UNIVERSITAT ROVIRA I VIRGILI

EFFECTS OF ARCHITECTURAL DESIGN VARIABLES ON ENERGY AND ENVIRONMENTAL PERFORMANCE OF OFFICE BUILDINGS

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Effects of architectural design variables on energy and environmental performance of office buildings

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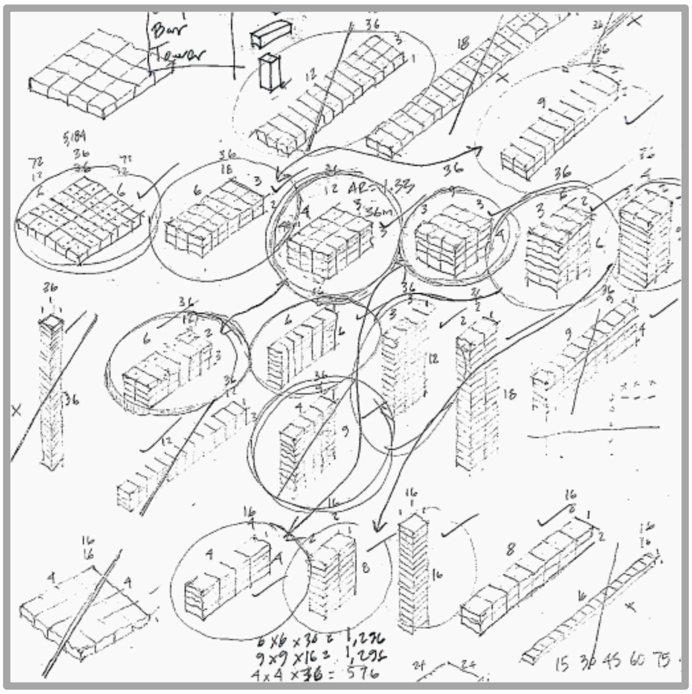
A thesis submitted in partial fulfillment of the requirements of Universitat Rovira i Virgili for the degree of Doctor of Philosophy



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WE STATE that the present study, entitled "Effects of Architectural Design Variables on Energy and Environmental Performance of Office Buildings", presented by Arturo Ordoñez Garcia for the award of the degree of Doctor, has been carried out under our supervision at the Department of Mechanical Engineering of this university, and that it fulfils all the requirements to be eligible for the European Doctorate Award.

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Abstract

Nowadays, it is widely recognized the role of buildings in the high rates of energy consumption that characterize contemporary societies, as well as in global problematics such as climate change, depletion of natural resources and environmental pollution. In this context, energy efficiency of buildings has become a crucial aspect of national and international energy policies. Nevertheless, the design of high performance buildings is not a simple assignment, because they represent complex systems that have to fulfill multiple goals, often contradictory.

This research addresses a methodological approach to better understand the effects that architectural design variables have on energy, environmental and economic performance of office buildings. It explores some of the analysis methods that offer greater potential, and considers especially four representative Spanish climate zones: A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos. The research process consisted of four main phases, each addressing one key question:

1. How can be systematically defined the architectural design variables, in order to study their impacts on energy, environmental and economic performance of buildings?

The first phase involved the development of a **parametric simulations project**, based on the programs EnergyPlus and jEPlus. Its main purpose was to define the most significant architectural design variables and characterize them by a number of parameters organized into a consistent framework. The parametric project includes 7 architectural design variables (shape, WWR, orientation, thermal mass, insulation, number of glass panes and glass type) and three complementary variables (infiltration level, usage intensity and HVAC saving option). In its basic form, the project allows exploring a search space of 7,776,000 design solutions, although the variables and options can be easily reduced to focus on certain aspects of building performance, or to match different research requirements. The parametric project was also conceived as the basis to accomplish the remaining parts of the research.

2. Which are the architectural design solutions that offer optimal energy, environmental and economic performance?

The second phase addressed a set of **optimization analyses** by means of evolutionary algorithms, performed with the program jEPlus+EA. It was intended to identify the architectural design solutions that produce the lowest energy, environmental and economic impacts. Three different optimization scopes were implemented, regarding their performance objectives: (A) total energy loads, (B) operational CO_2 and initial cost, and (C) global CO_2 and global cost. Among the main findings are the following:

- Building shapes with low-to-medium height and high aspect ratio offer the best overall performance, considering the different optimization scopes and climate zones.
- Reducing the amount of glazing as much as possible seems to be an important strategy to optimize building performance.
- Coinciding with other studies, the optimal orientation in the different optimization scopes and climate zones is close to 0.0º, i.e. the larger facades facing north and south.
- High levels of thermal mass show favorable effects in terms of energy performance, but increase the initial cost and the embodied CO_2, which affect its overall performance.
- Envelope insulation offers clear benefits when heating demands are high, but these benefits seem to have a limit. Furthermore, high insulation could be detrimental when cooling demands are dominant.

- Double-glazing can be considered a good overall choice considering the different optimization scopes and climate zones.
- The spectrally selective in the first place, and the low-e in the second one, are the glass types that offer the best overall performance.

Regarding the comparison of the optimization scopes, it is remarkable that optimizing office buildings exclusively with basis on their energy performance could lead to sub-optimal solutions from a more comprehensive point of view. On the other hand, it is also evident that choosing solutions with low initial cost leads to very poor solutions in terms of global CO_2 and global cost.

