally, several hypotheses are developed to explain the changes in parameters' behaviors from one model to another.

4.1) Pool of case studies

To cover a wide range of designs, this analysis is taking into consideration 26 building models (a collection of both real-world projects and reference building models presented in ASHRAE 90.1 2013 [84]) in which 13 are low-rise and 13 are high-rise. According to Barlett et al. (2003), low-rise buildings are defined as buildings with 3 stories or less, and the remaining are defined as high-rise buildings [85]. The model files were provided by two different sources: the building energy consultant Akonovia, and DOE [86]. The idea is to cover a wide enough range of buildings while excluding low-rise residential buildings. An example of low-rise and high-rise buildings can be seen in Figure 4.1.



a) Low-rise DOE Warehouse model

b) High-rise DOE High-rise apartment model

Figure 4.1: Example of low- and high-rise buildings used in this study

Models provided by Akonovia vary between single and multi-use buildings. Multi-use buildings are the buildings with more than one building type (Table 3.7), for example, a building that contains retail areas as well as dining areas. The cases present a variety of building types and rises. Details of all building models provided by Akonovia can be seen in Table 4.1. In the table, the details of each building model's geometry and building types are displayed. Geometry characteristics include the number of stories and building rise (low- or high-rise depending on the number of stories), as well as the measurements related to the building height, the summation of the entire building floor area, and finally, the roof and wall areas (surfaces where roof and wall insulation are added respectively).

Table 4.1: Akonovia models details (modified from [70])

BUILDING MODEL NAME	NUMBER OF FLOORS	RISE	HEIGHT (m)	GROSS FLOOR AREA (m^2)	ROOF AREA (m^2)	EXTERIOR WALL AREA (m^2)	BUILDING TYPE(S)
Clinique Dentaire	2	Low-rise	8.02	1005.35	537.35	634.62	Health care clinic
Poly St	10	High-rise	40.42	16500.26	5525.22	7919.33	School/university
Capwood	18	High-rise	57	39922.74	3127.77	9450.09	Dining: cafeteria/fast food, health care clinic, office, multi-unit residential building, storage garage
Arch TP	8	High-rise	37.82	776.29	325.63	476.04	Office
Arch Vit	8	High-rise	37.82	776.28	325.63	476.04	Office
Arch VRF	8	High-rise	37.82	776.29	325.63	476.04	Office
Copie 25	8	High-rise	49.93	5947.02	5477.19	4818.32	Gymnasium, Dining: cafeteria/fast food
Copie 27	8	High-rise	49.93	5952.20	5477.19	4818.32	Gymnasium, Dining: cafeteria/fast food
Islo 5	2	Low-rise	8.5	6690.13	2996.87	2034.11	Exercise center, health care clinic

ASHRAE 90.1 reference buildings used by this study have been developed by the U. S. Department of Energy (DOE) and three of its national laboratories, in collaboration with the ANSI/ ASHRAE/ IES Standard 90.1. These 17 models represent about 80% of the commercial (and high-rise residential) floor area in the United States [86]. In this pool of models, there are 11 low-rise and 5 high-rise buildings. Details of the investigated models can be found in Table 4.2.

Table 4.2 DOE models and details

BUILDING MODEL NAME	NUMBER OF FLOORS	RISE	HEIGHT (m)	GROSS FLOOR AREA (m^2)	ROOF AREA (m^2)	EXTERIOR WALL AREA (m^2)	BUILDING TYPE(S)
Full-Service Restaurant	1	Low-rise	3.05	510.97	569.50	228.54	Dining: family
High-Rise Apartment	10	High-rise	30.48	7836.55	783.64	2704.59	Multi-unit residential building
Hospital	5	High-rise	25.62	22422.23	4353.16	6524.30	Hospital
Large Hotel	6	High-rise	19.21	11345.31	1978.83	4580.58	Hotel/motel
Large Office	12	High-rise	51.48	46320.32	3563.11	6953.70	Office
Medium Office	3	Low-rise	11.88	4982.20	1660.73	1324.80	Office
Mid-Rise Apartment	4	High-rise	12.2	3134.55	783.64	1235.15	Multi-unit residential building
Outpatient	3	Low-rise	9.15	3804.01	1373.29	1224.28	Health care clinic
Primary School	1	Low-rise	3.96	6871.11	6871.01	1632.86	School/university
Quick Service Restaurant	1	Low-rise	3.05	232.26	258.83	159.89	Dining: cafeteria/fast food
Retail Stand-alone	1	Low-rise	6.1	2319.05	2270.18	1093.10	Retail area
Retail Strip Mall	1	Low-rise	5.18	2090.32	2090.32	1013.29	Retail area
Secondary School	2	Low-rise	7.92	19592.03	11768.21	3879.17	School/university
Small Hotel	4	High-rise	11.57	4013.41	1003.35	1510.42	Hotel/motel
Small Office	1	Low-rise	3.05	510.97	598.76	221.85	Office
Supermarket	1	Low-rise	6.1	4180.64	4145.15	1109.91	Retail area
Warehouse	1	Low-rise	8.53	4835.14	4529.86	2411.67	Warehouse

4.2) Sensitivity of EUI and NPW to input parameters

To analyze the sensitivity of outputs (EUI and NPW) to the studied energy influential parameters, the range of outputs for each parameter (minimum and maximum) were considered separately for each model. The significance of the impact of each parameter for each output was statistically tested (through a t-test) to evaluate whether the selected parameters are significant enough to be considered in the development of a recommender system. The t-test was based on the percentage increase in the output (from minimum to maximum value), caused by each parameter in each model, over the 26 models, while using a range of significance threshold from 0.5% to 10% for both EUI and NPW ((3.6.4) Output analysis section). The purpose of testing a range of threshold values is to find the appropriate value to be used in testing the significance of NPW (i.e. threshold with the same level of significant parameters as the 3% value used for the EUI t-test) ((3.6.4) Output analysis section). Results for both EUI and NPW are reported in Figure 4.2.

Parameters in order of significance		Significance threshold (increase from EUI_{min} to EUI_{max} %)																			
		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10
1	HVAC	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.
2	WWR North	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.
3	WWR West	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.
4	WWR East	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
	Lighting Efficiency	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
5	WWR South	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
6	Window Type	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
7	Roof Insulation	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
8	Wall Insulation	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
9	Lighting Type	N.S.	N. S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.

Parameters in order of significance		Significance threshold (increase from NPW_{min} to NPW_{max} %)																			
		0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10
1	HVAC	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.
2	WWR North	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.
	WWR South	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.
3	WWR West	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
4	WWR East	S.	S.	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
5	Window Type	S.	S.	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
6	Lighting Efficiency	S.	S.	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
7	Roof Insulation	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
	Wall Insulation	S.	S.	S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
9	Lighting Type	S.	N. S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.

Figure 4.2: Results of t-test for based on a range of thresholds (a: EUI output; b: NPW output)

In Figure 4.2, details of t-tests' results are shown for all analyzed thresholds. There, it is observable that HVAC is always the top parameter in the order of significance for both EUI and NPW. Following the HVAC parameter are the window to wall ratios in both EUI and NPW. The order of WWR parameters in terms of façade, however, appears to be different in the two analyses, which could be because most south side walls are larger than east and west, increasing the installation cost and therefore making WWR south more significant in terms of NPW. After WWR, window type and lighting efficiency are the parameters that follow. In the significance ranking based on EUI, lighting efficiency is placed higher but, when considering NPW, window type appears to be more significant. This slight shift is explained by a major cost increase of installing more efficient lighting, the installation costs overrules the energy savings. Finally, the last three parameters in terms of significance are roof insulation, wall insulation, and lighting type. They maintain their spots in both EUI and NPW rankings.

To better analyze the behavior of both EUI and NPW in terms of significance test (t-test), the ratio of significant parameters was analyzed against the tested threshold values (Figure 4.3). While EUI is slightly more sensitive than NPW, due to its greater slope, their distributions show very similar levels of linear behavior (linear with R^2 = 0.9342 for EUI and 0.9414 for

NPW). Thus, based on the used 3% threshold for the EUI significance test (found in the literature [71]), the appropriate NPW threshold (i.e. with the same level of significant parameters as the 3% value used for EUI) to be used in this study is 1.5%.

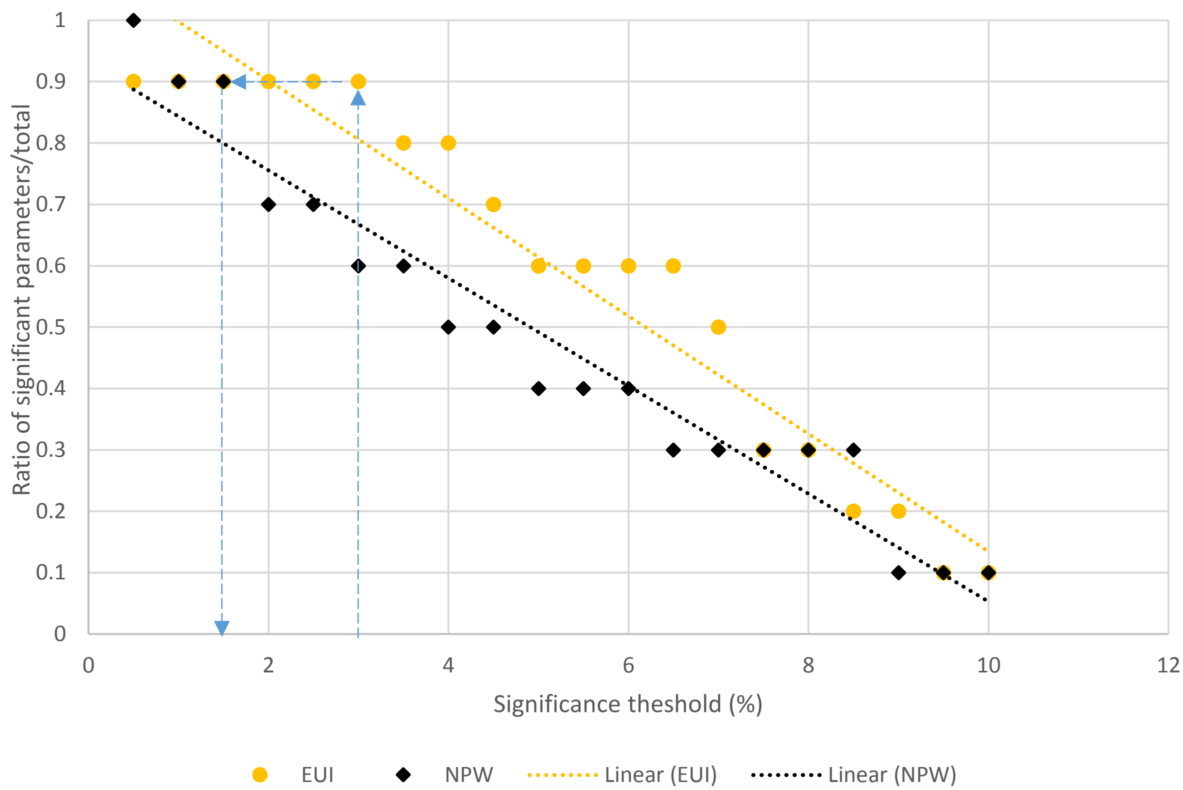


Figure 4.3: Frequency distribution for a range of t-test thresholds

Based on the selected thresholds to be used to analyze EUI and NPW, decisions were taken based on the parameters' significance. The EUI and NPW results have shown that all architectural and HVAC system parameters appear to impact the output significantly (Figure 4.2). For the lighting systems, however, only the lighting efficiency aspect was found to have a significant impact. The lighting type is the only parameter that shows a nonsignificant behavior. Due to its small impact in both EUI and NPW, it was decided that the lighting type parameter will not be considered for the remainder of this analysis.

4.3) Sensitivity of parameters to case studies

The previous section contributed to highlighting building energy influential parameters from two important aspects of energy consumption and cost. It also provided an overall order of parametric significance. Though, based on this analysis, it is not possible to say whether a parameter's level of impact will remain invariant from one case to another. To be able to answer this question, the parameters were classified based on their level of impact.

To begin assigning the level of impact for each parameter (in every model), both the percentage increase in the output and their respective rankings were considered. To divide the parameters based on their respective levels of impact, the 3-point discretization method (ES-M) was used ((3.6.4) Output analysis). This method's technique involves the division of continuous distributions at 0.1, 0.5 and 0.9 percentiles. In this analysis, the relationship between the ranking of the parameters and their normalized impact on the output (for each model) is being discretized (Figure 4.4). The classification of each parameter in every model depends on which area of the continuous distribution they were located in. In the graphs (Figure 4.4), each dot represents a different parameter and the impact level areas are divided between 0 to 0.1 percentile (low-impact), 0.1 to 0.5 percentile (mid-low impact), 0.5 to 0.9 percentile (mid-high impact), and 0.9 to 1 percentile (high-impact).

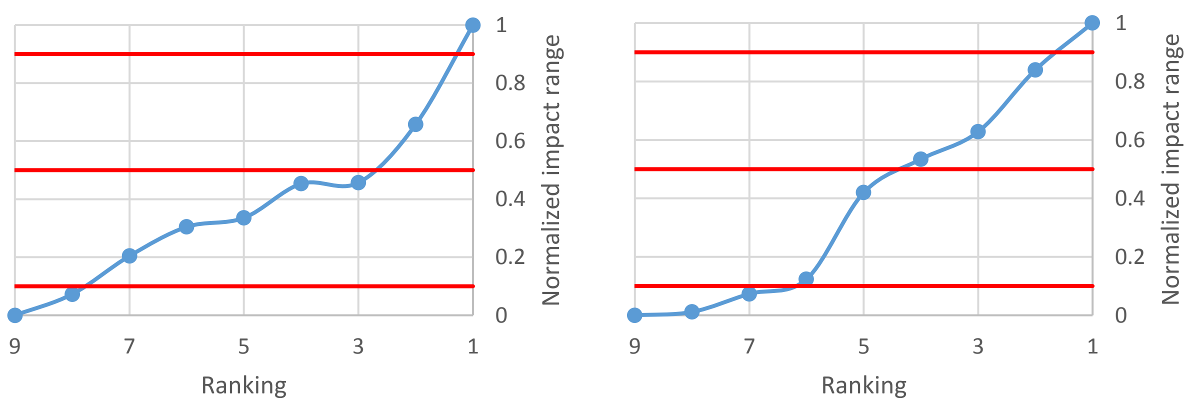


Figure 4.4: 3-point discretization procedure for parameter classification, through ES-M method, for Retail Standalone model (a: EUI; b: NPW)

After classifying all the significant parameters based on their impact level, it was noted that, for both EUI and NPW results, the HVAC type is always in the high impact class (graph can be found in Appendix 2). The invariance of HVAC type significance leads to the conclusion that this parameter's level of impact is not sensitive to the investigated building model. For that reason, the remainder of this analysis will exclude the HVAC type parameter (by adding it to the list of very high-impact parameters in all building types). The same classification procedure was then repeated without the HVAC system type parameter.

After reclassifying the remaining parameters (into the four groups of high, mid-high, mid-low and low impact), the results show that no other parameter remains completely invariant (in terms of the level of impact) among different models. Therefore, it is then possible to analyze the level of impact of each parameter and evaluate their sensitivity to the building model. The frequency distribution of each parameter in their respective levels is represented in Figure 4.5. There, it was observed that all parameters show at least some level of sensitivity, due to their appearance in multiple levels of impact. The graph also shows that a few parameters, such as WWR north and roof insulation, appear in fewer impact groups from the viewpoint of NPW (compared to EUI). The opposite happens to wall insulation and WWR east, which leads to a suggestion that the sensitivity of certain parameters might differ depending on the analyzed output (EUI or NPW).

The given classification results show that the impact of energy influential design parameters (except for HVAC system) is sensitive to the analyzed case study. This sensitivity suggests that different building characteristics, which are not the energy influential design parameters, also influence the energy and cost performance of a building. More specifically, different building characteristics (to be investigated in the following section) can control the level of impact that energy influential parameters can have on building performance.

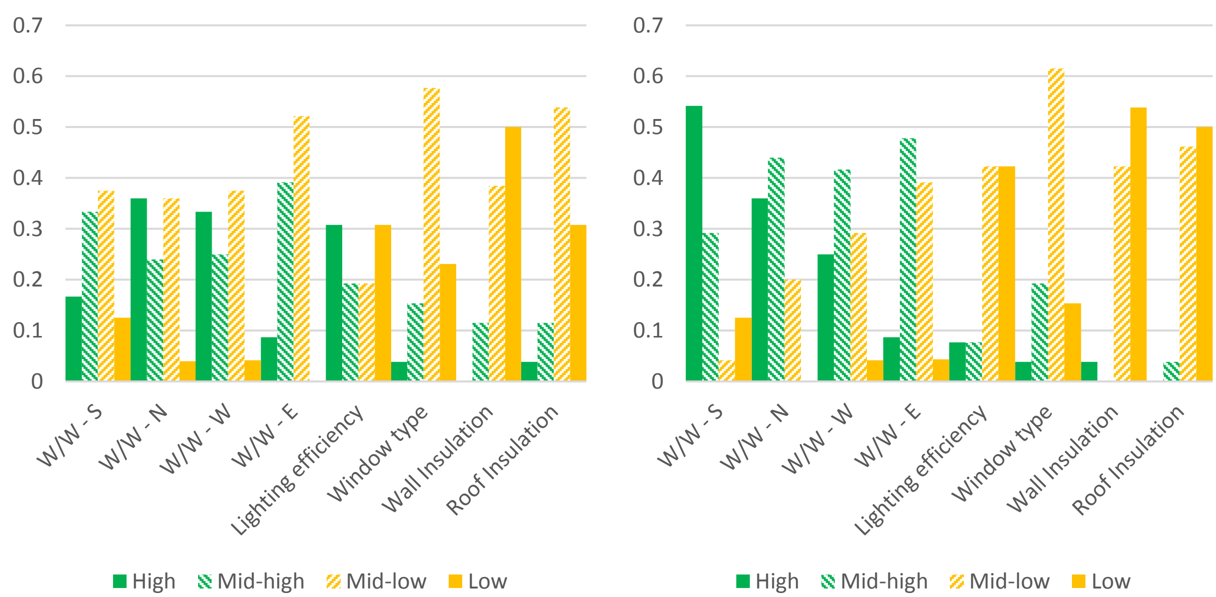


Figure 4.5: Frequency distribution of impact classes after excluding the HVAC system parameter (a: EUI; b: NPW)

4.4) Investigation of parameters' sensitivity in different groups of buildings

To identify which building characteristics are more strongly correlated with differences in behavior, the same procedure of analyses (from sections 4.2 and 4.3) was repeated within different subsets of data, split based on various building characteristics. The first grouping was splitting the models based on their rise (low- and high-rise), while the second grouping was dividing buildings based on their energy consumption profile (low and high heating consumptions).

(4.4.1) Building rise

As previously mentioned, low-rise buildings are defined as buildings with 3 or fewer stories. By dividing the analyzed cases into low- and high-rise buildings, the two samples are left with 13 building models in each, which forms a balanced dataset.

Statistical Significance

The same procedure used in previous sections for testing significance was performed for low- and high-rise buildings separately. Based on the investigation of thresholds 3% and 1.5% for EUI and NPW respectively, significant parameters were identified. The analysis results for both EUI and NPW can be found in Table 4.3.

Table 4.3: EUI (3% threshold) and NPW (1.5% threshold) t-test results for low- and high-rise buildings

Parameter	**EUI**		**NPW**	
	Low-rise	**High-rise**	**Low-rise**	**High-rise**
Wall Insulation	N.S.	S.	N.S.	N.S.
Roof Insulation	S.	N.S.	S.	N.S.
WWR South	S.	S.	S.	S.
WWR North	S.	S.	S.	S.
WWR East	S.	S.	S.	S.
WWR West	S.	S.	S.	S.
Window Type	S.	S.	S.	S.
Lighting Efficiency	S.	S.	S.	S.
HVAC	S.	S.	S.	S.

By analyzing the results of significance tests, two cases of change when moving from low- to high-rise buildings were noticed. 'Wall insulation' shows a nonsignificant behavior in low-rise and significant in the high-rise, while 'roof insulation' has the opposite behavior. This shift in the results of these two parameters suggests that building attributes related to rise may contribute to the difference in the behavior of design parameters. This variation can also be explained by the relative size of the component (where insulation is applied) in comparison with the body of the building. For example, if a building is very tall and narrow, the insulation added to the small roof area will have a lower impact than the insulation added to a short building which has a horizontal spread. The same explanation goes for other insulation parameters, such as wall and window.

The NPW results, on the other hand, have only one difference between low- and high-rise; ‘roof insulation’ is a significant parameter in the low-rise group and nonsignificant in the high-rise. This variation can be also explained with the same principle as the energy performance results. On the wall insulation, however, the parameter reacts differently when compared to the EUI results. It shows to be nonsignificant for both low- and high-rise buildings. That is probably due to the installation costs of the walls. With a relatively large surface area in comparison to the roof, the construction cost becomes large as well in both cases, which decreases the impact caused by the added insulation.

Ranking Classification

To evaluate the sensitivity of parameters to models within the analyzed groups, the same procedure used in section 4.3 was followed. The resulting frequency distributions of each parameter based on EUI is presented in Figure 4.6. The distributions show that, regardless of the building’s rise, most parameters are still very sensitive to the analyzed building model. This suggests that more building characteristics (than only the rise) influence the performance behavior of energy influential parameters; thus, other building characteristics should be investigated too. The graphs also show that window parameters such as window type and window to wall ratio (which can also influence the indoor temperature of a building) generally have a higher impact than wall and roof insulation. This may suggest that, even though window parameters are significant, they can still be impacted by the same building attributes that impact roof and wall insulation (i.e. the relative size of the component in comparison with the body of the building).