3. What is the relative importance of the main architectural design variables, considering a wide range of performance indicators?

The third phase comprised the application of two global **sensitivity analysis** methods, Morris and Sobol, for investigating the relative importance of each architectural design variable in terms of its impact on energy, environmental and economic performance of buildings. The study was also aimed to compare the effectiveness of both sensitivity analysis methods. Among the main conclusions are the following:

- Shape and WWR are the most influential design variables among the different output variables and climate zones. They are followed by insulation and thermal mass, in the second place, and glass type and number of panes in the third place.
- As expected, the importance of factors changes widely depending on the output variable and the climate zone. Hence, it is not possible to rank the design variables in a scale of importance that is suitable for any performance indicator or climate zone.

Regarding the comparison of the sensitivity analysis methods, the Morris method provided good qualitative data about the sensitivity of the input factors with low computational cost. This method appears to be a suitable approach for models with many design variables when computational cost is a concern. The Sobol method showed great capability to estimate in a detailed and quantitative way the impact of the input factors. Its high computational cost represents an important disadvantage, but it is advisable to use this method whenever possible.

4. Which are the numerical parameters that best describe the architectural design variables, and thus can be used to predict building performance?

The fourth phase involved the implementation of **artificial neural networks** for creating meta-models that are able to predict seven output variables (heating, cooling and lighting loads, as well as operational CO_2, global CO_2, initial cost and global cost). The study was aimed in the first place to test and validate a number of parameters, in terms of their capability to represent numerically the architectural design variables. 16 input parameters were finally selected to describe the design variables of the parametric project, including four parameters that describe the building shape (*ExternalSurface/Volume*, *Wall/Volume*, *Roof/Volume* and *Wall/ExternalSurface*), two parameters that describe opaque constructions (*global heat capacity* and *global thermal resistance*) and three parameters that describe the glazing (*U-factor*, *SHGC* and *Visible transmittance*).

The meta-models where tested by comparing simulations results versus values predicted by the ANNs, using independent samples of 600 randomly selected design solutions for each climate zone. The statistics of the errors between the predicted values and the simulated ones generated very low mean relative errors (around 1.5%). Similarly, linear regression analysis showed good adjustment among both set of data, with R^2 values near to 1.0. It means that the input parameters selected for feeding the ANNs are a good representation of the architectural characteristics of buildings.

In summary, the analyses implemented as part of this research offer, together, a better understanding of the impacts that the architectural design variables have on energy, environmental and economic performance of office buildings. Though it is important to consider the limits imposed by the research itself, the results provide information that can be valuable to guide decision-making during the architectural design process. They can also help to broaden the criteria currently used in the development of energy codes and sustainability certification systems. Nevertheless, hopefully the most important contribution of this research is that proposes and implements a methodological approach that can address energy and environmental problems of the buildings from a more holistic point of view.

Resumen

En la actualidad es ampliamente reconocido el papel de los edificios en el elevado consumo energético que caracteriza a las sociedades contemporáneas, así como en problemas globales como el cambio climático, el agotamiento de los recursos naturales y la contaminación ambiental. En este contexto, la eficiencia energética de los edificios se ha convertido en un aspecto crucial de las políticas energéticas nacionales e internacionales. Sin embargo el diseño de edificios con elevadas prestaciones no es una tarea simple, ya que se trata de entidades complejas que deben cumplir múltiples cometidos, a menudo contradictorios.

Esta tesis plantea un enfoque metodológico para comprender mejor los efectos que las principales variables de diseño arquitectónico tienen en el desempeño energético, medioambiental y económico de los edificios de oficinas, implementando algunos de los métodos de análisis con mayor potencial y considerando cuatro zonas climáticas de España (A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos). Busca contribuir al desarrollo de enfoques y métodos que faciliten la toma de decisiones durante el proceso de diseño arquitectónico, especialmente en las etapas iniciales. También busca generar información que ayude a mejorar los criterios aplicados en los códigos energéticos y los sistemas de certificación sostenible. La investigación incluye cuatro partes principales, cada una de las cuales busca responder a una pregunta clave planteada en la investigación.

¿Cómo se puede caracterizar las variables de diseño arquitectónico que tienen mayor impacto en el desempeño energético, medioambiental y económico de los edificios?

La primera parte consiste en el desarrollo de un **proyecto de simulaciones paramétricas** basado en los programas EnergyPlus y jEPlus. Su cometido principal es definir las variables de diseño arquitectónico más significativas, y caracterizarlas mediante una serie de parámetros organizados en torno a un marco conceptual coherente. El proyecto paramétrico define siete variables de diseño arquitectónico (forma, proporción de acristalamiento, orientación, nivel de masa térmica, nivel de aislamiento, número de vidrios y el tipo de vidrio), más tres variables complementarias (nivel de infiltración, intensidad de uso y opción de ahorro energético del sistema HVAC) . En su forma básica, facilita la exploración de 7,776,000 soluciones de diseño, aunque las variables y opciones de diseño se puede reducir fácilmente para ajustarse a diferentes requerimientos de investigación. El proyecto paramétrico se concibe también como la base para llevar a cabo las partes restantes de la investigación.

¿Cuáles son las soluciones de diseño arquitectónico que generan un desempeño óptimo de los edificios en términos energéticos, medioambientales y económicos?