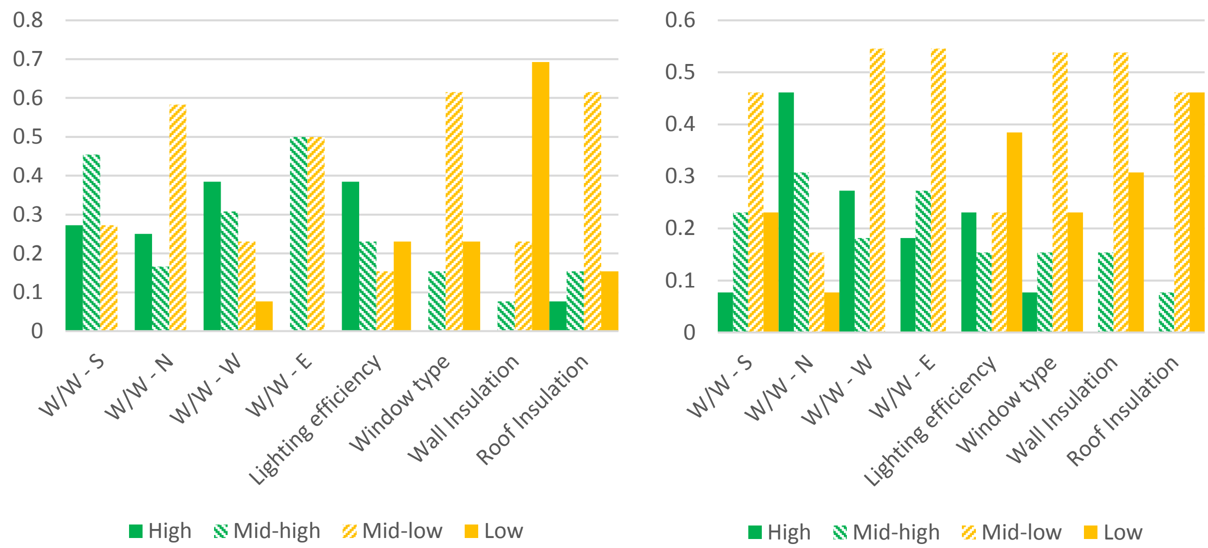


Figure 4.6 EUI frequency distribution for different building groups (a: low-rise; b: high-rise)

The same analysis was carried out on NPW. The frequency distributions of each parameter based on NPW impact can be seen in Figure 4.7. Like the significance test, the distribution graph shows that wall insulation is the least sensitive parameter in both low- and high-rise buildings. Also like the previous test, the high-rise roof insulation parameter appears to be slightly sensitive. The remaining parameters, on the other hand, are either sensitive or very sensitive to the analyzed building models in at least one of the two building groups. This suggests that for NPW too, more building characteristics (than building rise) must be investigated to explain the behavior of energy-efficient parameters.

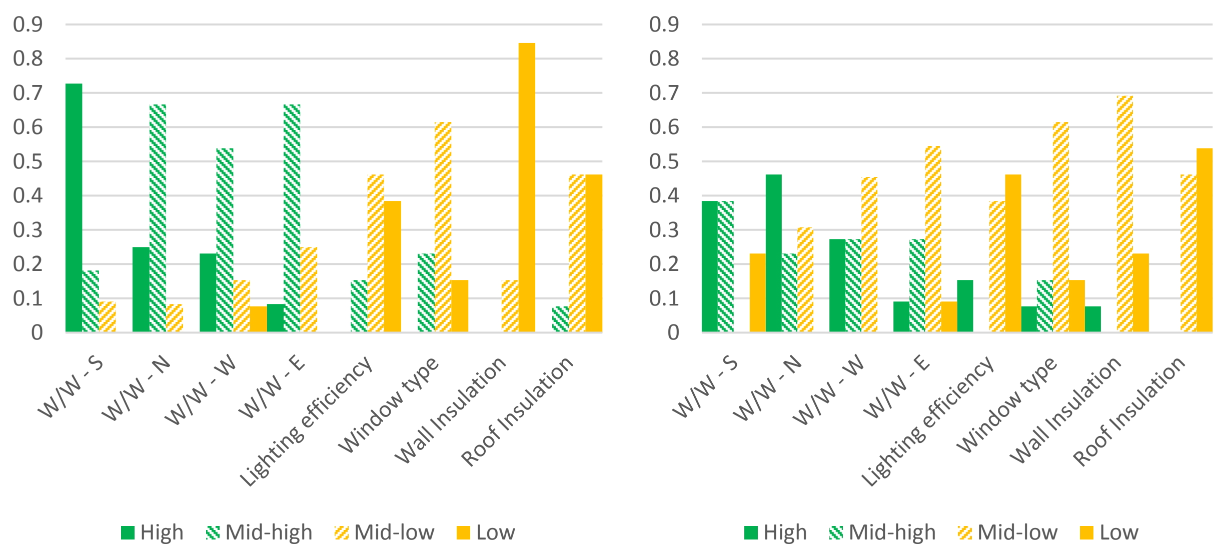


Figure 4.7 NPW frequency distribution for different building groups (a: low-rise; b: high-rise)

(4.4.2) Energy consumption profile

Buildings can be grouped based on the similarity of their energy consumption profiles (i.e. the similarity in fractions of energy being used in for different purposes). In this study, since the focus is on buildings in cold climates, the percentage of energy consumed for heating purposes is the main representative of the energy profile. Buildings that use a considerable amount of energy for other equipment (e.g. hospital's exam machines) consequently have a lower percentage of their energy going to heating, which normally depends on the activities happening in the building (building types). In this analysis, buildings are separated between those with more than 50% of their energy being used for heating purposes (high heating consumption), and buildings with 50% or less used for heating (low heating consumption). By dividing the model's dataset, the samples are left with 14 building models in the high heating consumption group and 12 building models in the low heating consumption group.

Statistical Significance

Once Again, by using the same procedure previously explained, the significance test was performed for both low and high heating consumption sub-sets. The results of both analyses for EUI and NPW are found in Table 4.4. By analyzing significance test results for both low and high heating consumption groups, it is noticeable that three parameters have different behaviors within the different groups. Wall insulation, roof insulation, and window type parameters have a nonsignificant EUI behavior when a lower percentage of the building energy is used for heating purposes. All three mentioned parameters can impact the energy consumption of a building because of their ability to retain heat in the building. Therefore, if a low percentage of energy is going to heating, then, consequentially, lower will be the impact of parameters that also influence the heating performance.

Table 4.4: EUI (3% threshold) and NPW (1.5% threshold) t-test for low and high heating percentage buildings

Parameter	EUI		NPW	
	Low heating consumption	High heating consumption	Low heating consumption	High heating consumption
Wall Insulation	N.S.	S.	N.S.	S.
Roof Insulation	N.S.	S.	N.S.	N.S.
WWR South	S.	S.	S.	S.
WWR North	S.	S.	S.	S.
WWR East	S.	S.	S.	S.
WWR West	S.	S.	S.	S.
Window Type	N.S.	S.	S.	S.
Lighting Efficiency	S.	S.	S.	N.S.
HVAC	S.	S.	S.	S.

The NPW analysis shows similar behavior. In the low heating consumption, both roof and wall insulations remain nonsignificant for the same reasons as the one discussed in the EUI analysis. Window type, in this case, shows to be significant, which is the case due to its installation costs. In the high heating consumption group, wall insulation and lighting efficiency appear to be nonsignificant. The wall insulation is not a surprise since it has often shown a nonsignificant behavior when analyzing NPW. Lighting efficiency, on the other hand, appears to be nonsignificant in terms of cost, because when the high percentage of energy is focused on heating, lower will be the percentage used for lighting, which translates into lower energy impact.

Testing the significance of parameters in the two types of building profiles made it possible to understand a new type of building characteristics that can influence the impact behavior of design parameters. Though the consumption profile (percentage of energy allocated to each use) is not a known numeric parameter at the early stages of design, the building type (Table 3.7) can provide a general idea of the building's consumption profile.

Ranking Classification

The same procedure used in previous sections for classifying the impacts of parameters was performed for low and high heating consumption buildings separately. EUI results (Figure 4.8) show that, in the high heating consumption group, all parameters' impact is highly sensitive to the analyzed case study. In the low heating percentage group, on the other hand, insulation parameters show much lower sensitivity. Meanwhile, the lighting efficiency parameter shows the opposite behavior. Similar behavior can be seen in the NPW analysis (Appendix 2).

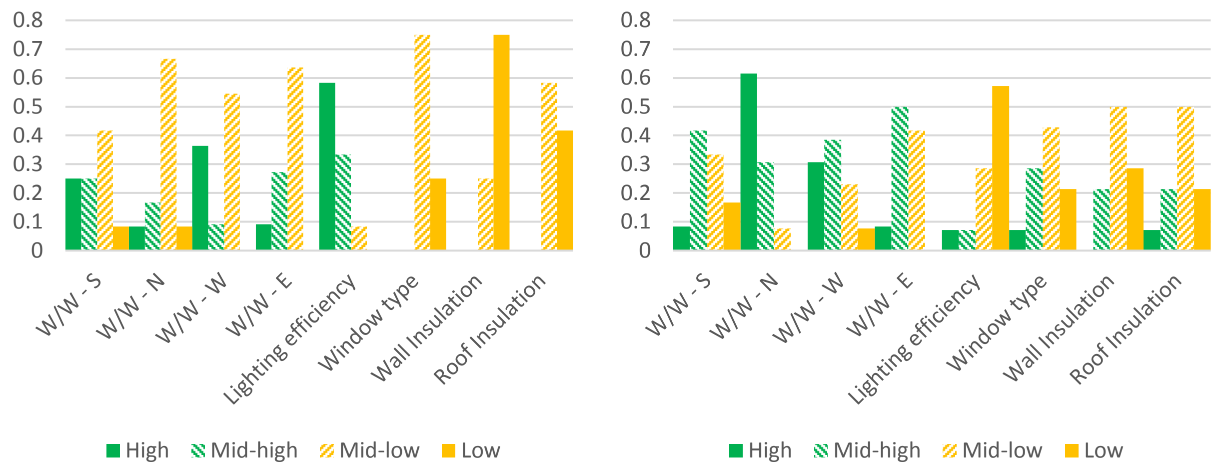


Figure 4.8: EUI frequency distribution for different building groups (a: low heating; b: high heating)

4.5) Hypotheses

Based on the findings of previous sections, three main categories of building attributes that influence the significance of design parameters in controlling building energy performance were identified. For each category, a set of specific building characteristics is being suggested as important characteristics for analyzing the behavior of building parameters. The three main categories of attributes are building rise, proportions of horizontal and vertical external enclosure, and energy consumption profile. For each category, different attributes are being considered that are believed to represent the discussed impacts on parametric behavior. Details of attributes, their categories and the design parameters that they are believed to influence are displayed in Table 4.5.

Table 4.5: Summary of hypotheses

Category	Attributes	Unit	Affected parameters
Building rise	Number of stories	N/A	Wall insulation and roof insulation
	Height	m	
Proportions of the horizontal and vertical external enclosure	Wall area/ Roof area	N/A	Wall insulation, roof insulation, and window type
	Number of stories/ Roof area	m^{-2}	Roof insulation
	Height/ Roof area	m^{-1}	
	Volume/ Roof area	m	
	Number of stories/ Wall area	m^{-2}	Wall insulation and window type
	Height/ Wall area	m^{-1}	
	Volume/ Wall area	m	
	South/ North/ East and West Wall area/ Total external wall area	%	WWR South / North / East and West
	South/ North/ East and West wall area/ Volume	m^{-1}	WWR South / North / East and West
Energy consumption profile	Heating %	%	Wall insulation, roof insulation, window type, WWR (all facades), and lighting efficiency

In the next chapter, the contribution of each of these characteristics to the impact of the affected parameters is investigated.

Chapter 5 – Evaluation and Discussion

In this chapter, the contribution of each of the above-mentioned characteristics to the impact of the affected parameters is being investigated, while ignoring the correlation among design parameters. The first part of the chapter will provide the details of the correlation analyses performed based on OAT sampling. Next, the details of correlation analyses performed based on global sampling will be shown. Then, finally, a summary of the hypotheses verification along with the suggested attributes to be considered by the recommender system will be discussed.

5.1) Correlation Analysis with OAT Sampling

This section is displaying the results of correlation analyses based on scenarios generated through OAT sampling. Based on the attribute categories highlighted in Table 4.5, this section is being divided into 3 main sections: building rise; proportions of horizontal and vertical external enclosure; and energy consumption profile. Some graphs displaying the analyzed data points are shown throughout the sections, the remainder are shown in Appendix 3.

(5.1.1) Building Rise

Based on the hypotheses summarized in Table 4.5, this section is investigating the attributes that fit into the 'Building rise' category. Both, the number of stories and the building height were analyzed in terms of EUI and NPW. To test the developed hypotheses, a linear correlation (Pearson) analysis was performed to investigate the relationship between the building attributes and the impact caused by changing roof and wall insulations (separately).

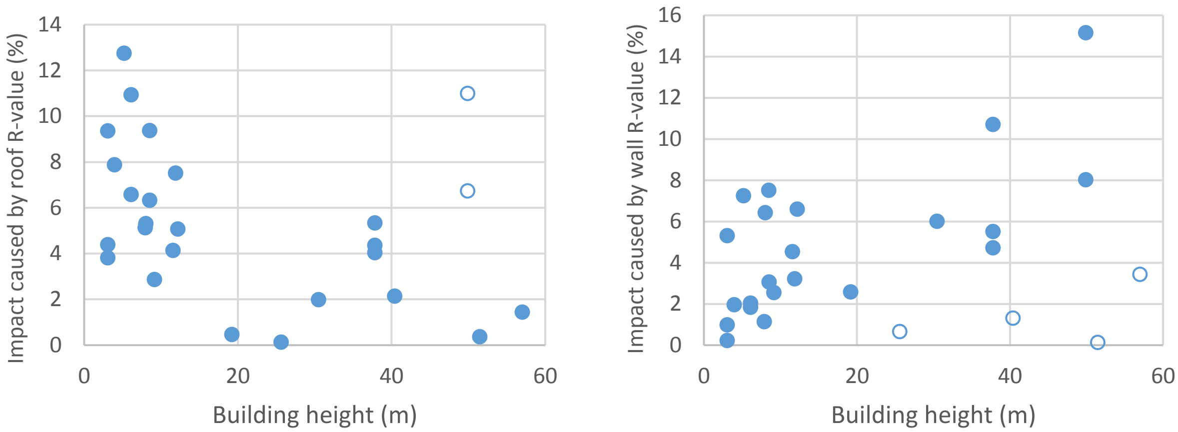


*Figure 5.1: Correlation of EUI impact due to building height (a: roof impact; b: wall impact) *blank datapoints represent outliers*

In terms of EUI, roof and wall insulation impact show a strong correlation with building rise attributes. Roof insulation has a strong negative correlation with both 'number of stories' and 'building height', which means that taller buildings are less impacted by the variation of roof insulation R-value, in comparison to shorter buildings. On the other hand, wall insulation shows some positive correlation with the 'number of stories' and strong positive correlation with building height, which means that the variation of wall insulation shows a greater impact on taller buildings.

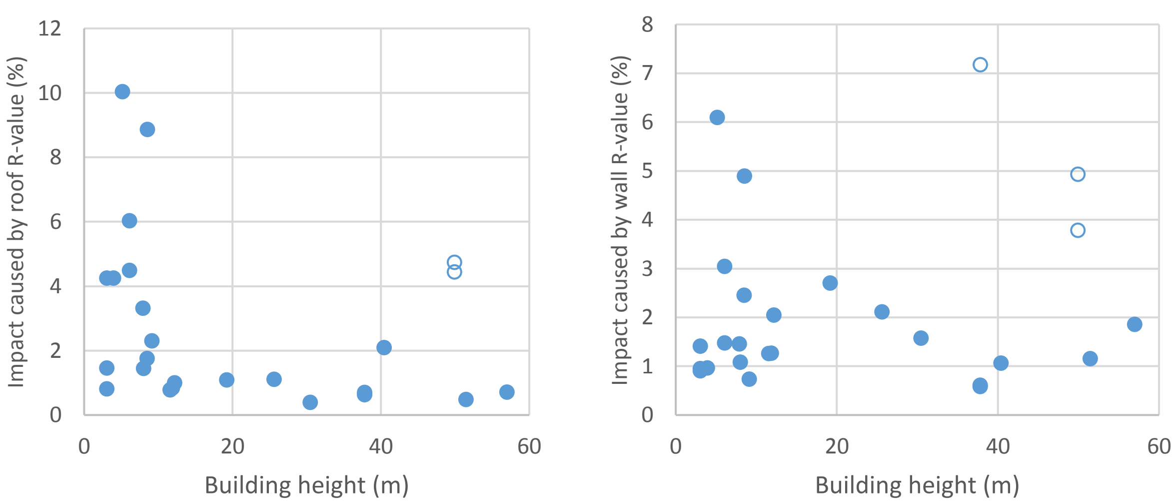


*Figure 5.2: Correlation of NPW impact due to building height (a: roof impact; b: wall impact) *blank datapoints represent outliers*

When it comes to NPW, some negative correlation is observed when considering the impact of the roof insulation onto the building rise attributes while a weak negative correlation was shown with wall insulation. Though the roof insulation parameter results are very similar when comparing EUI to NPW, the wall insulation results show a drastic shift, it goes from positive to negative correlation. The negative correlation behavior found in the NPW analysis shows that wall insulation has a lower impact on taller buildings, which happens due to the large installation costs spent to have wall insulation in the entire building. Details of Pearson correlation values can be found in Table 5.1. The discussed findings suggest that the building rise details in the form of the number of stories and/ or building height do affect the impacts caused by the application of energy influential parameters.

Table 5.1: Building rise attributes' Pearson correlation values for EUI and NPW impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	**Affected parameters**	**EUI**	**NPW**
Number of stories	Roof insulation	-0.65	-0.51
	Wall insulation	0.57	-0.23
Height	Roof insulation	-0.61	-0.48
	Wall insulation	0.69	-0.24

(5.1.2) Proportions of the horizontal and vertical external enclosure

The second group of building attributes investigated in this study is enclosed in the ‘proportions of horizontal and vertical external enclosure’ category. As seen in Table 4.5, these attributes can influence the impact of a variety of design parameters including roof insulation, wall insulation, window type, and window-to-wall ratio. This section is divided into 6 subsections. The first 5 will be covering details of correlation analysis results for each building attribute. Those include wall area/ roof area; roof area related attributes; wall area related attributes; percentage area for façades compared to overall wall area; and relative area of façades compared to building volume. The last subsection of this chapter provides a summary of the discussed results.

Wall Area/ Roof Area

As previously mentioned, there are 3 design parameters influenced by the ratio of the wall over roof area: roof insulation, wall insulation, and window type. When considering the EUI data, both roof insulation and window type show a strong correlation with ‘wall area/ roof area’, negative strong correlation with roof insulation and positive with window type. When looking at wall insulation, on the other hand, some positive correlation was found after setting aside (as outliers) buildings with 10 stories or more, which suggests that these might need to be analyzed separately from the rest of the buildings.

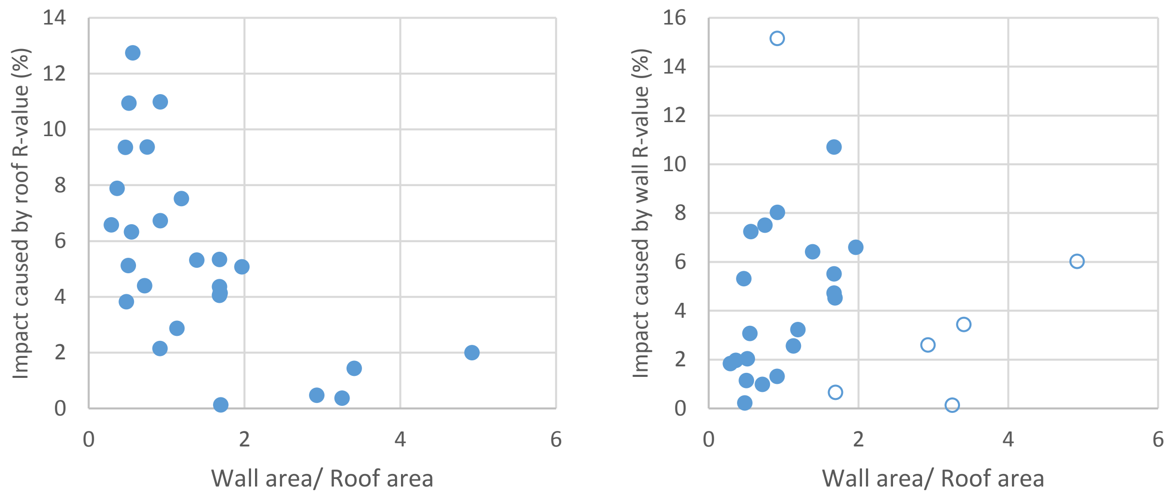


Figure 5.3: Correlation of EUI impact due to ratio of wall area over roof area (a: roof impact; b: wall impact)
**blank datapoints represent outliers*

Similarly, to the previously analyzed attributes, the NPW results show less correlation than EUI. That can be explained by the nonlinear behavior of the building cost performance. In this case, the roof impact still shows a strong correlation with the ratio attribute while both wall insulation and window type show no correlation. Also like it was discussed in the previous section, the installation costs of wall components (wall insulation and window type) highly impact the building's cost performance, affecting the level of correlation with the ratio between wall and roof areas.

Roof Area Related Attributes

While analyzing the size of the building component roof to investigate the influence of its insulation on the building's energy performance, attributes involving its area were analyzed. Here, the relationship of building stories, building height, and building volume with the area of the roof is being investigated.

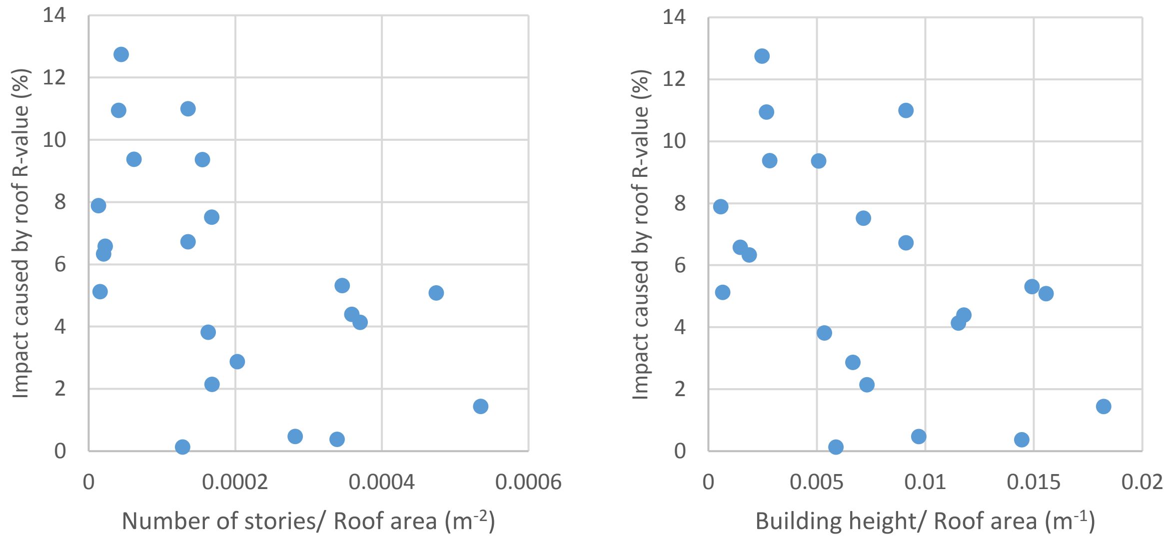


*Figure 5.4: Correlation of EUI roof impact due its relative size (a: number of stories/ roof area; b: building height/ roof area) * outliers were removed, original graph can be found in Appendix 3*

When analyzing in terms of EUI, all three attributes show at least some negative correlation. 'Stories/ roof area' and 'height/ roof area' with some negative correlation, and volume over roof area with a strong negative correlation. This shows that all three are relevant attributes when investigating the impact of roof insulation but the attribute volume over the roof area appears to have a stronger correlation with the EUI impact. When looking at NPW, on the other hand, the correlation levels show opposite behavior, stories, and height attributes on the strong negative correlation range, while volume attribute shows only some negative correlation.