La segunda parte aborda un **análisis de optimización** mediante algoritmos evolutivos, llevado a cabo mediante el programa jEPlus+EA. El propósito central fue identificar las soluciones de diseño arquitectónico que producen impactos ambientales y económicos más bajos. Se consideraron tres alcances distintos en lo que respecta a los objetivos de desempeño: (A) carga energética total, (B) CO_2 operacional y coste inicial, y (C) CO_2 global y coste global. Entre los resultados más significativos podemos resaltar los siguientes:

- Las formas con altura media-baja y elevada relación de aspecto ofrecen en general el mejor desempeño, considerando los diferentes alcances de optimización y zonas climáticas.
- Reducir la cantidad de acristalamiento tanto como sea posible parece ser una estrategia importante para optimizar el desempeño del edificio, independientemente de la zona climática.
- La orientación óptima en todos los alcances de optimización y zonas climáticas está cerca de 0.0º, es decir, con las fachadas más largas orientadas al norte y al sur.

- Elevados niveles de masa térmica tienen efectos favorables en términos de eficiencia energética, pero aumentan el coste inicial y el CO_2 incorporado, lo que afecta su viabilidad general.
- El aislamiento térmico ofrece claros beneficios cuando las demandas de calefacción son elevadas, pero estos beneficios parecen tener un límite. Por otra parte, un elevado aislamiento podría ser perjudicial cuando predominan las demandas de refrigeración.
- El acristalamiento doble se puede considerar una buena elección en general, considerando los diferentes alcances de optimización y zonas climáticas.
- El vidrio espectralmente selectivo en primer lugar, y el bajo emisivo en segundo, son los tipos de vidrio que ofrecen el mejor desempeño en general.

En lo que respecta a la comparación de los diferentes alcances de optimización, es notorio que optimizar los edificios de oficinas exclusivamente a partir de su desempeño energético podría llevar a soluciones sub-óptimas en el contexto de un alcance más amplio. Por otro lado, es evidente que la elección de soluciones con bajo coste inicial conduce a soluciones poco óptimas en cuanto al CO_2 global y el coste global.

¿Cuál es la importancia relativa de las variables de diseño arquitectónico, considerando un amplio rango de indicadores del desempeño?

La tercera parte involucró la aplicación de dos métodos de **análisis de sensibilidad**, Morris y Sobol, con el fin de establecer la importancia relativa de cada variable de diseño arquitectónico en el desempeño energético, medioambiental y económico de los edificios. Esta parte también tuvo como objetivo comparar la efectividad de los dos métodos empleados. Entre las principales conclusiones se pueden resaltar las siguientes:

- La forma y la proporción de acristalamiento son en general las variables de diseño más influyentes, considerando los diferentes indicadores de desempeño y zonas climáticas. Después de ellos se ubican el aislamiento y la masa térmica, en segundo lugar, y el tipo y número de vidrios en tercer lugar.
- Como era de esperar, la importancia de los factores cambia marcadamente en función del indicador de desempeño y de la zona climática. En ese sentido, no es posible clasificar las variables de diseño en una escala de importancia que sea adecuada para cualquier indicador de desempeño y/o zona climática.

En cuanto a la comparación de las dos técnicas de sensibilidad, el método Morris ofreció datos cualitativos de buena calidad respecto a la sensibilidad de las diferentes variables de diseño, con un bajo coste computacional. Este método parece ser una opción adecuada cuando se tiene modelos con muchas variables de diseño y/o el coste computacional es una limitante. El método Sobol, por otro lado, demostró gran capacidad para estimar de manera detallada y cuantitativa el impacto de las variables de diseño. Su alto coste computacional representa una desventaja importante, pero es recomendable utilizar este método siempre que sea posible.

¿Cuáles son los parámetros numéricos que mejor describen a las variables de diseño de diseño arquitectónico, y por lo tanto pueden ser usados para predecir el desempeño de los edificios?

La cuarta parte consistió en la implementación de **redes neuronales artificiales** para crear meta-modelos que fueran capaces de predecir, con razonable precisión, siete indicadores de desempeño (las cargas de calefacción, refrigeración e iluminación, así como el CO_2 operacional y global, y los costes inicial y global). El cometido principal de esta parte de la investigación fue poner a prueba y validar un conjunto de parámetros, en términos de su capacidad para representar numéricamente las variables de diseño arquitectónico. Finalmente se seleccionaron 16 parámetros para representar las variables de diseño del proyecto paramétrico, incluyendo cuatro que describen la forma (*SuperficieExterior/Volumen*, *Muro/Volumen*, *Cubierta/Volumen*, y *Muro/SuperficieExterior*), dos que describen las propiedades de los cerramientos opacos (*Capacidad térmica global* y *Resistencia térmica global*), y tres que describen las propiedades del acristalamiento (*Factor-U*, *SHGC* y *transmitancia visible*).

Para comprobar la precisión de los meta-modelos se compararon valores predichos por ellos contra resultados de simulación, empleando muestras aleatorias de 600 soluciones de diseño para cada zona climática. Las estadísticas de error entre los valores predichos por los meta-modelo y los simulados produjeron errores relativos medios muy bajos (alrededor de 1.5%). Del mismo modo, los análisis de regresión lineal mostraron un buen ajuste entre los dos conjunto de datos, con valores de R^2 cercanos a 1.0. Esto significa que los parámetros numéricos que fueron seleccionados para generar las redes neuronales pueden representar de manera adecuada las características arquitectónicas de los edificios, dentro de los límites impuestos por esta investigación. Así mismo, los resultados indican que los meta-modelos podrían utilizarse con relativa confianza como modelos sustitutos para ampliar y mejorar otros métodos de análisis.

En resumen, los análisis llevados a cabo como parte de esta investigación ofrecen una mejor comprensión de los impactos que las variables de diseño arquitectónico tienen sobre el desempeño energético, medioambiental y económico de los edificios de oficinas. Aunque es importante tomar en cuenta los límites impuestos por la propia investigación, los resultados ofrecen información que puede ser de gran valor para guiar la toma de decisiones durante el proceso de diseño arquitectónico. También pueden contribuir a ampliar los criterios que se utilizan actualmente en el desarrollo de los códigos energéticos y los sistemas de certificación de sostenibilidad. Sin embargo, quizá una de las mayores aportaciones de la investigación es que plantea y pone en práctica un enfoque metodológico que permite abordar los problemas energéticos y ambientales de los edificios desde una perspectiva más holística.

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Table of content

List of figures

List of Tables

Chapter 1. Introduction

1.1. Research approach

During the last decades, global problems such as climate change, depletion of natural resources and environmental pollution have become more visible and recognized. Although there have been some debates regarding their origin, their impact, and even their real existence, many governments and organizations have recognized these problems and implemented specific actions to solve or mitigate them. For instance, countries from the European Union have agreed on the ambitious Framework for climate and energy [1]. This agreement, planned for the period between 2020 and 2030, includes a 40% decrease in greenhouse gas emissions compared to 1990 levels; at least a 27% share of renewable energy consumption; and at least 27% energy savings compared with the business-as-usual scenario. Furthermore, at the 2015 Paris climate conference 195 countries adopted, for the first time, a universal, legally compulsory agreement to implement the actions required to keep the increase in global average temperature to well below 2°C above pre-industrial levels [2]. One of the key goals of the agreement is to reach the peak of global emissions as soon as possible, and thereafter reduce them gradually.

The role of buildings in the excessive energy consumptions that characterize contemporary societies, and therefore in the global problematic above mentioned, is also well recognized. A study conducted in 2007 [3] pointed out that the contribution of buildings to the overall energy consumption in developed countries had reached 40%, even surpassing industry and transport sectors. Furthermore, according to the European Commission, the building sector is responsible for 36% of CO_2 emissions in Europe [4]. Therefore, energy efficiency of buildings has become a key aspect of the strategies to reduce global emissions and mitigate the climate change. In that line, practically all countries in the European Union have now established energy codes that cover residential and nonresidential buildings, as well as both new constructions and renovations [5].

Most of the energy consumed in buildings is associated with items that are intended to achieve adequate indoor environmental conditions, i.e. HVAC and lighting systems. The amount of energy consumed by the HVAC systems varies markedly depending on the climate zone and the building type, but according to Perez et al. [3], in developed countries it accounts for about 50% of total energy consumption in buildings. According to the same source, the energy consumed by lighting systems represents about 25%. The remaining energy consumption is mainly associated with the usage of appliances and equipment.

Energy consumption associated with HVAC and lighting systems mainly depends on four factors: the climate of the site, the usage requirements, the architectural features of the building, and the characteristics of the systems themselves. The first two factors should usually be assumed as design constraints, because they precede the design process and the designers have little or no influence on them. On the other hand, the architectural features and the characteristics of mechanical systems clearly represent design decisions: although there are often practical and legal limits, designers can choose from multiple options.

It is clear that both, the architectural features of buildings and the characteristics of their mechanical systems, are important factors to reduce energy consumption and environmental impacts. Moreover, it would be desirable to solve these factors in a coordinated way, in order to get the best possible results, as exemplified by Shapiro and Sirt [6]. Architecture and engineering should work more closely together to achieve high quality buildings in every sense [7]. However, one of the main assumptions in this research is that the architectural features should be addressed in the first instance, mainly because:

- During the design process, architectural decisions start well before the definition of mechanical systems. At least general characteristics of buildings are decided from the early design phases, as a response for multiple determining factors, such as functional requirements, characteristics of the site and urban and building regulations. Usually, the specific type and characteristics of the HVAC systems are defined from the features and requirement of the building, not vice versa.
- Buildings should be efficient on their own. It is at least illogical, from both energy and environmental point of view, to implement high efficiency mechanical systems in buildings with inefficient architectural features. Furthermore, the use of high-quality mechanical systems in inefficient building does not even guarantee that good comfort levels can be achieved.
- There are some impacts of buildings that have little to do with their mechanical systems and much with their architectural features. For instance, the embodied CO_2, which strongly contributes to the global CO_2 emissions of the building, mainly depends on the selection of materials and construction products. Understanding how to reduce these impacts is a key aspect.