Wall Area Related Attributes

Like the roof-related attributes, the attributes related to the size of the wall were also investigated. In this case, however, more than the impact of just one design parameter is being looked at, here both the wall insulation and window type parameters are being tested.

When looking at the EUI results for window type, it was seen that there is no linear correlation between window type impact and any of the investigated building rise attributes, and only weak negative correlation with the 'volume/ wall area' attribute. Wall insulation, on the other hand, shows some positive correlation with building stories and height attributes while also showing a weak positive correlation with volume-related attributes.

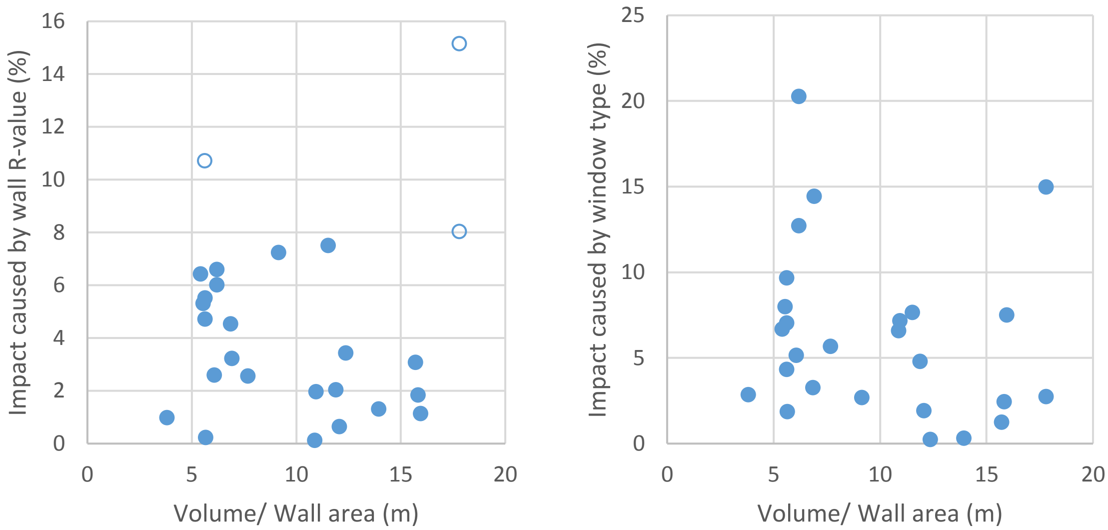


*Figure 5.5: Correlation of EUI impact due to ratio of volume over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

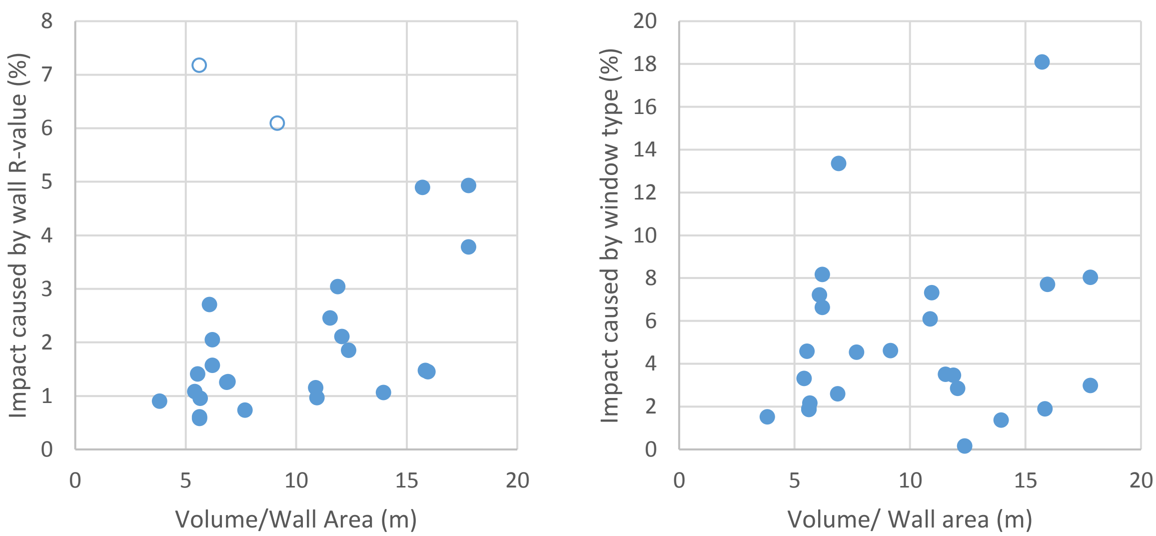


*Figure 5.6: Correlation of NPW impact due to ratio of volume over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

The NPW data, on the wall insulation side, shows a strong positive correlation with the ‘volume/ wall area’ attribute, which means that the NPW impact is greater when the building has a greater volume compared to the external wall area. Remaining analyses show no and some negative correlation between wall insulation and ‘height/ wall area’ and ‘stories/ wall area’ respectively, and weak level of correlation between window type parameter and all three attributes.

Percentage Area for Façades Compared to Overall Wall Area

When performing the same analysis to investigate the relationship between the impact of WWR for each façade and their respective ratio of the total external wall, each façade was analyzed separately.

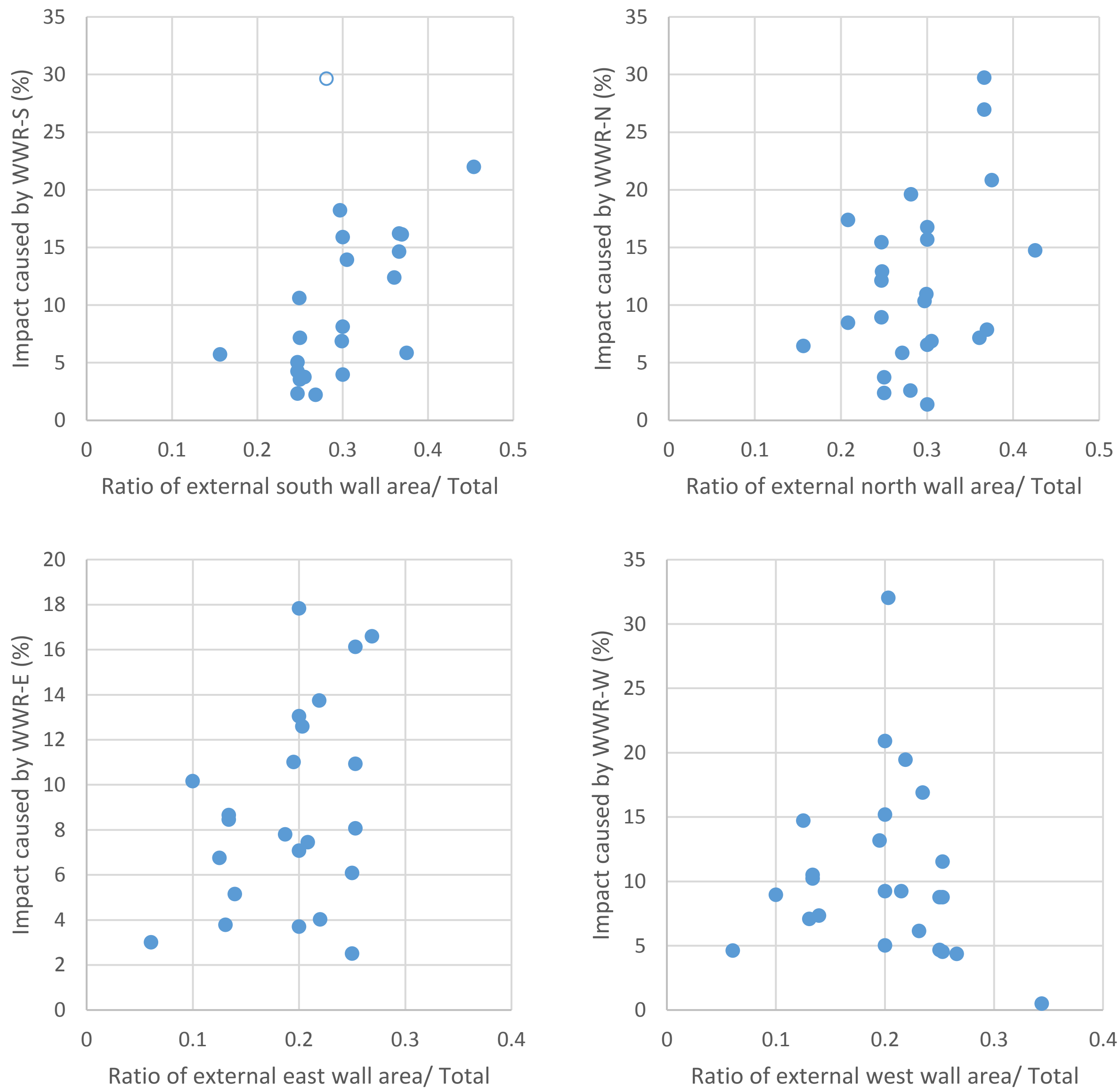


*Figure 5.7: Correlation of EUI impact due to facade wall percentage (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*

When analyzing the calculated correlation values for this analysis, it was observed that both south and north façade analyses showed a strong positive correlation in terms of EUI. Similarly, in terms of NPW, the south façade analysis also showed a strong positive correlation, while the north façade showed only a weak correlation. The remaining facades showed very different behaviors. In the EUI analysis, west and east facades showed no and some positive correlation, respectively. And, on the NPW side, both show similar levels of negative correlation -0.37 on the east façade and -0.40 on the west facade.

Percentage Area for Façades Compared to Building Volume

A similar procedure to the previous one was used to analyze the impact of WWR, but in this case, using the building volume instead of the total external wall area. This analysis, differently from the previous subsection analysis, shows negative levels of correlation for all facades in terms of EUI, which suggests that when greater the façade wall, greater will be the WWR impact. The analyzed facades, however, show different levels of correlation. Both south and west facades have a weak correlation, while north and east show some and strong correlations, respectively. The NPW side, on the other hand, shows no correlation between 'façade area/ volume' and WWR on the east and west sides, a weak positive correlation on the north side and weak negative correlation on the south side.

Summary of Analysis

Based on the investigations performed in this section, a summary table was developed containing all calculated Pearson correlation values for EUI and NPW impact analyses (Table 5.2). As previously mentioned, in this study, Pearson correlation values from 0 to ±0.2 are translated into no correlation; ±0.2 to ±0.4 are considered to have weak correlation, ±0.4 to ±0.6 have some correlation, ±0.6 to ±0.8 have a strong correlation, and ±0.8 to ±1 have a very strong correlation.

Table 5.2: Proportions of horizontal and vertical external enclosure attributes' Pearson correlation values for EUI and NPW impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	Affected parameters	EUI	NPW
Wall area/ Roof area	Roof insulation	-0.63	-0.61
	Wall insulation	0.52	-0.12
	Window type	0.65	-0.01
Number of stories/ Roof area	Roof insulation	-0.54	-0.66
Height/ Roof area	Roof insulation	-0.49	-0.61
Volume/ Roof area	Roof insulation	-0.62	-0.43
Number of stories/ Wall area	Wall insulation	0.44	-0.40
	Window type	0.08	-0.36
Height/ Wall area	Wall insulation	0.54	-0.17
	Window type	0.07	-0.33
Volume/ Wall area	Wall insulation	-0.35	0.63
	Window type	-0.21	0.20
Facade wall area/ Total external wall area	WWR South	0.68	0.63
	WWR North	0.38	0.66
	WWR East	0.36	-0.37
	WWR West	-0.12	-0.40
Volume/ Facade wall area	WWR South	-0.34	-0.42
	WWR North	-0.40	0.28
	WWR East	-0.61	0.02
	WWR West	-0.25	-0.07

(5.1.3) Energy consumption profile

Finally, the last category of building attributes investigated in this study is the ‘energy consumption profile’ category, which focuses on the percentage of energy being used for heating in a building. The following graphs are showing the relationship between the percentage of the building energy going to heating and the analyzed design parameters (roof insulation, wall insulation, WWR, window type, and lighting efficiency).

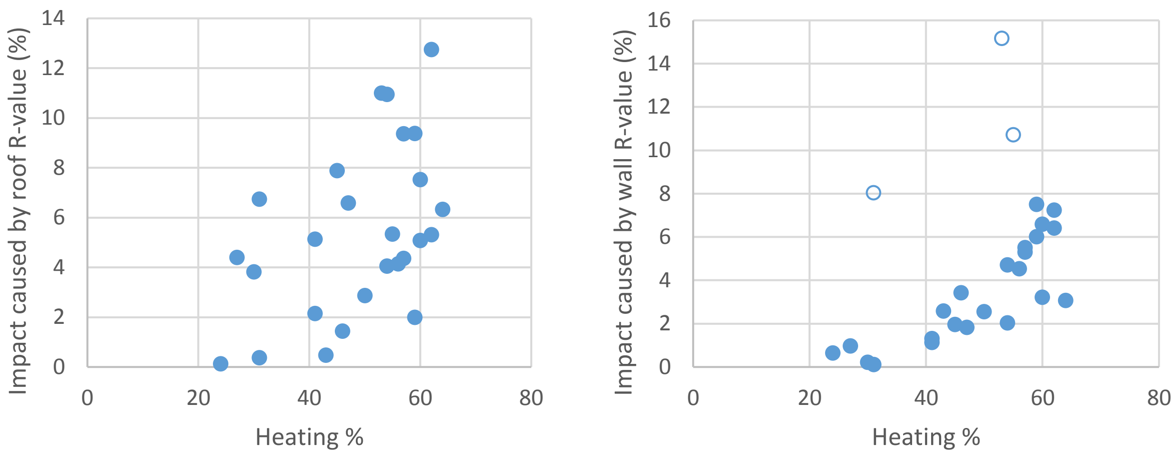


*Figure 5.8: Correlation of EUI impact due to the portion of the building's total energy going towards heating (a: roof insulation; b: wall insulation) *blank datapoints represent outliers*

The analysis based on the building's heating percentage highlights one main difference within the parameters. The lighting efficiency parameter has a negative correlation with heating percentage while all other parameters show a positive correlation for both EUI and NPW. This happens because, differently from the other parameters, lighting efficiency does not influence the indoor temperature of the building. Thus, the lower the heating percentage, greater will probably be the percentage of energy being used by lighting systems.

Results of correlation analysis also show that, except for WWR south with a weak correlation, all parameters have at least some correlation in terms of EUI. On the NPW side, similar behavior is seen. In general, however, EUI results have higher correlation levels than the NPW results. Thus, NPW analysis shows that parameters always have at least a weak level of correlation with the heating percentage attribute. For better visualization of the points discussed in this section, the Pearson correlation values can be found in Table 5.3.

Table 5.3: Energy consumption profile attribute's Pearson correlation values for EUI and NPW impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	Affected parameters	EUI	NPW
Heating %	Roof insulation	0.49	0.26
	Wall insulation	0.82	0.26
	WWR South	0.32	0.46
	WWR North	0.63	0.50
	WWR East	0.61	0.45
	WWR West	0.53	0.43
	Window type	0.56	0.36
	Lighting efficiency	-0.69	-0.39

5.2) Correlation Analysis with Global Sampling

This section is displaying the results of correlation analyses based on scenarios generated through Monte Carlo sampling. To accomplish this global correlation analysis, the average output (EUI) of scenarios with the lowest and highest values for each parameter were considered separately. Except for the window type parameter, which is not a numerical parameter, all design parameters were investigated based on their impact on a one percent variation to the design parameter input value. In the case of window type, the two windows that predominantly showed minimum and maximum energy consumption were taken into consideration.

Based on the attribute categories highlighted in Table 4.5, this section is divided into three main subsections: building rise; proportions of horizontal and vertical external enclosure; and energy consumption profile. Some graphs displaying the analyzed data points are shown throughout the sections, the remaining are shown in Appendix 4.

(5.2.1) Building Rise

Based on the hypotheses summarized in Table 4.5, this section is investigating the attributes that fit into the ‘Building rise’ category. Both, the number of stories and the building height were analyzed in terms of EUI. The data used for the Pearson correlation analyses were graphed and are being displayed in Figure 5.9. The analyzed graphs and correlation coefficients show that both, the number of stories and the building height show the same level of correlation to the insulation parameters’ impact (some positive correlation).

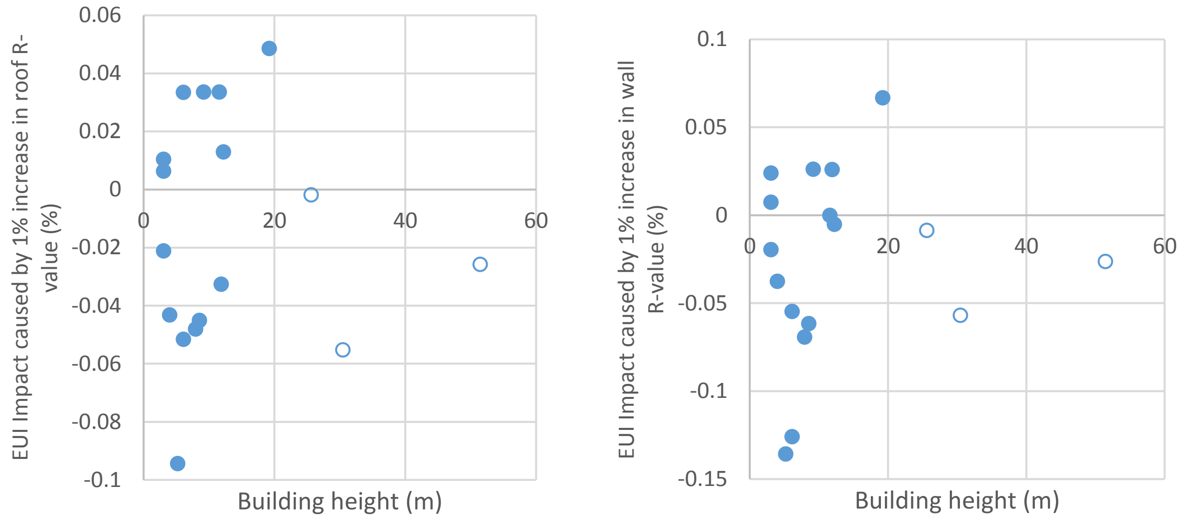


*Figure 5.9: Correlation of EUI impact due to number of stories and building height (a: roof impact; b: wall impact) *blank datapoints represent outliers*

Table 5.4: Building rise attributes' Pearson correlation values for EUI impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	Affected parameters	EUI
Number of stories	Roof insulation	0.52
	Wall insulation	0.56
Height	Roof insulation	0.43
	Wall insulation	0.46

(5.2.2) Proportions of the horizontal and vertical external enclosure

The second group of building attributes being investigated in this study is enclosed in the 'proportions of horizontal and vertical external enclosure' category. As seen in Table 4.5, these attributes can influence the impact of a variety of design parameters: roof insulation, wall insulation, window type, and window-to-wall ratio. To cover the details of correlation analysis for the mentioned attributes, the first 5 subsections will be displaying correlation analysis results for the relevant building attributes (wall area/ roof area; roof area related attributes; wall area related attributes; percentage area for façades compared to overall wall area; and relative area of façades compared to building volume). After that, a summary and discussion of the results will be provided.

Wall Area/ Roof Area

As previously mentioned, there are 3 design parameters influenced by the ratio of the wall over roof area: roof insulation, wall insulation, and window type. When looking at the data and correlation coefficients, both roof and wall insulations show a strong correlation with the 'wall area/ roof area'. Meanwhile, window type shows only weak but still positive correlation.

Roof Area Related Attributes

While analyzing the size of the roof component to investigate the influence of its insulation on the building's energy performance, attributes involving its area were analyzed (the relationship between building stories, building height and building volume with the area of the roof). The data used in the investigation is being displayed in Figure 5.10. The results of this analysis show that the relationships between the number of stories and roof area, as well as building height and roof area, show some positive correlation to the EUI impact caused by roof insulation. The attribute involving building volume, on the other hand, shows only a weak positive correlation.