Architectural design involves many variables, which for the sake of simplicity can be grouped into two main categories: geometric configuration and envelope composition. The category of geometric configuration includes variables such as general shape, distribution of glazing and orientation. The category of envelope composition, on the other hand, includes the composition of opaque constructions (walls, roofs, floors) and translucent surfaces (windows, curtain walls, skylights). There are many studies that have addressed the impact of these architectural design variables on energy performance of buildings. Without trying to make an exhaustive review, below are some examples:

- Depecker et al. [8] studied the relationship between building shape and heating energy consumption, considering two different climates. 14 building shapes were studied with basis on their shape coefficient, i.e. the external surface divided by the volume. According to the authors, the heating energy consumption is proportional to the shape coefficient (or inversely proportional to the compactness) in the climate with very cold and barely sunny winters, but this is not the case for the mild climate, where no recommendations regarding the shape factor could be done.
- AlAnzi et al. [9] implemented a comprehensive parametric analysis by means of whole-building energy simulations, aiming to develop a simplified method to estimate the impact of shape on energy efficiency of office buildings in Kuwait. 105 forms were studied for the same building with 12,500 m^2 floor area, including rectangular, cross, L, T, H and U shapes. However, the height of the building (20 floors) remained the same in all cases. Additionally, the analysis included window to wall ratios from 0 to 0.75 as well as 6 glazing types characterized by the solar heat gain coefficient (SHGC). It was concluded that the impact of shape on building energy performance mainly depends on three factors: relative compactness (RC), window to wall ratio (WWR) and glazing type defined by its solar heat gain coefficient (SHGC). From these parameters the authors proposed a correlation equation that hypothetically can be used during the early design phases to assess the impact of shape on building energy efficiency.
- Gratia and De Herde [10] developed a set of parametric simulations by means of the program TRNSYS, in order to study the effect of several variables, such as insulation level, internal gain, ventilation strategies, thermal mass, orientation, solar gains and shading devices, on energy and daylighting performance of office buildings in Belgium. From the results they propose strategies like increasing insulation and air-tightness to reduce heating loads in winter (taking care of overheating); limiting and controlling internal gains; selecting the adequate windows area and orientation; using natural ventilation in summer to avoid overheating; and using thermal mass to increase the beneficial effect of ventilation.
- Many researchers have studied the thermal and energy performance of opaque constructions, especially those located in the external envelope. Some studies only analyzed the effects of

thermal insulation, often trying to find the optimal insulation levels under certain conditions [11] [12] [13] [14] [15] [16]. Other researchers have focused on the impact and optimization of thermal mass [17] [18] [19] [20] [21] [22]. Finally, other investigations have addressed simultaneously insulation and thermal mass, especially regarding the effect of different material distribution in the internal structure of constructions [23] [24] [25] [26] [27] [28] [29]. It is noticeable that virtually all those woks, because of their specialization level, have focused on a certain part of the problem. For example, the majority focuses on one of the constructions, usually external walls. Only a few have included different weather conditions. Also, not always the impacts are addressed for both summer and winter conditions.

- Cordoba et al. [30] studied the energy saving potential of using coated glasses in a double-glazing curtain wall of an office building located in Madrid, through energy simulations by means of the program DOE-2. They found reductions of approximately 12% in electricity consumptions when using solar control glass with thermal insulation.
- Noh-Pat et al. [31] analyzed thermal performance of double glazing units with and without solar control film, considering their use in hot climates. They concluded that the optimal separation between glass panes should be >= 6cm, in order to reduce heat gains. Additionally, the use of solar control films reduced about 55% the solar energy gains, compared to clear double glazing units.
- Goia et al. 2013 [32] investigated the optimal window-wall-ratio in a façade module for low energy office buildings, considering a temperate oceanic climate and four main orientations. The simultaneous impact on heating, cooling and lighting energy demands was addressed. They concluded that independently of the orientation, the optimal WWR is between 35% and 45%. North facades presented the highest difference between the optimal configuration and the worst one, while south facades shown the smallest difference.
- Vanhoutteghem et al. [33] evaluated the effects of windows on heating demand, daylighting and indoor environment of Danish near-zero-energy houses, considering the design variables window-floor-ratio, orientation and glazing composition. The simulations programs EnergyPlus and DAYSIM were used. The results shown a clear limit for energy savings by using solar gains in south-oriented spaces, as overheating may occur. On the other hand, low U-factors are needed in both north- and south oriented spaces in order to get reductions in space heating demands with large windows.

Understanding how the decisions about the design variables affect the energy performance of buildings is not an easy task. In the first place because the architectural design variables interact and affect each other, often in complex ways. For instance, the impact of a given composition of opaque constructions will depend largely on their proportion in building envelope. Likewise, the impact of a given WWR will be affected by the composition of the glazing and building orientation. In addition, the relative importance of architectural design variables depends heavily on the characteristics of the site (climate and microclimate), and the usage conditions of buildings (occupancy patterns, internal gains and control systems). For example, certain construction materials and products may be suitable under certain climate conditions, but not under others. Likewise, even buildings that have been designed correctly can be inefficient if are used, managed and/or controlled inadequately. Finally, it is important to consider that the architectural design variables have different costs of implementation and maintenance. Some, such as the orientation of the building, have costs that can be near to zero; others, such as automated solar shading systems, may involve very high costs.

In the context of the problems briefly explained above, nowadays it is necessary to implement methodological approaches and tools that, as far as possible, allow understanding the effects of the architectural design variables from a holistic, integral and comprehensive point of view. In this way the owners, designers and authorities would have more solid basis for making the right decisions at the right time. This is the general approach of this research project, which has been guided by four key questions:

1. How can be systematically defined the architectural design variables, in order to study their impacts on energy, environmental and economic performance of buildings?
2. Which are the architectural design solutions that offer optimal energy, environmental and economic performance?
3. What is the relative importance of the main architectural design variables, considering a wide range of performance indicators?
4. Which are the numerical parameters that best describe the architectural design variables, and thus can be used to predict building performance?