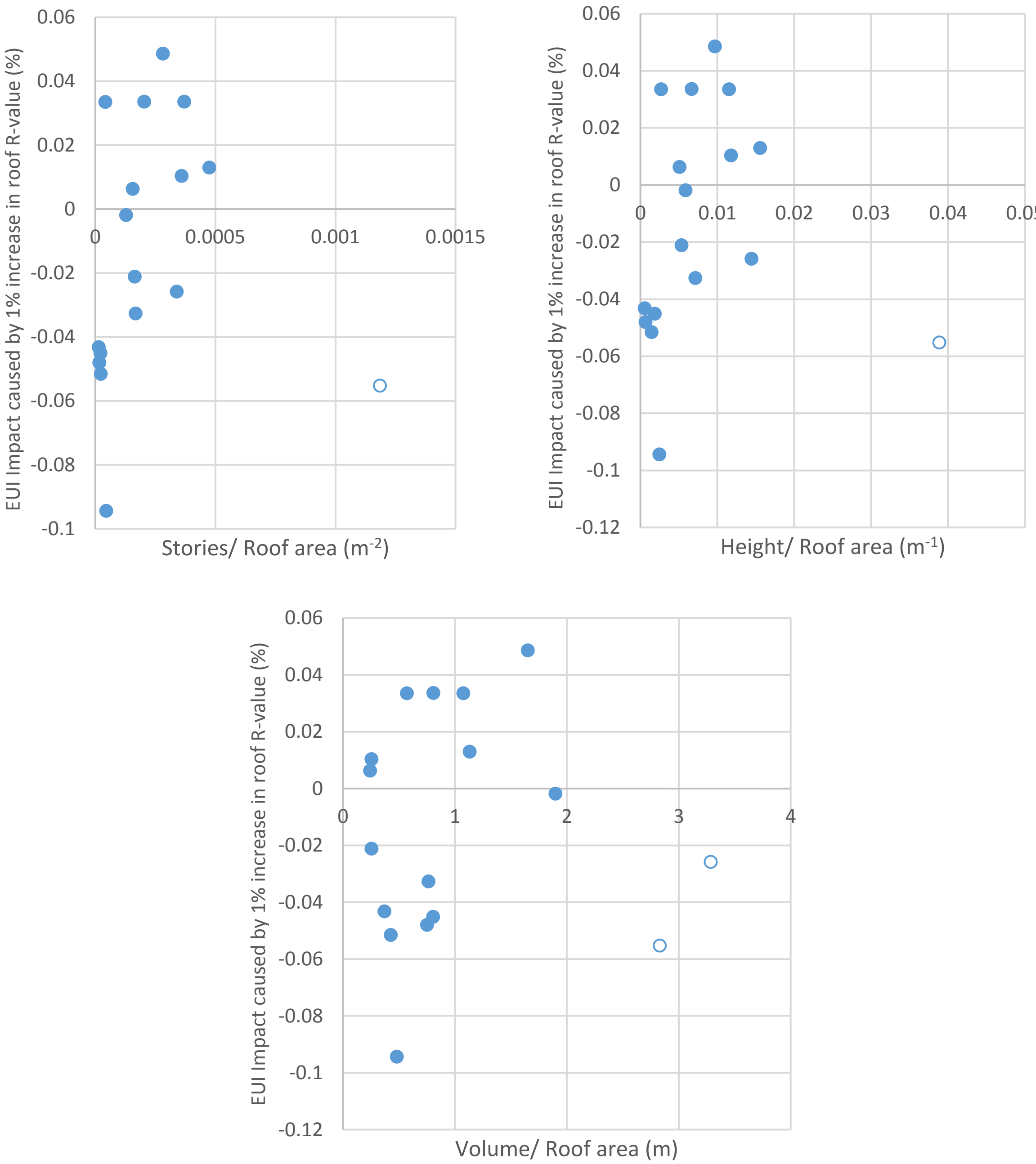


*Figure 5.10: Correlation of EUI roof impact due its relative size (a: number of stories/ roof area; b: building height/ roof area; c: volume/ roof area) *blank datapoints represent outliers*

Wall Area Related Attributes

Like the roof-related attributes, the attributes related to the size of the wall were also investigated. In this case, however, more than the impact of just one design parameter is being looked at, here both the wall insulation and window type parameters are being analyzed. There, along with the correlation analysis coefficient, it is observed that wall insulation and window type show some and strong positive correlation, respectively. When looking at the Pearson correlation coefficients for these in relationship to wall insulation and window type, similar behavior for both parameters was found, some positive correlation with ‘building height/ wall area’ and strong negative correlation with ‘building volume/ wall area’.

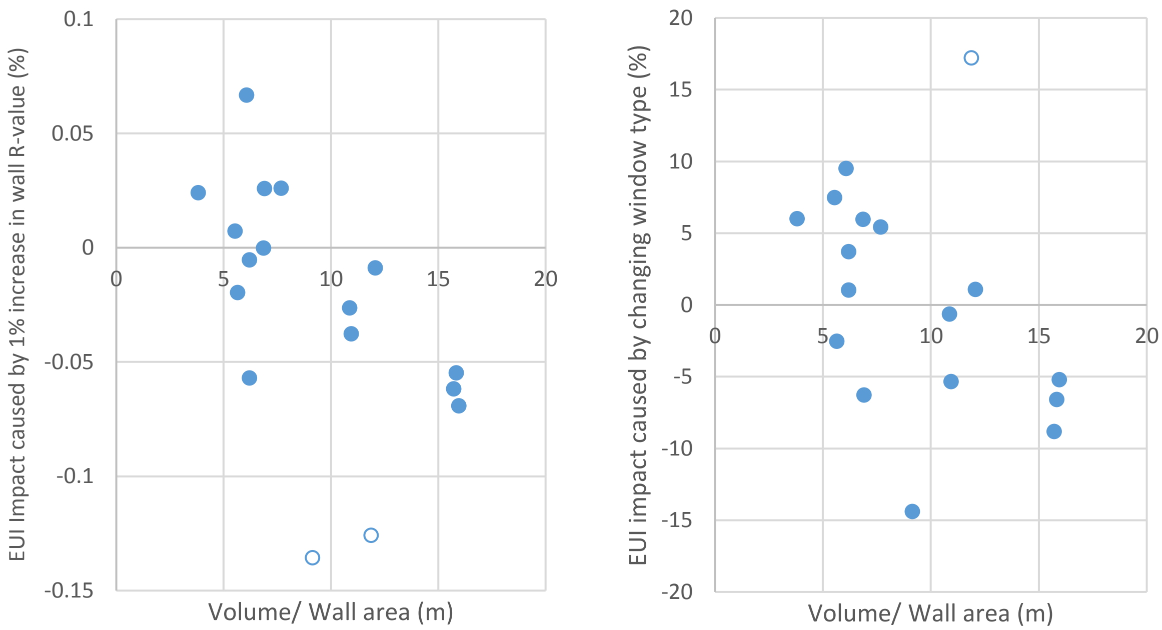


*Figure 5.11: Correlation of EUI impact due to ratio of volume over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

Percentage Area for Façades Compared to Overall Wall Area

When performing the same analysis to investigate the relationship between the impact of WWR for each façade and their respective ratio of the total external wall, all façades were analyzed separately. Details of analyzed data are being displayed in Figure 5.12. In this analysis, except for a strong correlation in the south façade, all façades show some correlation. The highlighted levels of correlation are positive in the south and north side, and negative in the east and west sides.

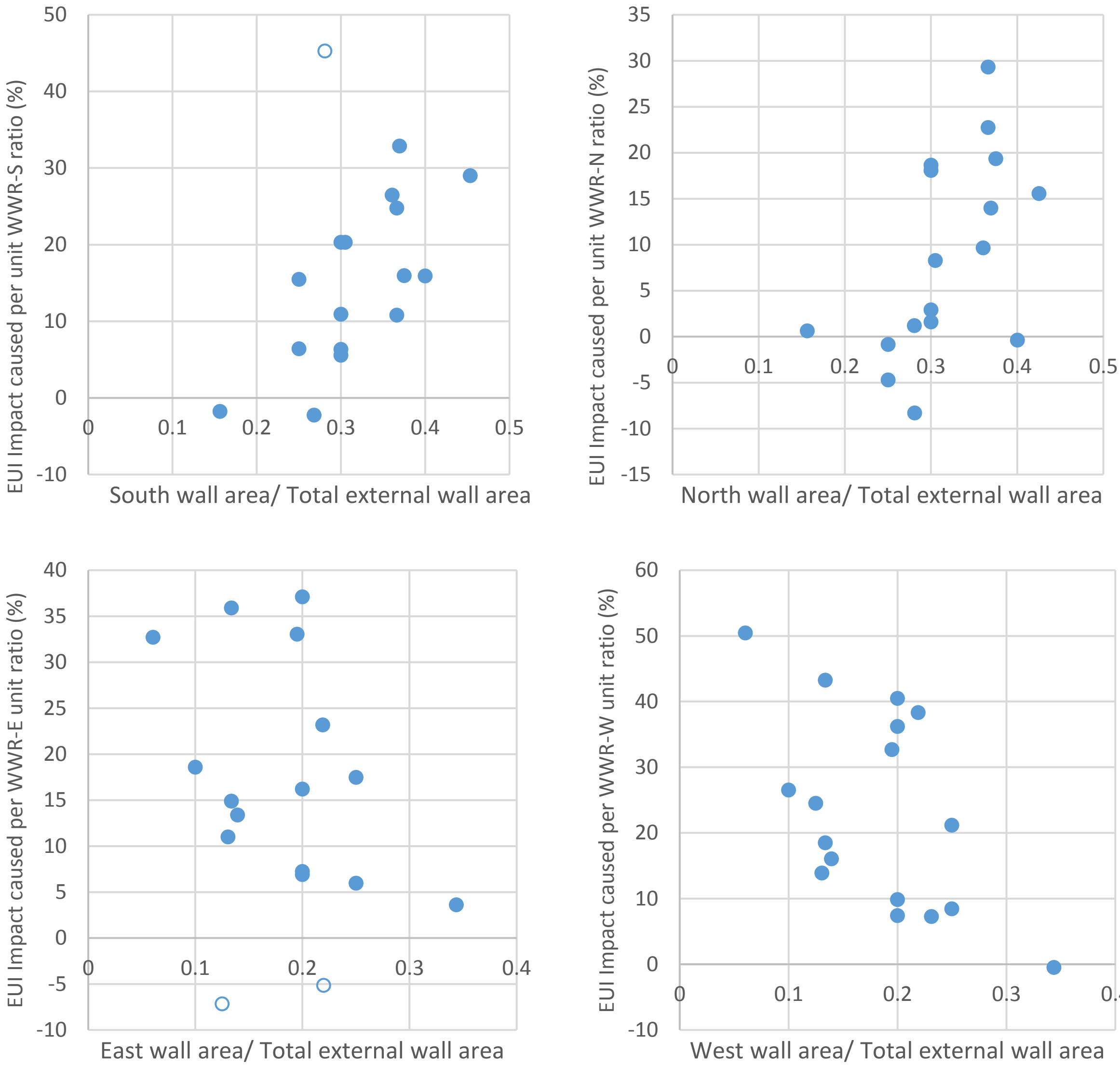


*Figure 5.12: Correlation of EUI impact due to facade wall percentage (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*

Percentage Area for Façades Compared to Building Volume

A similar procedure to the previous one was used to analyze the impact of WWR, but in this case, using the building volume instead of the total external wall area. The correlation investigation shows no correlation on the east and west façades, a weak negative correlation on the south side, and some negative correlation on the north side.

Summary of Analysis

Based on the investigations performed in this section, a summary table was developed containing all calculated Pearson correlation values for EUI impact analyses (Table 5.5). As previously mentioned, in this study, Pearson correlation values from 0 to ±0.2 are translated into no correlation; ±0.2 to ±0.4 are considered to have weak correlation, ±0.4 to ±0.6 have some correlation, ±0.6 to ±0.8 have a strong correlation, and ±0.8 to ±1 have a very strong correlation.

Table 5.5: Proportions of horizontal and vertical external enclosure attributes' Pearson correlation values for EUI impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	Affected parameters	EUI
Wall area/ Roof area	Roof insulation	0.25
	Wall insulation	0.62
	Window type	0.37
Number of stories/ Roof area	Roof insulation	0.58
Height/ Roof area	Roof insulation	0.52
Volume/ Roof area	Roof insulation	0.40
Number of stories/ Wall area	Wall insulation	0.55
	Window type	0.67
Height/ Wall area	Wall insulation	0.47
	Window type	0.57
Volume/ Wall area	Wall insulation	-0.70
	Window type	-0.60
Facade wall area/ Total external wall area	WWR South	0.72
	WWR North	0.55
	WWR East	-0.44
	WWR West	-0.53
Volume/ Facade wall area	WWR South	-0.31
	WWR North	-0.54
	WWR East	-0.02
	WWR West	0.03

(5.2.3) Energy consumption profile

Lastly, the category of building attributes being investigated in this section is the ‘energy consumption profile’, which focuses on the percentage of energy being used for heating in a building. The following graphs are showing the relationship between the percentage of the building energy going to heating and the analyzed design parameters (roof insulation, wall insulation, WWR, window type, and lighting efficiency). Figure 5.13 is displaying the data used in the EUI analysis.

The analyzed data shows that parameters that are lower in the ranking of significance appear to have lower levels of correlation (in general and when comparing to the previous OAT correlation analysis). Roof insulation, wall insulation, and window type show weak or no correlation with the buildings’ heating percentage, which are the case due to the variation of other more influential parameters. The remaining parameters, except for lighting efficiency, show positive correlations.

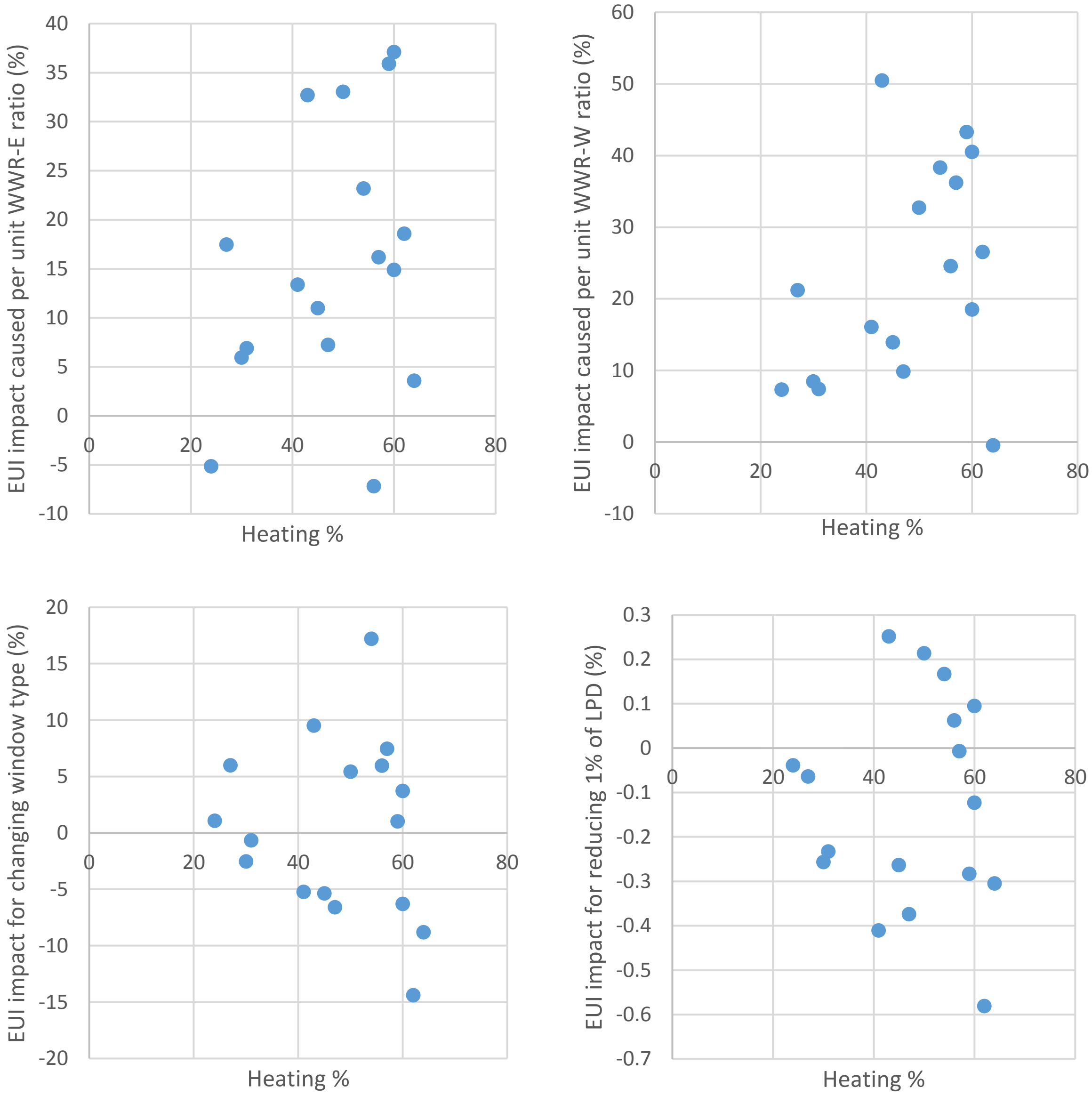


*Figure 5.13: Correlation of EUI impact due to the portion of the building's total energy going towards heating (a: WWR east; b: WWR west; c: window type; d: lighting efficiency) *blank datapoints represent outliers*

The lighting efficiency parameter, in this particular case, shows no correlation with heating percentage when the full dataset is analyzed. When separating it between low and high heating consumption profile buildings, however, correlation values show a very strong negative correlation (-0.83 for low heating consumption group, and -0.75 for high). Details of the

Pearson correlation coefficients for 'energy consumption profile' investigations can be seen in Table 5.6.

Table 5.6: Energy consumption profile attribute's Pearson correlation values for EUI impact caused by selected parameters (white cell: no correlation; light grey cell: some correlation; dark grey cell: strong correlation)

Attributes	**Affected parameters**	**EUI**
Heating %	Roof insulation	-0.17
	Wall insulation	-0.29
	WWR South	0.36
	WWR North	0.89
	WWR East	0.62
	WWR West	0.59
	Window type	-0.13
	Lighting efficiency	-0.03

5.3) Summary of the Results and Discussion

To finalize the verification of hypotheses developed by this study, the three categories of attributes are compared between the OAT and global correlation analyses for discussion. Based on this comparison, the parameters were classified as: parameters with the same level and type of impact (i.e. the same category and sign of correlation factor); parameters with the same type but a different level of impact; and parameters that show a different type of impact. An overview of parameters and respective classifications are provided in Table 5.7.

Table 5.7: Classification of design parameters based on OAT and global correlation analyses (white cell: same level and type of impact; light grey cell: same type but a different level of impact; dark grey cell: different type of impact)

Attributes	**Affected parameters**	**Attributes**	**Affected parameters**
Number of stories	Roof insulation	Facade wall area/ Total external wall area	WWR South
	Wall insulation		WWR North
Height	Roof insulation		WWR East
	Wall insulation		WWR West
Wall area/ Roof area	Roof insulation	Volume/ Facade wall area	WWR South
	Wall insulation		WWR North
	Window type		WWR East
Number of stories/ Roof area	Roof insulation		WWR West
Height/ Roof area	Roof insulation	Heating %	Roof insulation
Volume/ Roof area	Roof insulation		Wall insulation
Number of stories/ Wall area	Wall insulation		WWR South
	Window type		WWR North
Height/ Wall area	Wall insulation		WWR East
	Window type		WWR West
Volume/ Wall area	Wall insulation		Window type
	Window type		Lighting efficiency

Within the parameters showing the same level and type of impact throughout both OAT and global correlation analyses, three different conclusions can be made. There are the attributes that can be confidently considered important for the future of this study, the ones that should not be considered, and the ones that need further investigation. Due to their constant level of strong correlation, 'façade wall area/ total external wall area' is an important attribute when analyzing WWR south impact; and 'heating %' is an important attribute when analyzing WWR north and east impacts. On the other hand, due to their constant lack of correlation, both 'volume/ façade wall area' and 'heating %' are nonimportant attributes when analyzing WWR south. The remaining design parameters in this category, due to their constant level of some correlation, will need further investigation.

In the class of parameters that show the same type of impact with different levels, the parameters are showing a stronger level of correlation with their attributes in the OAT analysis and the ones with opposite behavior. The parameters showing a strong correlation in the global analysis are the ones being suggested by this study as important. The parameters showing some level of correlation in the global analysis and higher level in the OAT analysis are being suggested as important but further study is recommended. The remaining parameters (except for the ones with no correlation) needs further investigation.

For instance, it is observed that 'wall area/ roof area' and 'volume/ wall area' are important attributes when analyzing the impact of wall insulation. The same happens with 'stories/ wall area' and 'volume/ wall area' when analyzing window type impact. Along with these, is the correlation between lighting efficiency and 'heating %'. Although this parameter showed a stronger level of correlation with 'heating %' during the OAT analysis, global analysis results also show strong correlation behavior when the data points are separated between low and high energy consumption buildings. Lastly, based on its strong OAT analysis correlation and some correlation in the global analysis, the correlation between height and wall insulation is also considered important (even though further investigation is recommended). The remaining parameters from this class are suggested to go through further investigations.

Finally, the last group represents the parameters that have a completely different type of impact in the two analyses. This behavior can be observed in parameters that do not show any correlation in the OAT analysis, such as WWR east and west in correlation with 'façade wall area/ total external wall area' and 'volume/ façade wall area' respectively. The same behavior is observed with parameters that have low impact compared to other parameters, such as roof insulation, wall insulation, and window type when in correlation with 'heating %'. That is the case because the global analysis requires that all parameters be changed. Therefore, their impact can be overruled by the impact caused by the parameters with higher impact, which suggests that the relationship between the above-discussed design parameters and attributes are not relevant for the continuation of this study.

The roof insulation parameter, however, when analyzed with all the other attributes (related to building size), shows a special behavior: at least some level of correlation in both analyses but with opposite sign. This shift in global analysis happens for two reasons. First, because the outliers for all the analyzed global datasets were the two tallest buildings (only two above 6 floors in the dataset). That alone largely influences the correlation values (e.g. correlation coefficient goes from 0.05 to 0.518 when excluding the two tallest buildings from the analysis between roof insulation and the number of stories) since the analyzed attributes are related to buildings' proportions and height. And second, because roof insulation is one of the design parameters with the lowest impacts compared to other parameters (i.e. roof insulation shows an average of 5.53% impact while parameters such as WWR east and north show 11.36% and 11.38% respectively), which overrules the impact caused by the roof insulation. This special case, differently from the previous parameters found in this group, needs further research to evaluate the effect of taller buildings, and also because some correlation was observed during global analysis.

Chapter 6 – Concluding Remarks

BPS is a widely used tool to perform quantitative analysis of building designs. It also has the potential to help designers when making decisions on important parameters, such as the ones that are decided during the early design development stage. Today, however, due to a large number of possible scenarios at such an early phase, BPS is not being used to its potential. In the efforts to decrease the number of relevant energy influential parameters and scenarios to be evaluated in the early stages of building design, this study is providing a deeper look at correlation and dependencies within building and design parameters.

Outputs of this study include the identification of a set of less significant design parameters (overhang, orientation, and lighting type) that, during early stage decision-making, do not need to be analyzed with as many alternatives as others. It was also found during this study that the HVAC system type is always highly significant in terms of both EUI and NPW, and its level of impact does not vary when analyzing different models. The energy influential design parameters found to have a significant impact and be sensitive to the analyzed model include roof and wall insulations, window type, WWR, and lighting efficiency.

When it comes to correlation analyses, this study focused only on design parameters and their impact on building performance. Correlations between the parameters themselves were ignored. On the one hand, this will not be considered a limitation since all analyzed parameters can vary independently from one another. On the other hand, however, selection of value for one may logically affect the selection of others, for example, larger window to wall ratio might call for window types of specific parameters. Moreover, the correlation between an input parameter and the significance of other parameters' impact was also not considered. For example, larger WWR will increase the impact of window parameters on the building performance; the used methods, however, are unable to capture such high order correlations. To capture these kinds of correlations, more advanced data mining methods will be needed.

Analyzed building attributes were based on three categories: building rise attributes; proportions of horizontal and vertical external enclosure attributes; and energy consumption profile attributes. Results of the performed correlation analyzes showed that NPW generally has lower levels of correlation when compared to EUI. Also, it was found that both EUI and NPW have 6 combinations of building attributes and parameters showing strong correlation. In the future, these attributes can be used to train a recommender system that can recommend relevant building scenarios to be better analyzed by BPS, by taking into consideration both energy and cost aspects of performance.

6.1) Contributions

The fundamental contribution of this research was to provide a deeper look at correlation and dependencies within building characteristics and design parameters. To achieve this goal, the contributions of this project can be listed as the following:

(1) Multi-model screening of energy influential parameters (RO 1): Previous works had been reported on the parametric screening of building models through BPS. None of which, however, had performed such investigations with multiple building models. In response to this gap, the present thesis identified the most relevant design parameters in terms of EUI based on the overall ranking of parameters' impact, as well as the significance of the impact of each parameter throughout a pool of analyzed building models. These findings, differently from the previous works, can be used by designers and architects when designing new energy-efficient buildings.

(2) Construction and operation cost models for early-stage design development (RO 2): Existing cost models are technically limited due to the purpose of their development, which does not allow them to support a decision-making process during the early design development phase. During this study, parametric cost models that take in energy influential parameters and return their respective construction and operational costs were developed to enable analysis at an earlier stage. The developed cost models are now a useful tool for anyone working with energy simulation.

(3) Meta-level analysis of design parameters (RO 3): Based on the selected parameters and their cost-models, this study made it possible to investigate how building energy and cost performances are sensitive to design parameters; and, how the entire behavior of design parameters is sensitive to characteristics of the building model. This set of analyses was possible through OAT sampling and the results enabled a better understanding of the significance of parameters' impact, as well as their sensitivity to the case study. Again, due to the wide range of building models analyzed in this step, findings of this study are

applicable to other design projects, which would then be useful to designers and architects when designing a new building.

(4) Development and evaluation of hypothesis for possible cause roots for differences in parameters' behavior (RO 4 and 5): Through a meta-level analysis of design parameters this thesis studied the behavior of parameters separately in different building groups (rather than to the entire dataset). Differences observed in different analyzed groups allowed for the development of hypotheses that try to explain the reasons why different behaviors arise in different building models. The evaluation of these hypotheses made it possible to understand relationships between design parameter impacts and building characteristics. This is useful when making decisions during the building design process.

6.2) Impacts

The main impacts of this research can be summarized at three main levels:

(1) Design level: The deeper understanding of design parameters' impact, as well as its correlation with building attributes can directly benefit building designers. This can happen by providing a more straightforward direction on what design parameters should be focused on depending on the characteristics of the building.

(2) Building performance simulation level: Given the difficulties related to BPS at the early development stage (very large number of possible scenarios), the findings of this study can help designers limit the number of analyzed scenarios by focusing on parameters relevant to the building. This would significantly decrease the number of scenarios to be analyzed, making the analysis possible.

(3) Decision-making level: Reviewed studies showed that analysis of building performance through machine learning techniques have high levels of accuracy and speed. The gap found in these studies, however, was the fact that no deeper look was given to the attributes selected to train these algorithms. With that in mind, this study is filling that gap for the future application of machine learning techniques.

6.3) Limitations

The limitations of this study are listed as follows:

(1) Limited number of building models being analyzed: Data mining techniques usually require large amounts of data. This study benefitted from a pool of building models; however, a larger number of models would be needed to improve the accuracy of the results.

(2) Window details: Due to the structure of the OpenStudio measure responsible for changing window type, the parameters related to window type (e.g. U-value and SHGC) had to be applied in combination. Window type is limited to nine different options that bring in their respective values.

(3) HVAC details: HVAC systems, apart from their system type, have many other characteristics (e.g. COP). In this study, however, HVAC system analysis was limited to the different system types.

(4) Significance test: All significance tests used in this study are t-tests, which brings the assumption that all analyzed samples come from datasets that follow a normal distribution.

(5) Generation of random scenarios: Due to the nature of the analyzed parameters and the structure of the system used to automatically generate the global sample analysis, the analyzed scenarios were based on uniform distribution and were not generated in a conventional way. The scenarios are created (with the help of the system described in [11]) by generating every possible combination of the parameter inputs. With that in mind, the randomized part of this dataset happened when the parameter inputs were added to the system.

(6) Correlation analysis: The correlation analysis used in this study is the Pearson correlation, which is a measure of the strength of the linear relationship between variables. On top of the fact that this method is unable to identify nonlinear relationships, this measure is highly sensitive to outliers (although attempts were put in place to remove outliers from the data).

(7) Global correlation analysis for NPW output: Due to existing limitations in the software system used to generate NPW outputs, the global correlation analysis was only performed based on the EUI and not NPW.

6.4) Future works

To move forward with this study as well as address the above-mentioned limitations, a list of points is being suggested as “future works”. By no means, however, the “future works” are limited to the items displayed in this section. 4 potential continuations for this research are explained in the following paragraphs:

(1) Expand dataset of building models: Expanding the pool of building models used in the analysis will help increase the accuracy of the analysis.
(2) HVAC details: Implementing HVAC details will enable a more accurate overview of such systems.
(3) Non-parametric significance tests: There is no evidence, in the existing literature, to prove that the maximum impact caused by each parameter alone in the entire population of buildings will form a normal distribution. For that reason, the conclusions made based on the t-test might benefit from the use of a non-parametric significance test. Non-parametric significance tests do not assume anything about the distribution of the population.
(4) Non-linear correlation analysis: The existence of a large number of variables makes it more likely for relationships between design parameters and performance indicators to not be linear, especially when the cost of components is involved. To better analyze the existing relationship between design parameters' impact and building attributes, non-linear correlation analysis methods would be of great benefit.
(5) Global verification of hypotheses based on NPW outputs: For further evaluation of the hypothesized attributes in terms of NPW, a correlation analysis should be performed by using a global sample.
(6) More advanced data mining methods: Other than the correlations analyzed throughout this study, there are other orders of correlation that can provide relevant insights to designers. Due to the limitations related to sensitivity analysis itself (which is unable to capture higher order of correlations), more advanced data mining methods should be considered in the future works.
(7) Test classifiers: To develop the recommender system, a classifier method will be used. To decide what type of classifier should be used, multiple classifiers should be trained and tested to see which is most appropriate for the context proposed.

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Appendices

Appendix 1

The IDF files developed for the application of utility rates (explained in sections 3.3 and 3.4) are shown in this appendix.

Electricity - Rate D

```
!-Generator IDFEditor 1.50
!-Option SortedOrder

!-NOTE: All comments with '!-' are ignored by the IDFEditor and are generated automatically.
!-      Use '!' comments if they need to be retained when using the IDFEditor.


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:TARIFF ===========

UtilityCost:Tariff,
    HydroQC Rate D,           !- Name
    ElectricityPurchased:Facility,  !- Output Meter Name
    kWh,                      !- Conversion Factor Choice
    ,                         !- Energy Conversion Factor
    ,                         !- Demand Conversion Factor
    ,                         !- Time of Use Period Schedule Name
    ,                         !- Season Schedule Name
    ,                         !- Month Schedule Name
    ,                         !- Demand Window Length
    12.35,                    !- Monthly Charge or Variable Name
    ,                         !- Minimum Monthly Charge or Variable Name
    ,                         !- Real Time Pricing Charge Schedule Name
    ,                         !- Customer Baseline Load Schedule Name
    ,                         !- Group Name
    BuyFromUtility;           !- Buy Or Sell


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:CHARGE:BLOCK ===========

UtilityCost:Charge:Block,
    BlockEnergyCharge,        !- Utility Cost Charge Block Name
    HydroQC Rate D,           !- Tariff Name
    totalEnergy,              !- Source Variable
    Annual,                   !- Season
    EnergyCharges,            !- Category Variable Name
    ,                         !- Remaining Into Variable
    ,                         !- Block Size Multiplier Value or Variable Name
    1094.4,                   !- Block Size 1 Value or Variable Name
    0.0591,                   !- Block 1 Cost per Unit Value or Variable Name
    remaining,                !- Block Size 2 Value or Variable Name
    0.0912;                   !- Block 2 Cost per Unit Value or Variable Name
```

Electricity - Rate G

```
!-Generator IDFEditor 1.50
!-Option SortedOrder

!-NOTE: All comments with '!-' are ignored by the IDFEditor and are generated automatically.
!-      Use '!' comments if they need to be retained when using the IDFEditor.


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:TARIFF ===========

! Name
! Conversion Factor Choice
UtilityCost:Tariff,
    HydroQC Rate G,           !- Name
    ElectricityPurchased:Facility,  !- Output Meter Name
    KWh,                      !- Conversion Factor Choice
    ,                         !- Energy Conversion Factor
    ,                         !- Demand Conversion Factor
    ,                         !- Time of Use Period Schedule Name
    ,                         !- Season Schedule Name
    ,                         !- Month Schedule Name
    ,                         !- Demand Window Length
    12.33,                    !- Monthly Charge or Variable Name
    ,                         !- Minimum Monthly Charge or Variable Name
    ,                         !- Real Time Pricing Charge Schedule Name
    ,                         !- Customer Baseline Load Schedule Name
    ,                         !- Group Name
    BuyFromUtility;           !- Buy Or Sell


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:CHARGE:BLOCK ===========

! Charge Variable Name
! Tariff Name
! Source Variable
! Season
! Category Variable Name
! Remaining Into Variable
! Block Size Multiplier Value or Variable Name
! Block Size 1 Value or Variable Name
! Block 1 Cost per Unit Value or Variable Name
! Block Size 2 Value or Variable Name
! Block 2 Cost per Unit Value or Variable Name
UtilityCost:Charge:Block,
    BlockEnergyCharge,        !- Utility Cost Charge Block Name
    HydroQC Rate G,           !- Tariff Name
    totalEnergy,              !- Source Variable
    Annual,                   !- Season
    EnergyCharges,            !- Category Variable Name
    ,                         !- Remaining Into Variable
    ,                         !- Block Size Multiplier Value or Variable Name
    15090,                    !- Block Size 1 Value or Variable Name
    0.0981,                   !- Block 1 Cost per Unit Value or Variable Name
    remaining,                !- Block Size 2 Value or Variable Name
    0.0720;                   !- Block 2 Cost per Unit Value or Variable Name

UtilityCost:Charge:Block,
    BlockDemandCharge,        !- Utility Cost Charge Block Name
    HydroQC Rate G,           !- Tariff Name
    totalDemand,              !- Source Variable
    Annual,                   !- Season
    DemandCharges,            !- Category Variable Name
    ,                         !- Remaining Into Variable
    ,                         !- Block Size Multiplier Value or Variable Name
    50,                       !- Block Size 1 Value or Variable Name
    0,                        !- Block 1 Cost per Unit Value or Variable Name
    remaining,                !- Block Size 2 Value or Variable Name
    17.49;                    !- Block 2 Cost per Unit Value or Variable Name
```

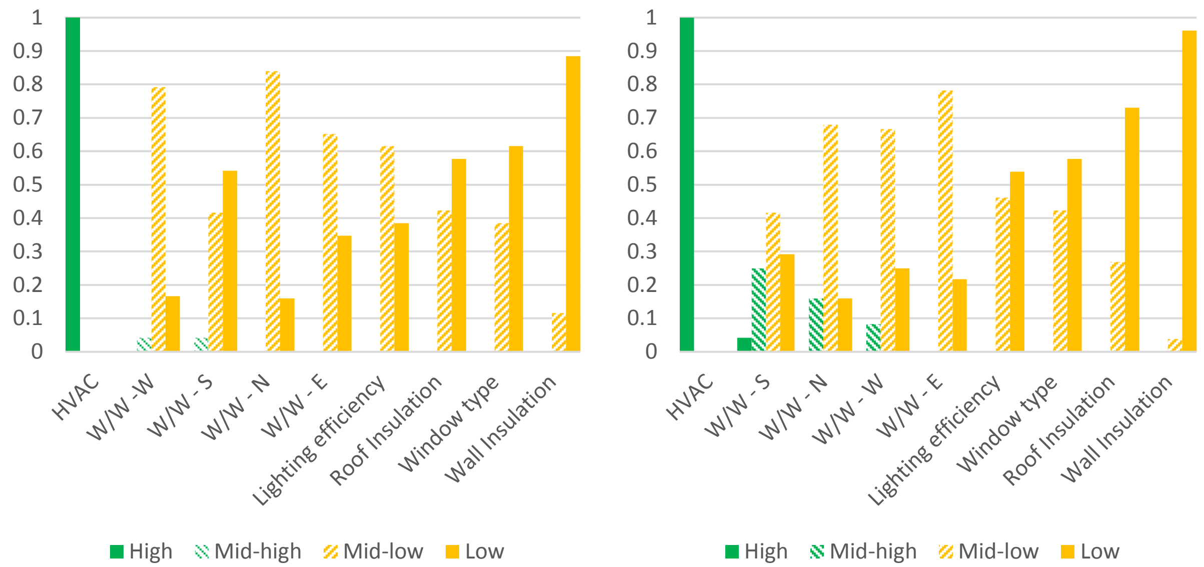
Electricity - Rate M

```
!-Generator IDFEditor 1.50
!-Option SortedOrder

!-NOTE: All comments with '!-' are ignored by the IDFEditor and are generated automatically.
!-      Use '!' comments if they need to be retained when using the IDFEditor.


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:TARIFF ===========

UtilityCost:Tariff,
    HydroQC Rate M,          !- Name
    ElectricityPurchased:Facility,  !- Output Meter Name
    kWh,                     !- Conversion Factor Choice
    ,                        !- Energy Conversion Factor
    ,                        !- Demand Conversion Factor
    ,                        !- Time of Use Period Schedule Name
    ,                        !- Season Schedule Name
    ,                        !- Month Schedule Name
    ,                        !- Demand Window Length
    ,                        !- Monthly Charge or Variable Name
    ,                        !- Minimum Monthly Charge or Variable Name
    ,                        !- Real Time Pricing Charge Schedule Name
    ,                        !- Customer Baseline Load Schedule Name
    ,                        !- Group Name
    BuyFromUtility;          !- Buy Or Sell


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:CHARGE:SIMPLE ===========

UtilityCost:Charge:Simple,
    BlockDemandCharge,       !- Utility Cost Charge Simple Name
    HydroQC Rate M,          !- Tariff Name
    totalDemand,             !- Source Variable
    Annual,                  !- Season
    DemandCharges,           !- Category Variable Name
    14.46;                   !- Cost per Unit Value or Variable Name


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:CHARGE:BLOCK ===========

UtilityCost:Charge:Block,
    BlockEnergyCharge,       !- Utility Cost Charge Block Name
    HydroQC Rate M,          !- Tariff Name
    totalEnergy,             !- Source Variable
    Annual,                  !- Season
    EnergyCharges,           !- Category Variable Name
    ,                        !- Remaining Into Variable
    ,                        !- Block Size Multiplier Value or Variable Name
    210000,                  !- Block Size 1 Value or Variable Name
    0.0499,                  !- Block 1 Cost per Unit Value or Variable Name
    remaining,               !- Block Size 2 Value or Variable Name
    0.037;                   !- Block 2 Cost per Unit Value or Variable Name
```

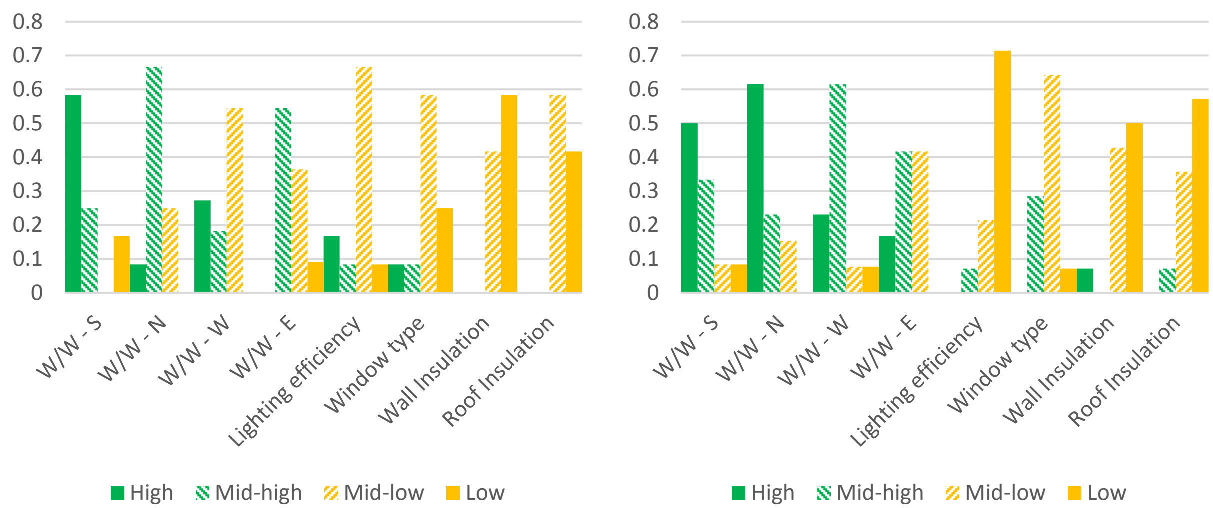
Gas - Rate D1

```
!-Generator IDFEditor 1.50
!-Option SortedOrder

!-NOTE: All comments with '!-' are ignored by the IDFEditor and are generated automatically.
!-      Use '!' comments if they need to be retained when using the IDFEditor.


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:TARIFF ===========

UtilityCost:Tariff,
    QuebecEnergirGasRate,    !- Name
    Gas:Facility,            !- Output Meter Name
    Therm;                   !- Conversion Factor Choice


!-   ===========  ALL OBJECTS IN CLASS: UTILITYCOST:CHARGE:BLOCK ===========

UtilityCost:Charge:Block,
    BlockEnergyCharge-Gas,   !- Utility Cost Charge Block Name
    QuebecEnergirGasRate,    !- Tariff Name
    totalEnergy,             !- Source Variable
    Annual,                  !- Season
    EnergyCharges,           !- Category Variable Name
    ,                        !- Remaining Into Variable
    ,                        !- Block Size Multiplier Value or Variable Name
    964.66,                  !- Block Size 1 Value or Variable Name
    0.733,                   !- Block 1 Cost per Unit Value or Variable Name
    3215.55,                 !- Block Size 2 Value or Variable Name
    0.5,                     !- Block 2 Cost per Unit Value or Variable Name
    9646.64,                 !- Block Size 3 Value or Variable Name
    0.433,                   !- Block 3 Cost per Unit Value or Variable Name
    32155.477,               !- Block Size 4 Value or Variable Name
    0.328,                   !- Block 4 Cost per Unit Value or Variable Name
    96466.43,                !- Block Size 5 Value or Variable Name
    0.2428,                  !- Block 5 Cost per Unit Value or Variable Name
    321554.77,               !- Block Size 6 Value or Variable Name
    0.1705,                  !- Block 6 Cost per Unit Value or Variable Name
    964664.311,              !- Block Size 7 Value or Variable Name
    0.1372,                  !- Block 7 Cost per Unit Value or Variable Name
    3215547.7,               !- Block Size 8 Value or Variable Name
    0.1137,                  !- Block 8 Cost per Unit Value or Variable Name
    remaining,               !- Block Size 9 Value or Variable Name
    0.0943;                  !- Block 9 Cost per Unit Value or Variable Name
```

Appendix 2



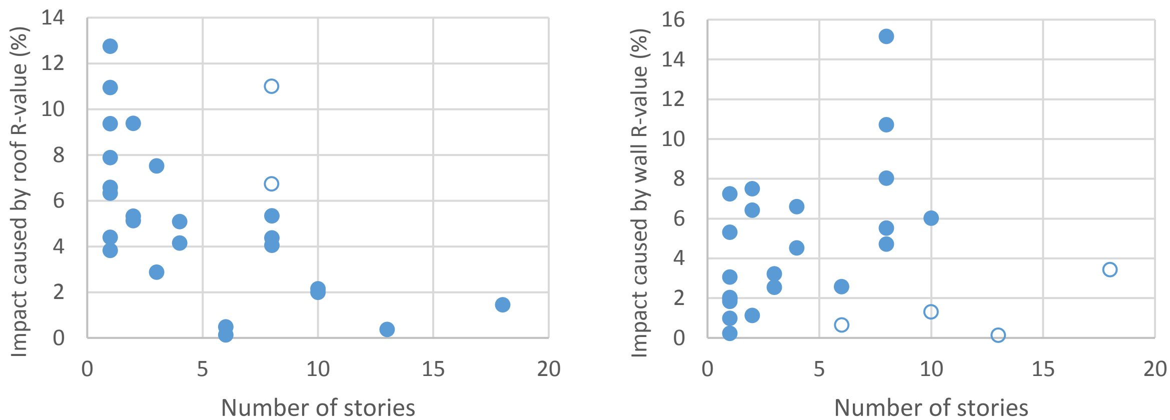
Frequency distribution of impact classes with HVAC parameter (a: EUI; b: NPW)