1.2. Objectives and scope

The general aim of this research is to contribute to the development of methodological approaches that provide a more comprehensive understanding of the architectural design variables, specifically in terms of their effects on energy, environmental and economic performance of office buildings. Such an approach could be valuable, for instance:

- To facilitate the decisions making during the architectural design process. Especially in the early phases, consistent and reliable information is required to guide the design strategies and achieve high performance buildings at a reasonable cost.
- To help improving and extending the criteria used in building energy codes and sustainability certification systems. Again, having information of this kind may allow to better influence the energy and environmental performance of building stock.

Four main objectives were defined, in order to accomplish this aim and guide the research process. They derive from the four key questions previously defined:

- To systematically define the main architectural design variables, in order to study their effects on energy, environmental and economic performance of office buildings.
- To identify the architectural design solutions that offer optimal energy, environmental and economic performance of office buildings, considering different climate zones.
- To determine the relative importance of the main architectural design variables, in terms of their impact on energy, environmental and economic performance of office buildings.
- To identify the numerical parameters which adequately describe the architectural design variables, and so can be utilized to calculate and predict energy, environmental and economic performance of office buildings.

Each objective was translated to a different task or analysis approach: (a) the development of a parametric simulations project; (b) the execution of a computational optimization analysis; (c) the implementation of sensitivity analysis; and (d) the development of meta-models from artificial neural networks.

As stated, one important purpose of this research is to provide a broad and comprehensive approach to understand the implications of architectural design variables. However, due the complexity and potentially excessive size of the problem, it was necessary to define its limits as clear as possible. Some important points about the scope of this research are explained below:

a) Three geometry-related variables (shape, WWR ratio and orientation) and four envelopment-related variables (insulation level, thermal mass level, number of glass panes and type of glass) have been considered. Two main criteria were used to select these design variables. The first criterion is that they are widely recognized in the literature as having significant impact on building energy performance. The second criterion is that all of them are always present in real life buildings. It is almost impossible to think about an office building without a specific shape, opaque constructions or glazing, at least considering current architectural trends and technological possibilities. Other design variables, which optionally can be included (or not), have been omitted. Examples of this kind of variables are shading devices, as well as specific passive techniques such as Trombe walls, ventilated facades or green roofs.

b) In all the different analysis approaches, buildings are assumed to operate in mechanical mode, i.e. they use heating, cooling and mechanical ventilation systems, if necessary, to keep adequate indoor conditions during occupied periods (see next point). Natural ventilation was not included, because the adequate control of such strategy under different climate conditions, including the avoidance of negative interference with the mechanical systems, goes beyond the practical limits of this research. However, there are two energy-saving strategies, associated with mechanical systems, which are included: free cooling and heat recovery. Especially the free cooling has effects similar to natural ventilation, as it involves the deactivation of the cooling system and the entry of outside air, when external conditions are adequate.

c) The simulation models have been defined in such a way that standard comfort levels are always met, with or without the help of the heating and cooling systems, independently of building characteristics. In other words, the comfort level is not addressed in this research as an output variable or a performance indicator, but as requisite and constraint for the operation of the building. Of course the indoor conditions and comfort level could be considered as indicators of buildings performance, but the methodological implications are out of the scope of this research. In any case, this issue can be regarded as a future extension of this study.

d) A wide range of building performance indicators have been used in the analyses, including energy loads, embodied and operational CO_2, and initial and operational cost. Of course there are many other possible indicators. For example, in recent years the use of Life Cycle Assessment methodologies (LCA) has increased significantly, trying to consider explicitly the impact of buildings on problems such as climate change, resource depletion, toxicity, eutrophication and acidification [34]. However, applying these methodologies to objects as complex as buildings still poses serious challenges, including the difficulty of the methodology itself and the lack of reliable data on many building components [35].

e) Four representative Spanish climate zones have been included in the different analyses: A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos. They cover from cooling-dominated to heating-dominated and from marine to continental climate conditions. Although the most extreme climate zones worldwide are not considered, the ones included in this research offer a range of external conditions that are wide enough to test and explore the applicability of the different analyses.

1.3. Methodology and structure of the thesis

This thesis applies a multi-methodological approach to investigate a specific problem, in this case the effect of architectural design variables on energy, environmental and economic performance of office buildings. This means that, rather than focusing on refining and/or expanding a specific analysis method, diverse methods were implemented around the same general problem. Therefore, the thesis is composed of four main chapters, one for each of the analysis methods that were implemented.

Chapter 2 involves the development of a parametric project based on EnergyPlus and jEPlus software packages. The parametric project aims to define the most significant architectural design variables and to characterize them by a number of options and parameters organized into a consistent framework. It is also conceived as the basis to accomplish the remaining research phases.

Chapter 3 addresses an optimization analysis by means of evolutionary algorithms. The analysis is performed with the programs EnergyPlus and jEPlus+EA, with basis on the previous parametric project. The optimization analysis is intended to identify the architectural characteristics that produce lower energy, environmental and economic impacts, taking into account different climatic conditions. Three different scopes of performance objectives are implemented and compared.

Chapter 4 involves the application of two sensitivity analysis methods, Morris and Sobol, in order to define the relative importance of each design variable in different climate conditions. A secondary objective is to assess to what extent this type of analysis can help to generate architectural design guidelines, especially for early project phases. Sensitivity analyzes are also based on simulation results generated by the parametric project.