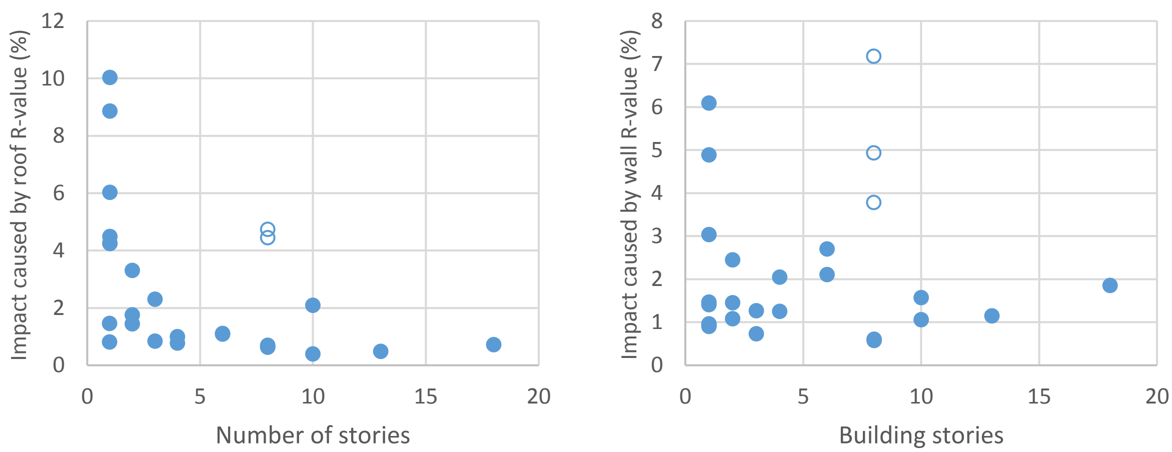
NPW frequency distribution for different building groups (a: low heating; b: high heating)

Appendix 3

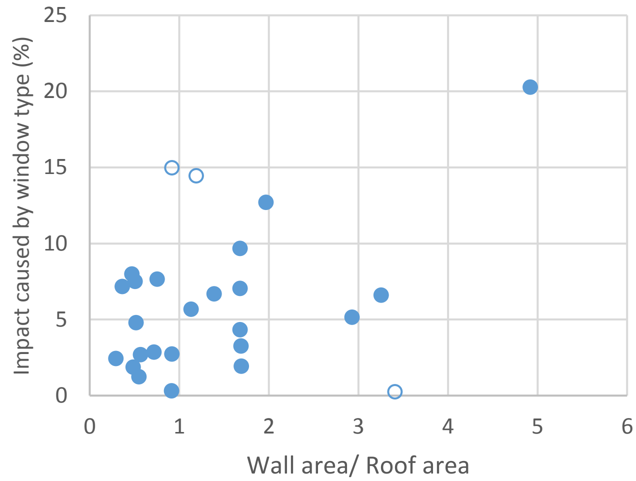
Graphs used in the OAT correlation analysis



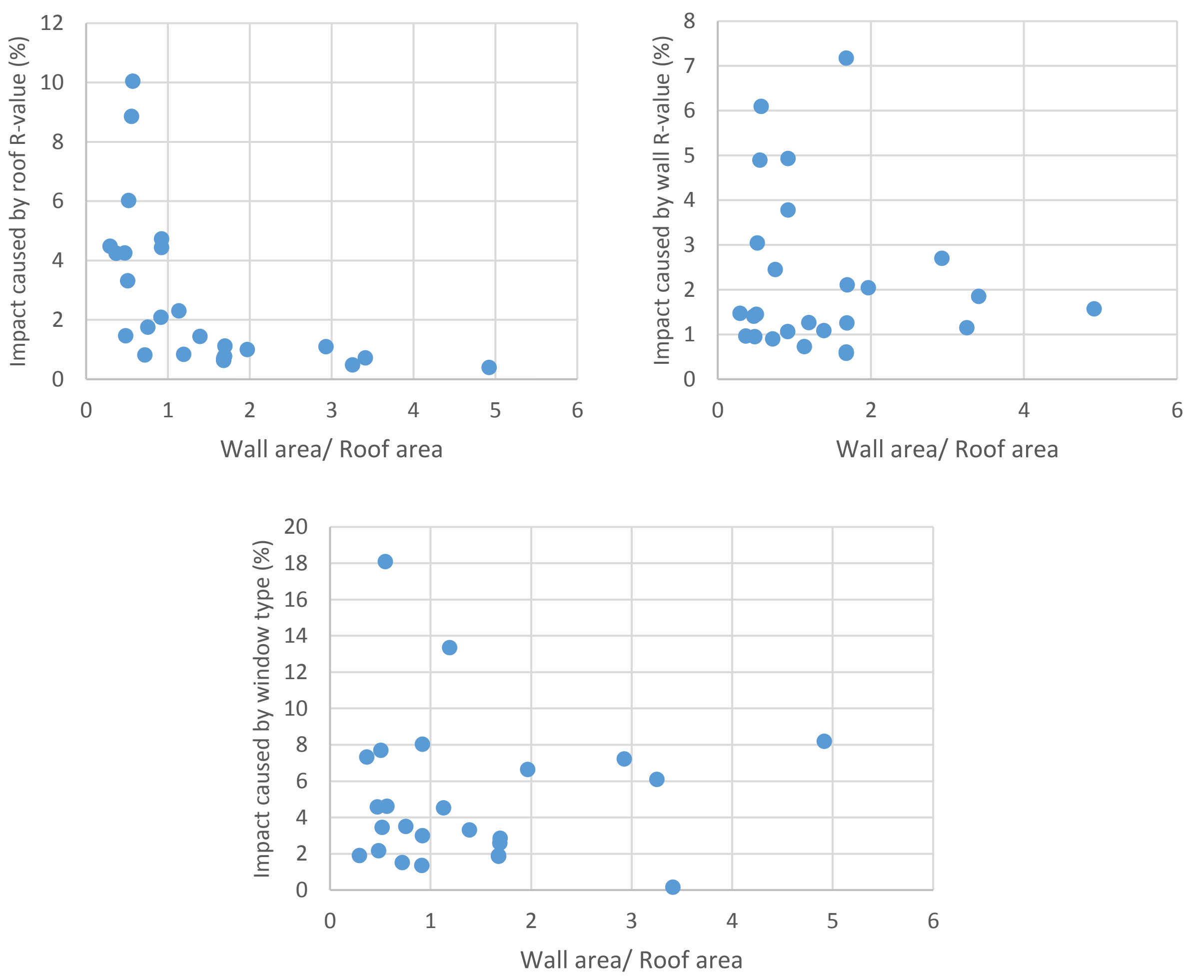
*Correlation of EUI impact due to building stories (a: roof impact; b: wall impact) *blank datapoints represent outliers*



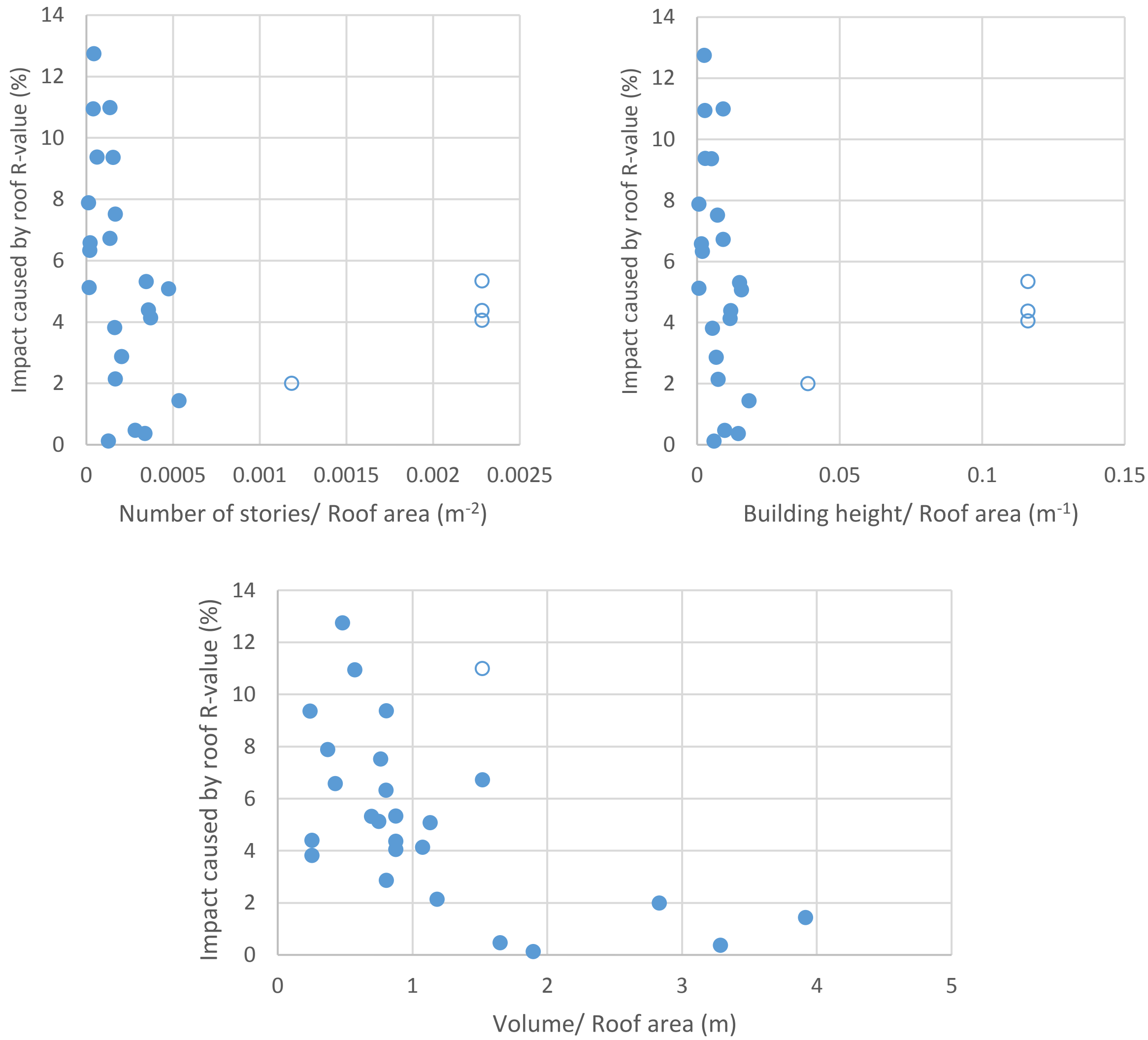
*Correlation of NPW impact due to building stories (a: roof impact; b: wall impact) *blank datapoints represent outliers*



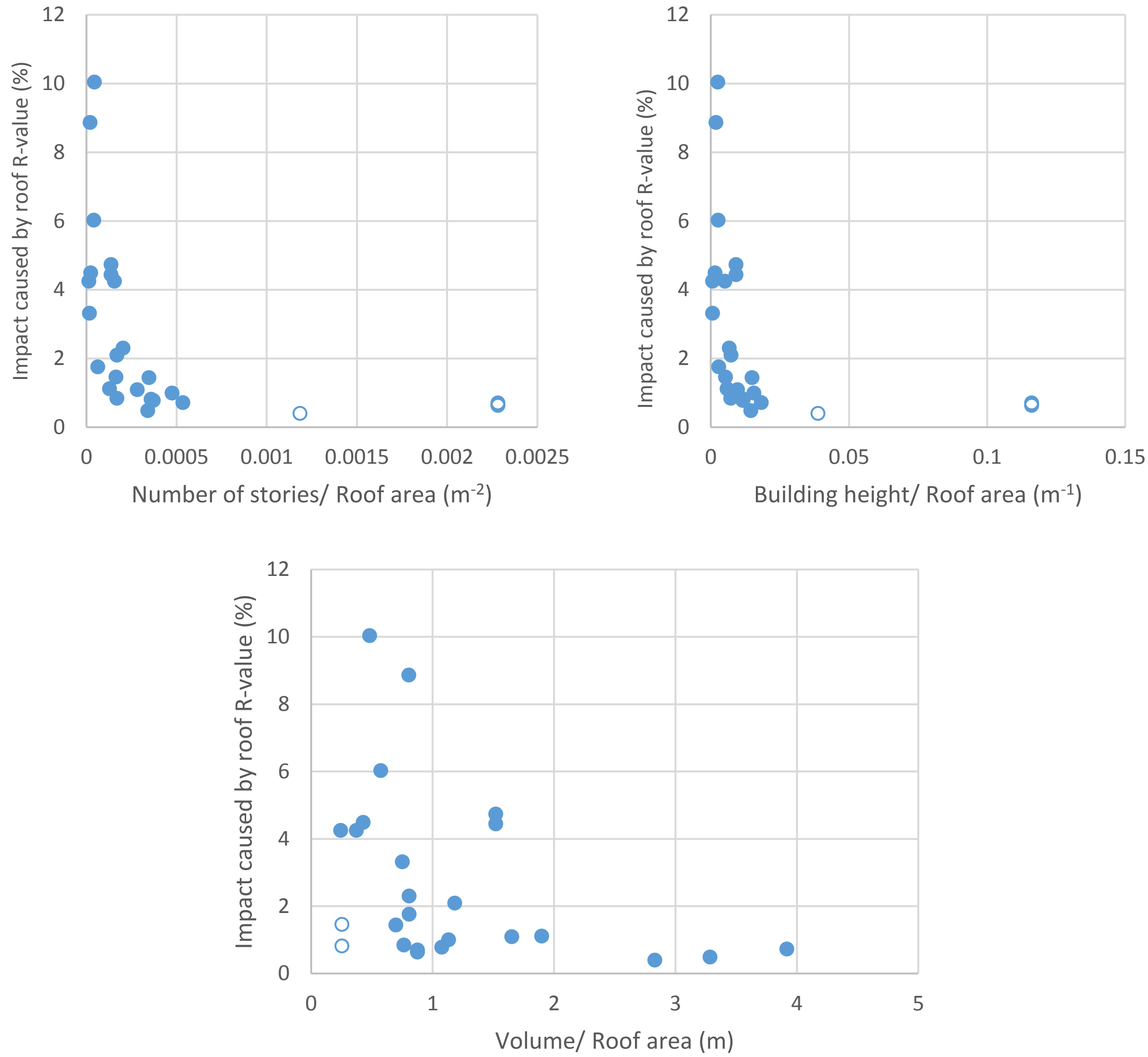
*Correlation of EUI impact due to ratio of wall area over roof area (window type) *blank datapoints represent outliers*



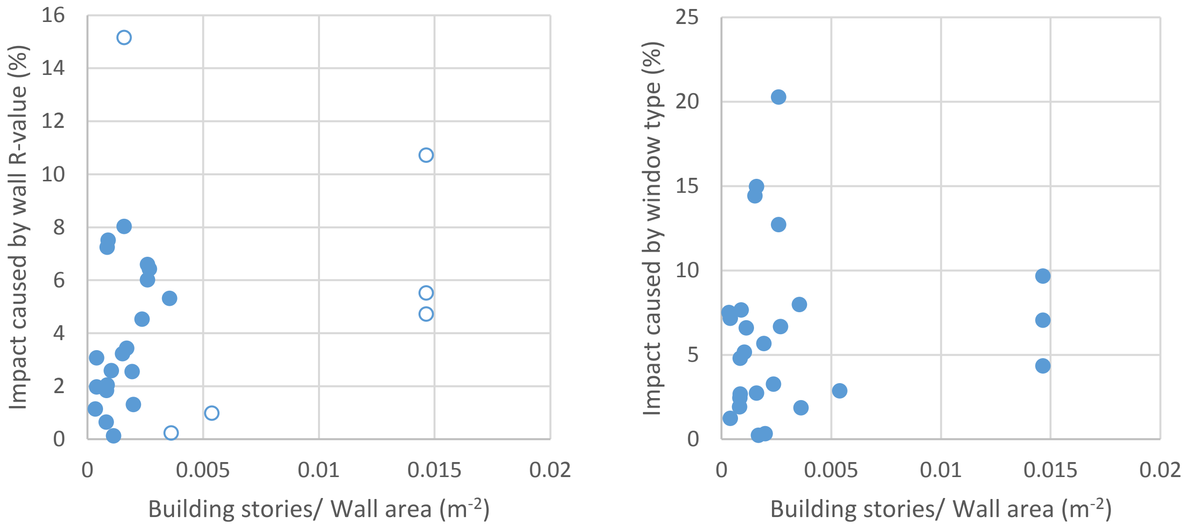
*Correlation of NPW impact due to ratio of wall area over roof area (a: roof impact; b: wall impact; c: window type) *blank datapoints represent outliers*



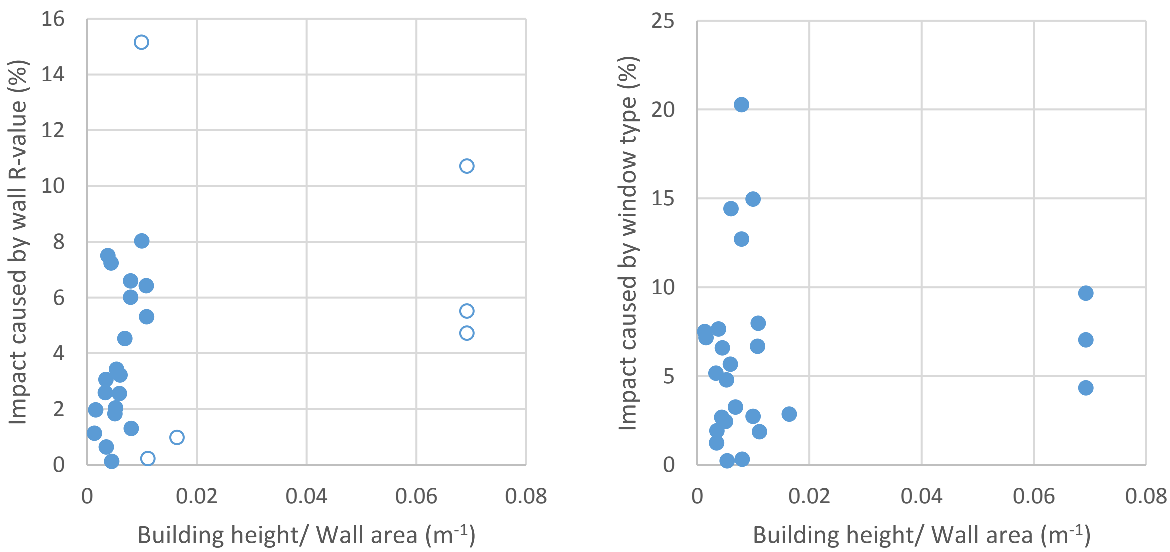
*Correlation of EUI roof impact due its relative size (a: number of stories/ roof area; b: building height/ roof area; c: volume/ roof area) *blank datapoints represent outliers*



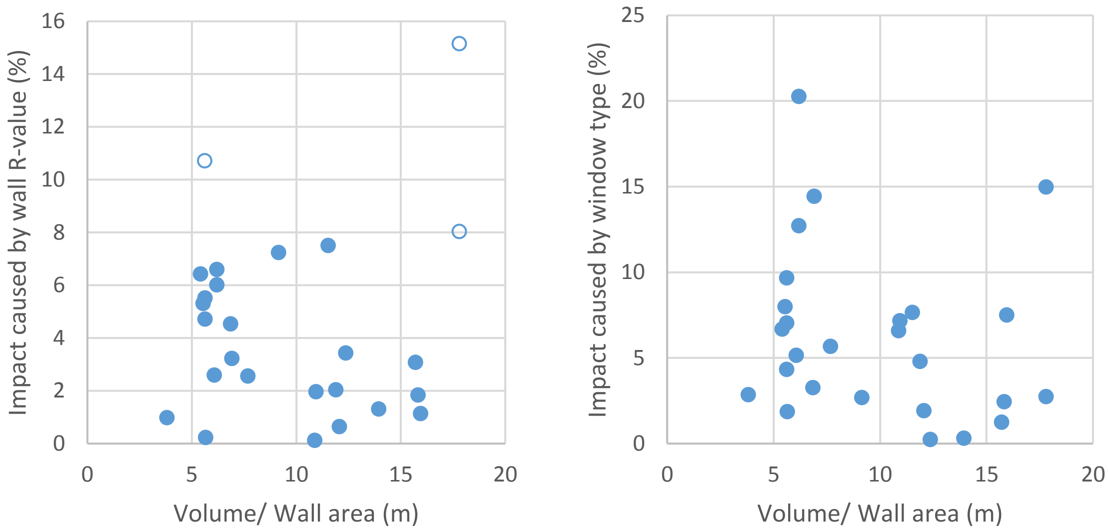
*Correlation of NPW roof impact due its relative size (a: number of stories/ roof area; b: building height/ roof area; c: volume/ roof area) *blank datapoints represent outliers*



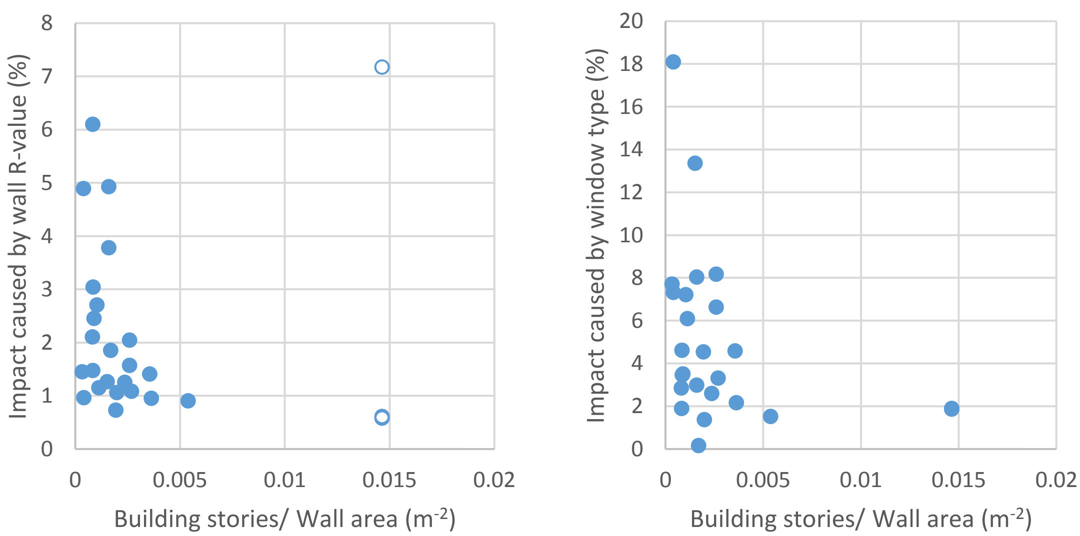
*Correlation of EUI impact due to ratio of stories over wall area (a: wall impact; b: window type impact)*blank datapoints represent outliers*



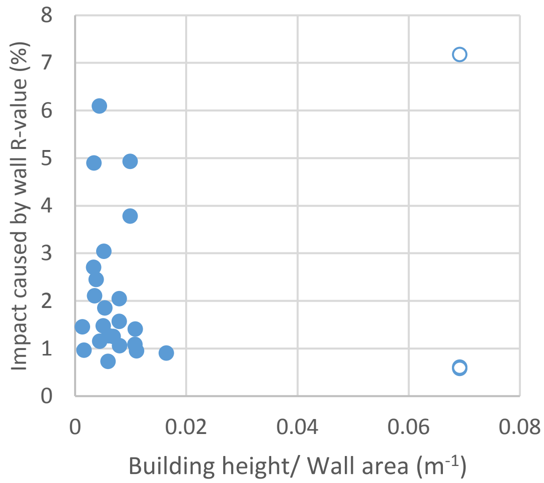
*Correlation of EUI impact due to ratio of height over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

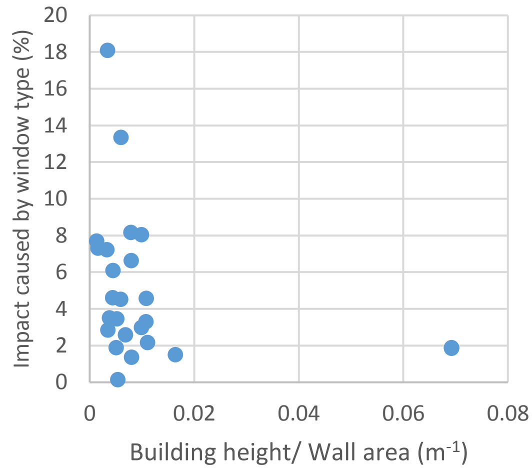


*Correlation of EUI impact due to ratio of volume over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

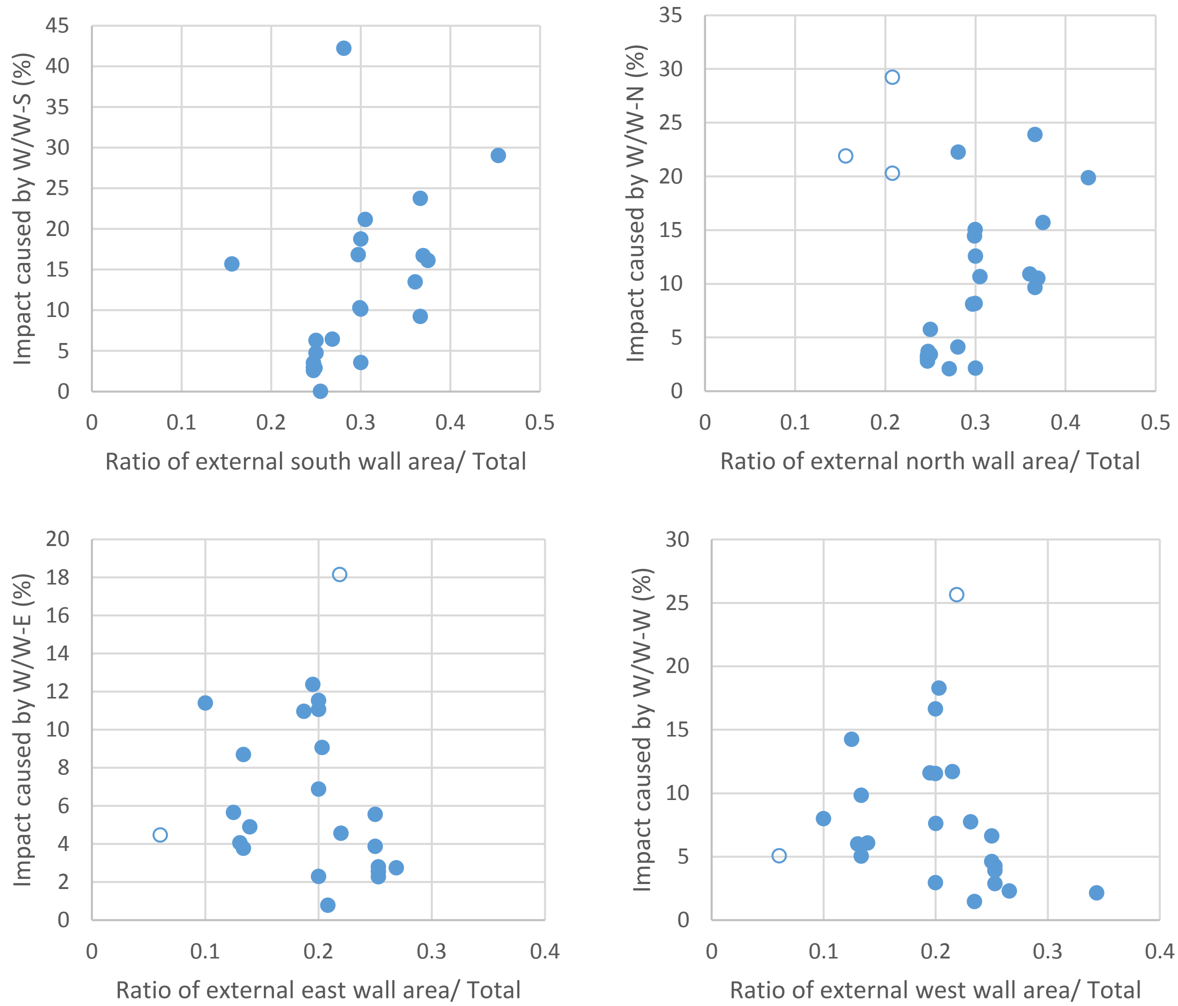


*Correlation of NPW impact due to ratio of stories over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*

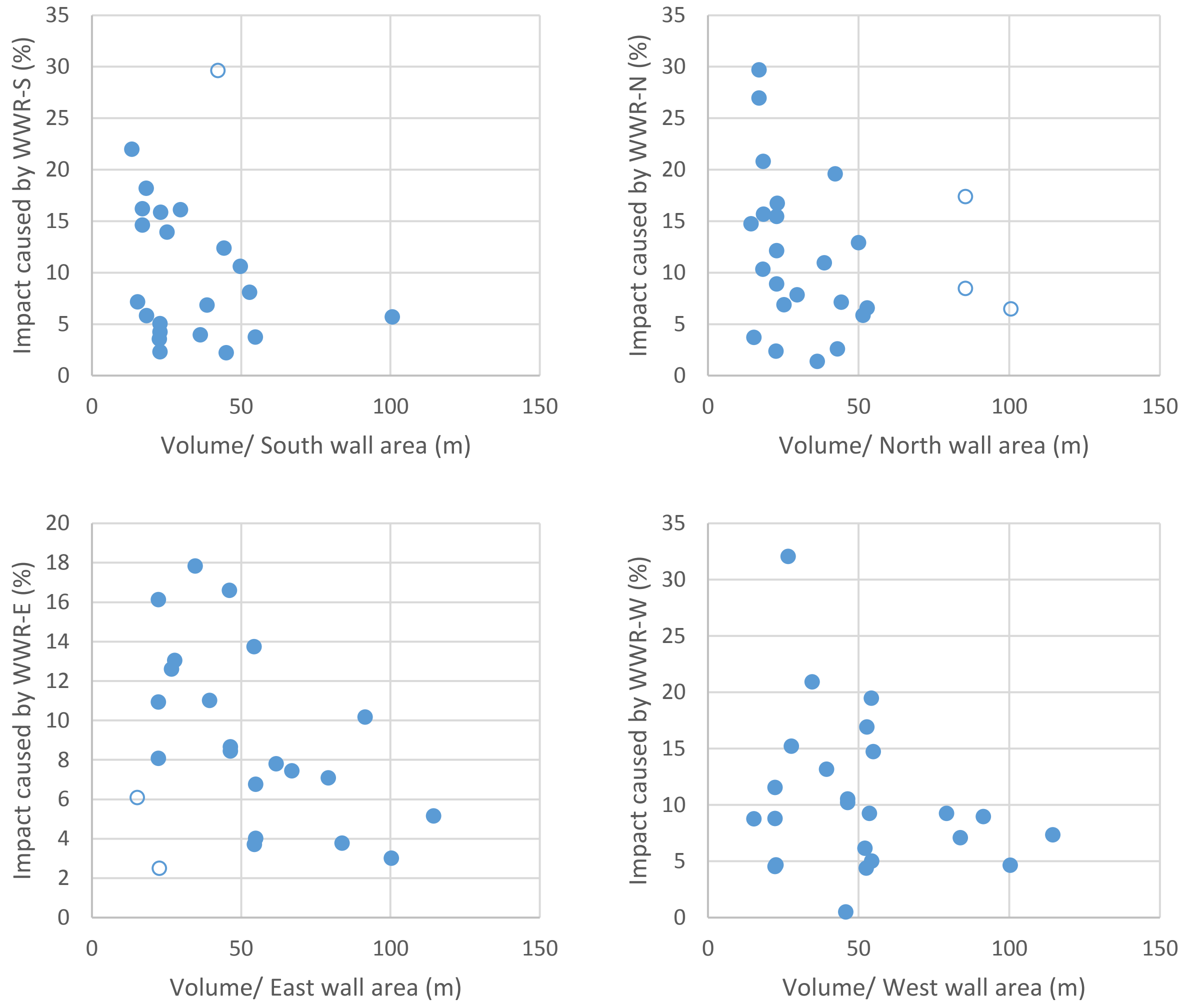




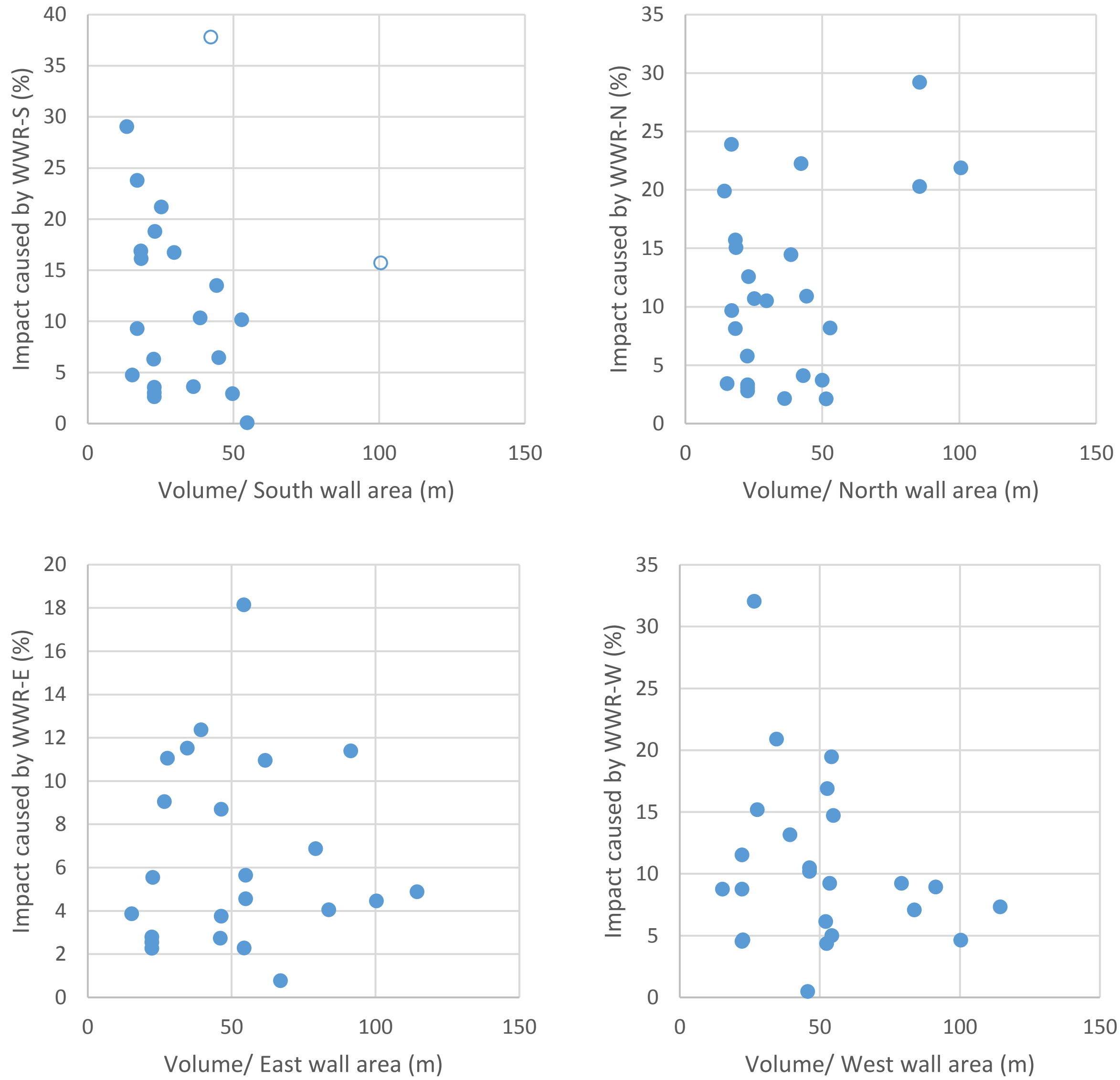
*Correlation of NPW impact due to ratio of height over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*



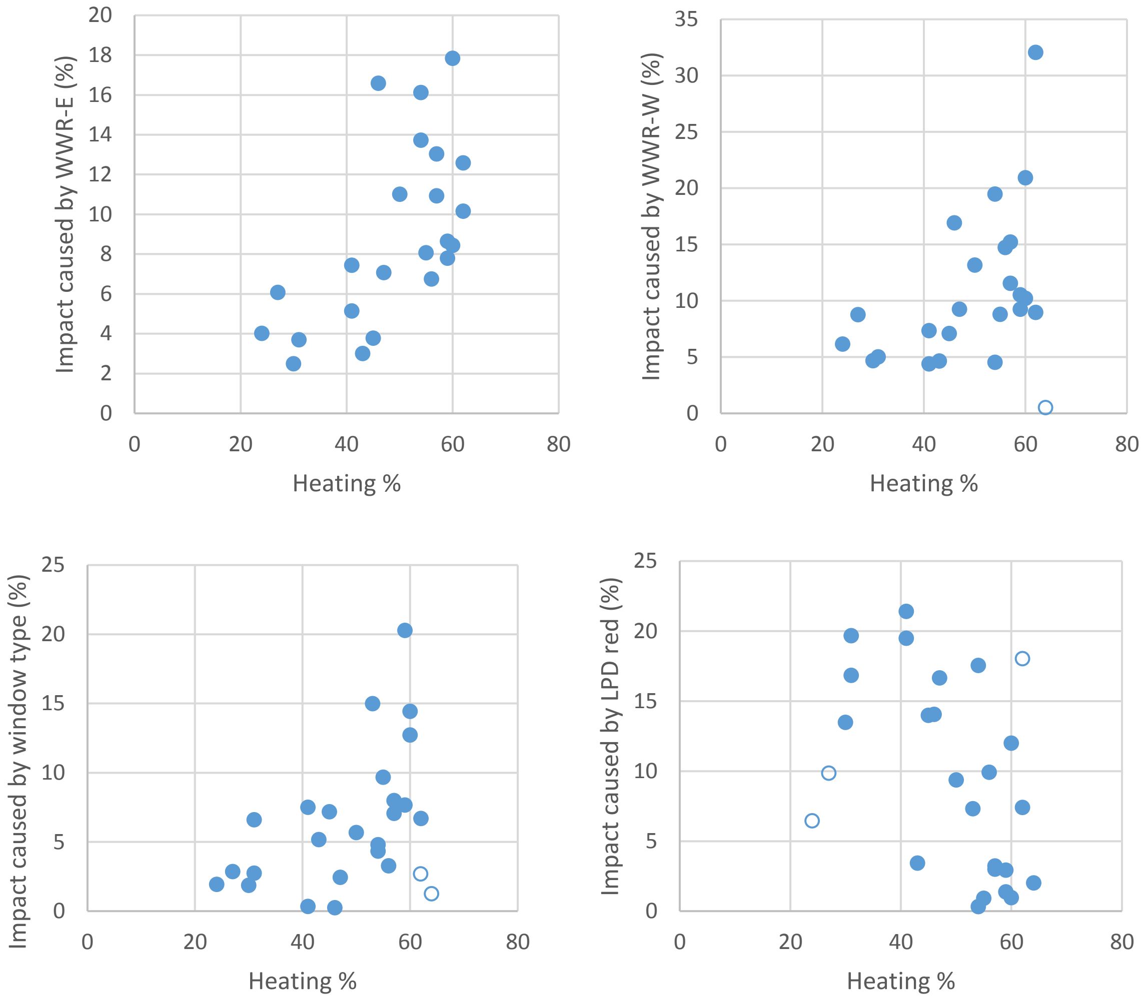
*Correlation of NPW impact due to facade wall percentage (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*



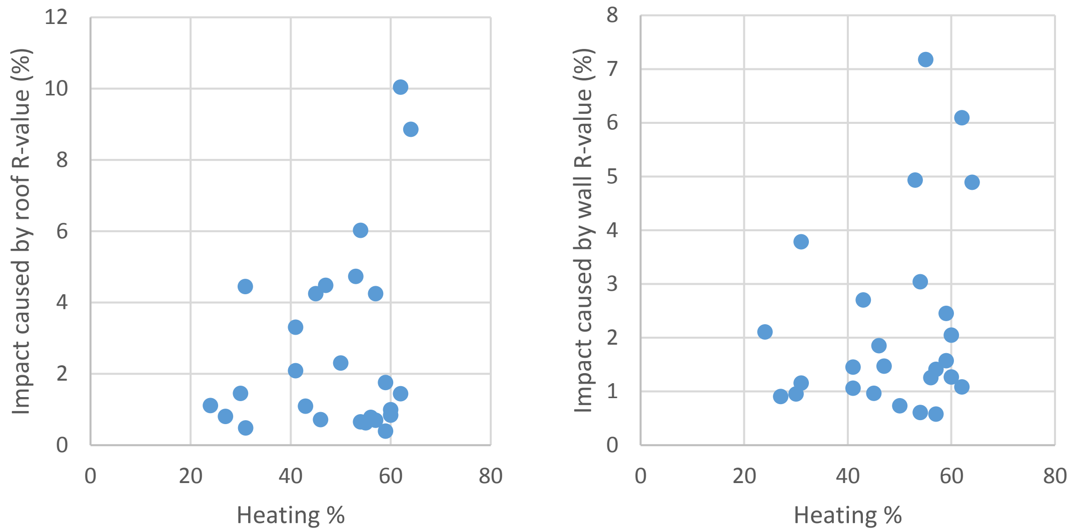
*Correlation of EUI impact due to relative area of facade compared to building volume (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*



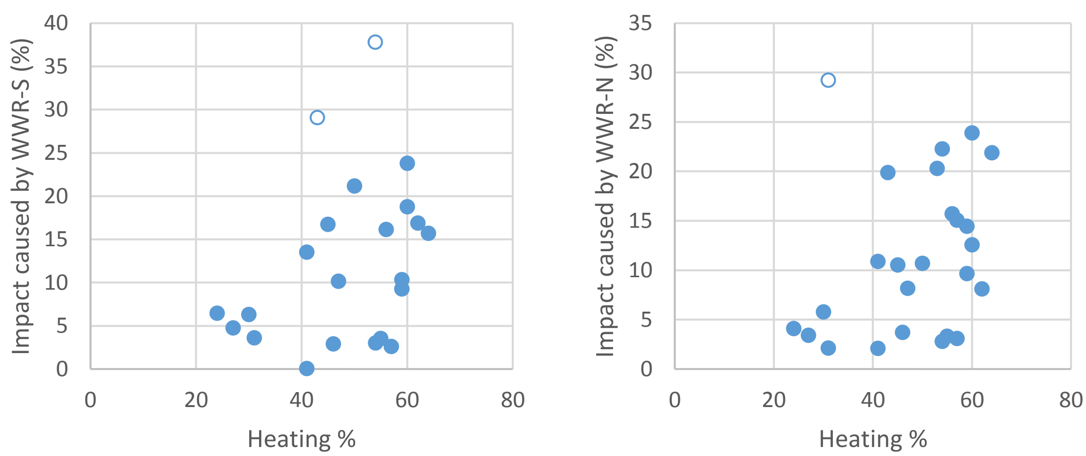
*Correlation of NPW impact due to relative area of facade compared to building volume (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*



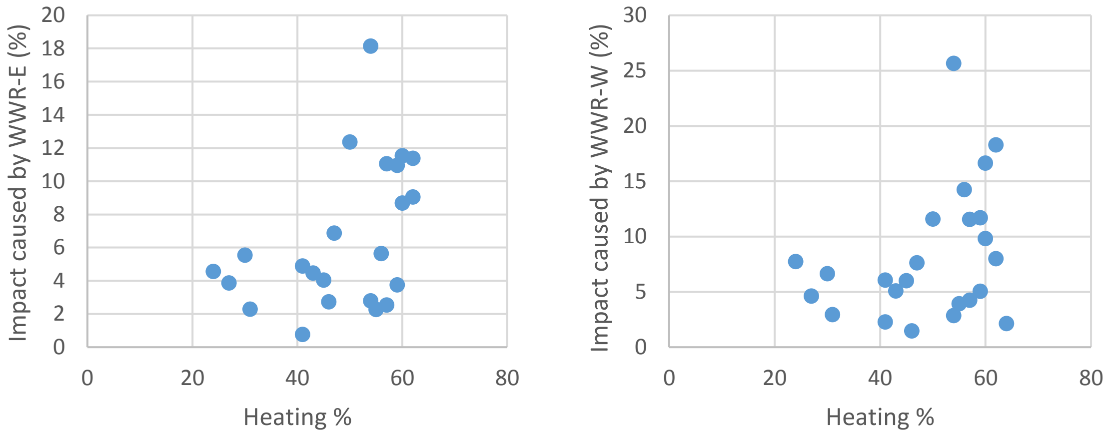
*Correlation of EUI impact due to the portion of the building's total energy going towards heating (a: WWR east; b: WWR west; c: window type; d: lighting efficiency) *blank datapoints represent outliers*