Chapter 5 addresses the implementation of artificial neural networks to create meta-models that are able to predict, with reasonable accuracy, the energy performance of buildings. The main objective is to test and validate a number of input parameters, in terms of their capability to represent the architectural characteristics of office buildings. Additionally, the meta-models could be used as surrogate models to extend the applicability of other analysis methods.

Chapter 2. Parametric simulations project

This chapter describes a parametric simulations project developed to study the impact that main architectural design variables may have on energy performance of office buildings, including heating, cooling and lighting energy loads. It defines the most important architectural design variables and characterizes them by a number of parameters. The design variables, mainly related to geometric configuration and envelope composition, are organized into a framework that enables their complex and nonlinear interactions to be analyzed. Furthermore, the project includes three variables that are not strictly architectural but may have a significant impact on building performance: the usage intensity, the air infiltration level and the application of HVAC system energy-saving measures. In order to illustrate the potential of the parametric project, it was used to assess the impact of the last three variables in all the climate zones defined by the Spanish Building Technical Code. One important hypothesis is that a parametric project with these characteristics can be used with different methods, such as sensitivity analysis, computational optimization and artificial neural networks, to better understand the energy and environmental implications of architectural design variables.

2.1. Introduction

Architectural design variables may have strong effects on the energy, environmental and economic performance of buildings. Therefore, the interest on studying them has increased noticeably in recent years. One of the most powerful approaches to evaluate the architectural design variables is by the use of whole-building simulation programs. EnergyPlus, TRNSYS, DOE-2 and IDA ICE are among the most recognized building simulation programs, but there are much more available [36]. Those programs are capable of modeling, realistically and in detail, the heat and energy flows that take place in the buildings and their associated mechanical systems. They often require many input data and a good level of expertise, but, in return, provide results that can be quite useful to improve building designs. However, buildings are complex objects whose components affect each other through nonlinear processes, and consequently the usefulness of simulation programs can be significantly reduced when they are used by simple trial and error processes, even if the analyst has good level of expertise. Thus, it has become necessary to assess energy efficiency of buildings through more systematic and consistent methods. One simple method that has shown to be quite useful is the execution of parametric simulations.

The term "parametric analysis" in this study defines a method in which series of calculations or simulations are run by a computer program, systematically changing the value of parameters associated to one or more design variables. The key feature of this approach is that allows evaluating the effect of individual design variables, reducing the noise usually present when simulations are made by modifying simultaneously several design variables. The parametric analysis, when is consistently applied, is an effective way to explore different design options and to establish relationships between them in order to generate design guidelines [37]. Parametric analysis methods are often reinforced with methods such as design of experiments and sensitivity analysis, in order to achieve more useful results. An appropriate parametric project can also be the basis for the development of computational optimization and predictive models.

2.1.1. Objectives of the study

The main goal of this study is to develop a consistent parametric simulations project, conceived as a framework for investigating the impact that main architectural design variables have on energy and environmental performance of office buildings, including the complex interrelations between them. In order to accomplish that goal, the following secondary objectives are pursued:

a) To define the most important and essential architectural design variables, in the context of energy and environmental performance of office buildings.

b) To establish, for each design variable, a reasonably wide range of design options. It is assumed that very restricted ranges of design options can reduce the usefulness of the parametric project, while very wide ranges could difficult its implementation.

c) To characterize the design variables and options by adopting a series of parameters that are relatively easy to understand and calculate, facilitating its use by any professional involved in the building design field.

2.1.2. Key concepts

There are four key concepts used in this study: design variable, design option, design solution and parameter. These concepts are described in some detail here.

The **design variable** is an independent aspect of a building, which can be modified through the design process, in an intentional and relatively free manner. Examples of design variables are the general shape of the building or the composition of its opaque constructions. Design variables usually have limits regarding their possible options. For example, the general shape may be limited by the characteristics of the property or by urban regulations. Each design variable is considered independent, even if interacts with other design variables to determine building performance.

The **design option** represents a possible choice for a design variable. For example, a cubic volume may be an option to define the general shape of the building. The design options can be defined as continuous or discrete solutions. The orientation of the building, for example, can be any value between 0º and 360º, or it can be defined at regular intervals: 15º, 30º, 45º, etc. Discrete options have been used for all the design variables in this study.

The **design solution** represents a particular building configuration, which includes one specific design option for each of design variables. In other words, a design solution denotes the combination of design options for a specific building.

Finally, the **parameter** defines quantitatively the design option. For example, the options of the design variable "orientation" can be defined exclusively by the parameter "angle from the geographical north". Instead, the options of the design variable "building shape" can be defined by combining several parameters such as compactness and aspect ratio. A definition consistent with our research states that a parameter is one of a set of measurable factors that define a system, determine its behavior and can be modified in experiments [38].

2.2. General characteristics of the project

The parametric project was mainly developed around the software packages EnergyPlus [39] and jEPlus [40]. EnergyPlus is one of the most recognized programs in the field of building energy simulation. It has been used as the main analysis tool in numerous research papers addressing a wide range of problems related with energy and environmental performance of buildings. In addition to its high performance features, EnergyPlus allows handling both the input data and the simulation results through text files, simplifying the integration with other programs. Note that the models geometry was developed in DesignBuilder [41] and then exported to EnergyPlus.