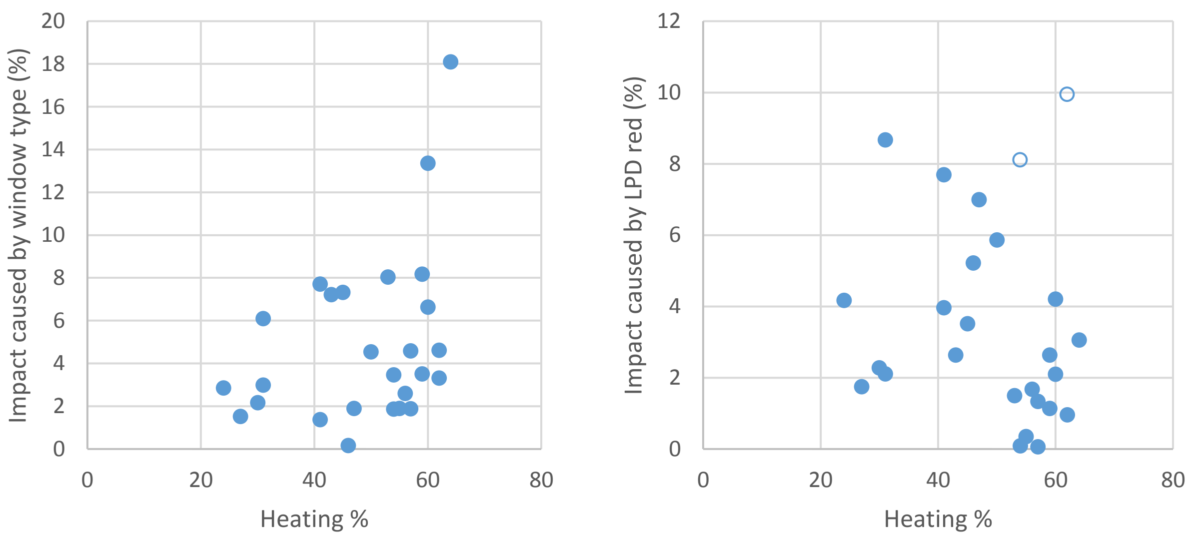
Correlation of NPW impact due to the portion of the building's total energy going towards heating (a: roof insulation; b: wall insulation)



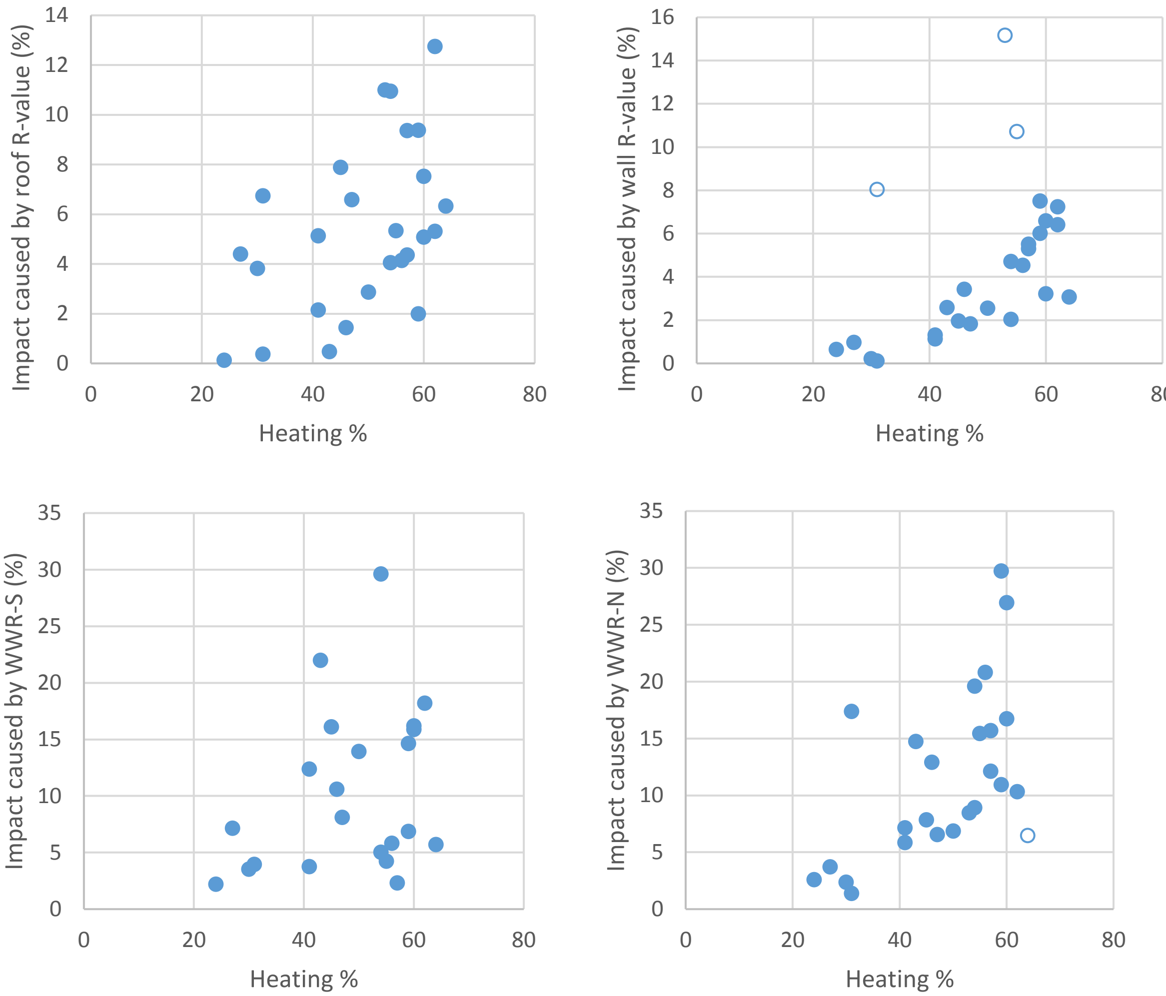
Correlation of NPW impact due to the portion of the building's total energy going towards heating (a: WWR south; b: WWR north)



Correlation of NPW impact due to the portion of the building's total energy going towards heating (a: WWR east; b: WWR west)



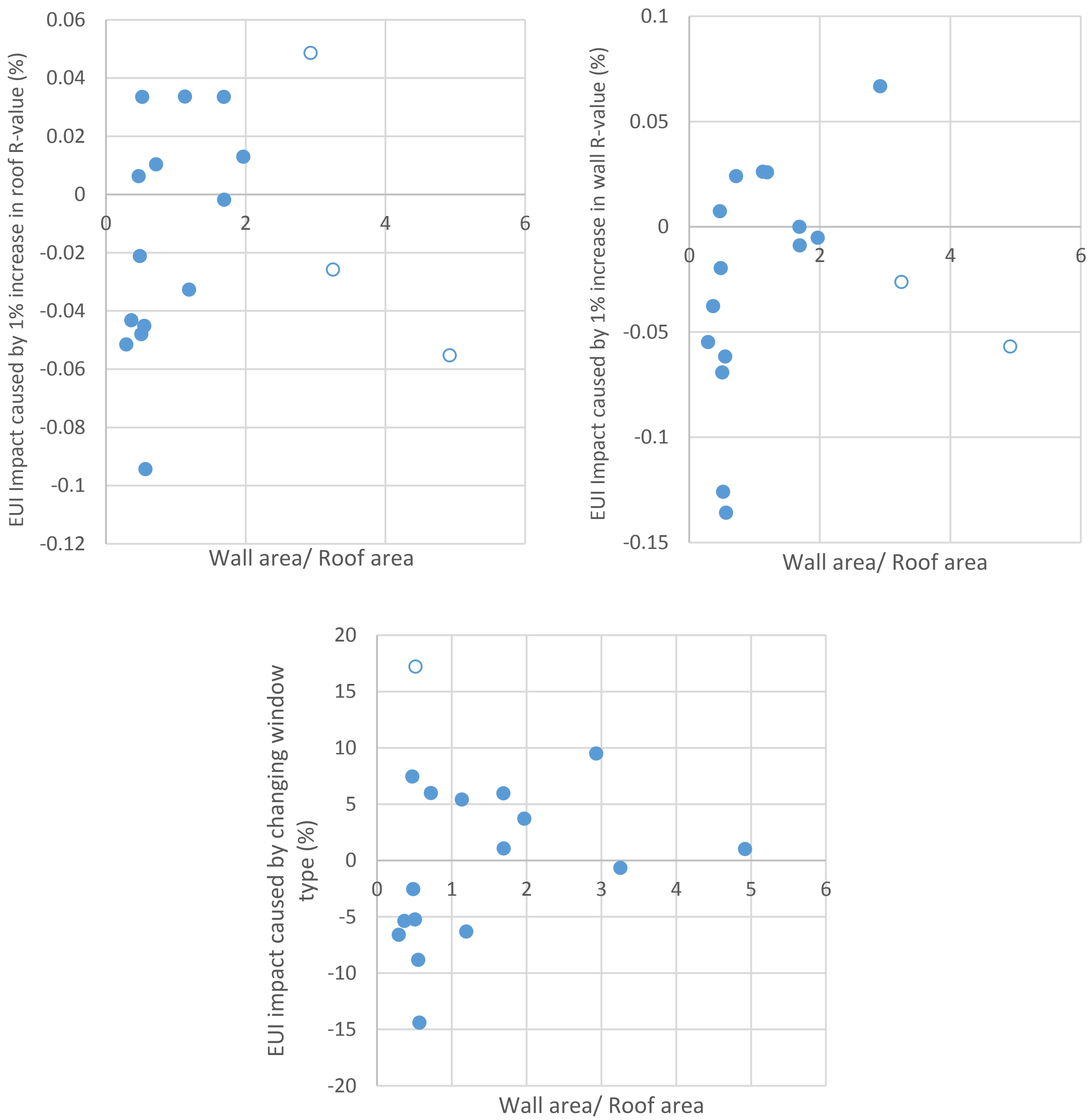
Correlation of NPW impact due to the portion of the building's total energy going towards heating (a: window type; b: lighting efficiency)



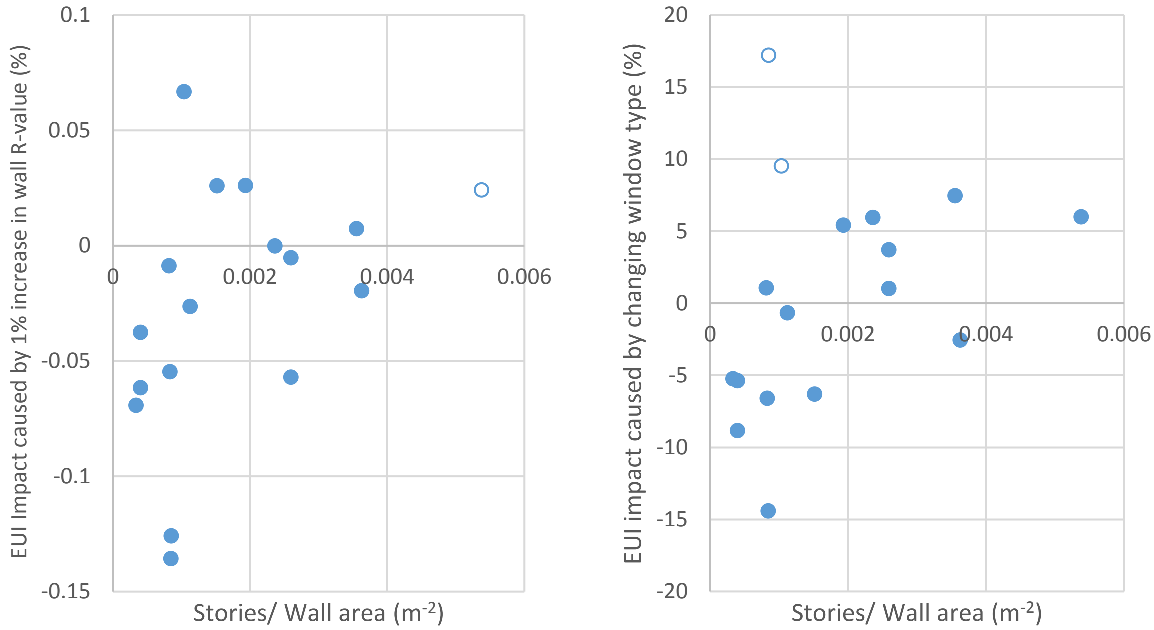
*Correlation of EUI impact due to the portion of the building's total energy going towards heating (a: roof insulation; b: wall insulation; c: WWR south; d: WWR north) *blank datapoints represent outliers*

Appendix 4

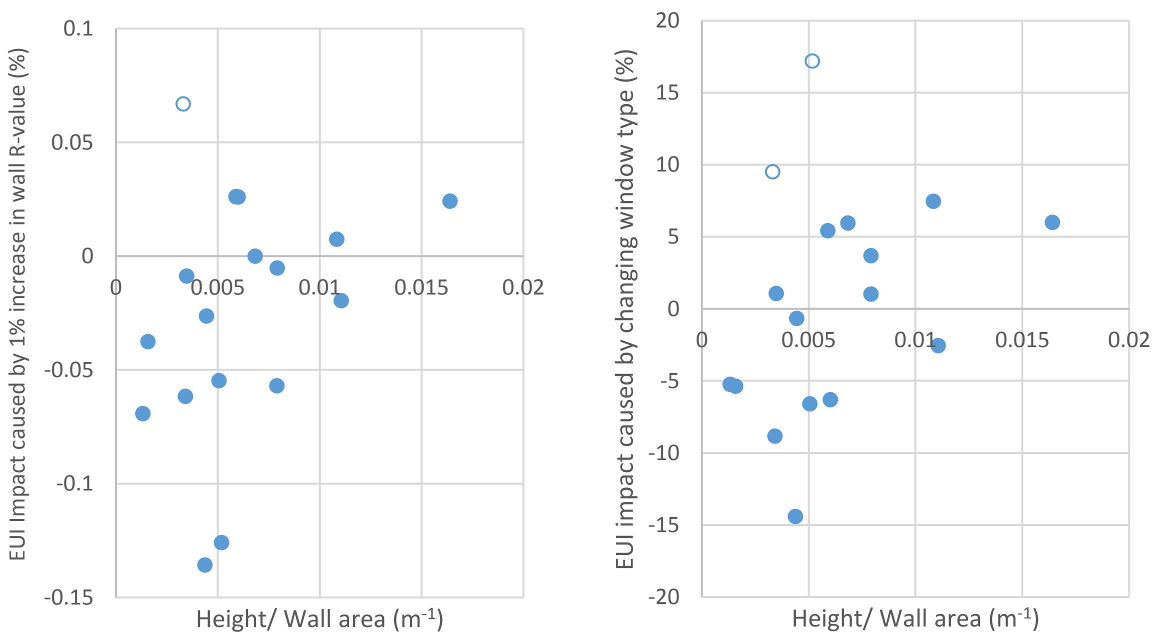
Graphs used in the global correlation analysis



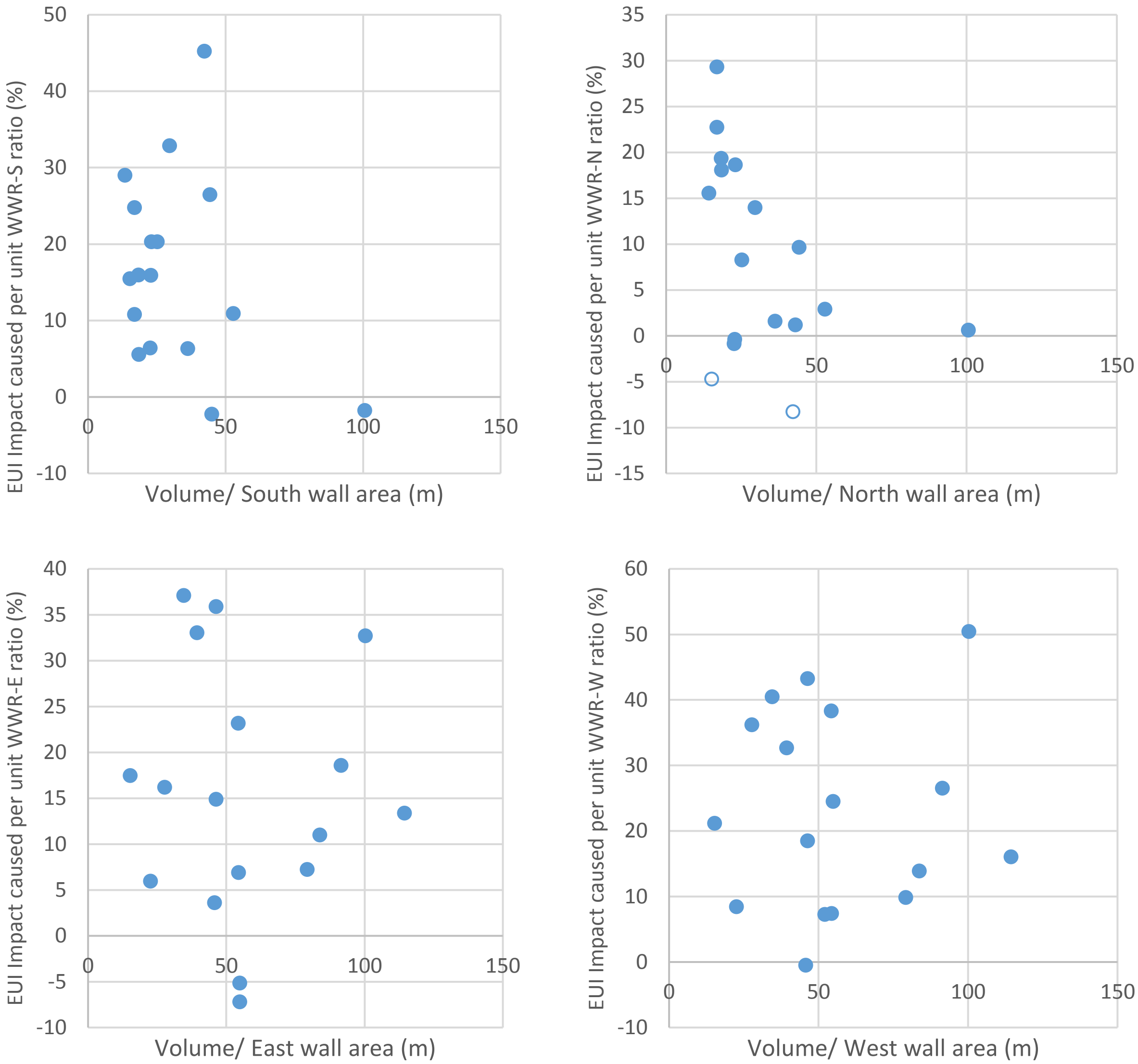
Correlation of EUI impact due to ratio of wall area over roof area (a: roof impact; b: wall impact; c: window type)
**blank datapoints represent outliers*



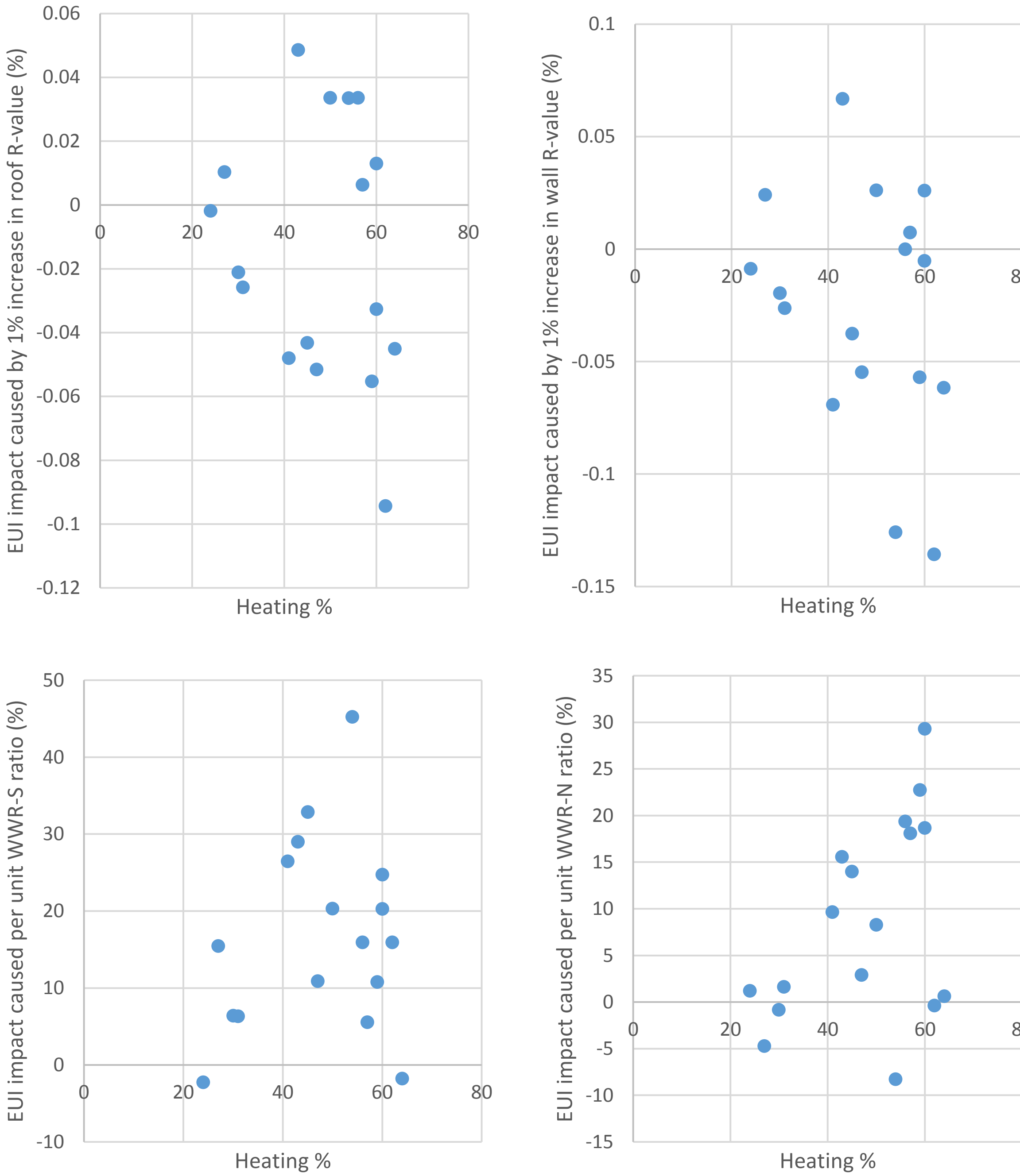
*Correlation of EUI impact due to ratio of stories over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*



*Correlation of EUI impact due to ratio of height over wall area (a: wall impact; b: window type impact) *blank datapoints represent outliers*



*Correlation of EUI impact due to relative area of facade compared to building volume (a: south façade; b: north façade; c: east facade; d: west facade) *blank datapoints represent outliers*



*Correlation of EUI impact due to the portion of the building's total energy going towards heating (a: roof insulation; b: wall insulation; c: WWR south; d: WWR north) *blank datapoints represent outliers*