On the other hand, jEPlus is a software package originally developed for creating complex parametric projects around EnergyPlus, though currently can be also used with other simulation programs. jEPlus allows defining multiple design parameters, each with their possible values, and then automatically create and run the required EnergyPlus simulation jobs [42]. It also allows users to extract and process the simulation results according to their requirements. One of the main benefits of the jEPlus environment is that any part of the EnergyPlus models can be assumed as a parameter, as long as it can be isolated and replaced by an alternative input or block text [43]. The design parameters are organized into a tree structure and stored into a project file, together with the execution settings of EnergyPlus. The program can simulate all possible combinations of the parameters in a given project, that is, the entire search space, or can simulate a sample generated by the Latin Hypercube method. In summary, jEPlus allows performing parametric and multifactorial studies that would be very difficult with manually defined simulation sets.

As shown in Figure 2.1, the parametric project includes 10 independent variables containing 81 design options. The architectural design variables comprise 16 shapes, 5 WWR, 8 orientation angles, 5 insulation levels, 5 thermal mass levels, 3 numbers of glass panes and 6 glass types. Note that the last four variables can be grouped and represented by 25 constructions options and 18 glazing options. Additionally, the project includes 3 infiltration levels, 3 usage intensity levels, and 3 options for HVAC saving strategy. With all these options, it is possible to simulate 7,776,000 design solutions for an office building with 5,184 m^2 of floor area, considering almost any climate and location. The parametric simulations can generate many of the outputs offered by EnergyPlus, such as energy loads associated to heating, cooling and artificial lighting, heat flows producing the thermal balances, and the data related to internal environmental conditions and comfort.

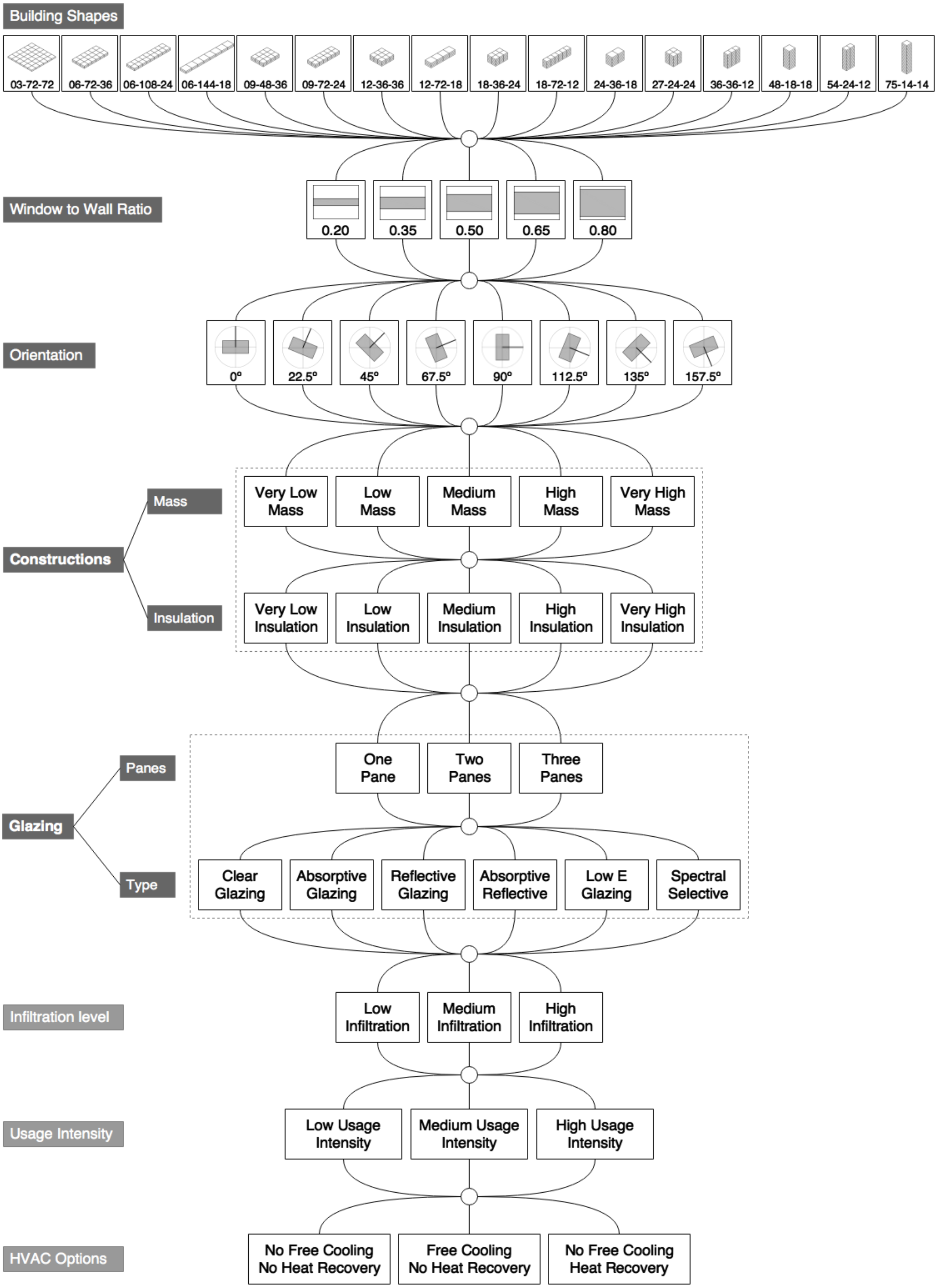

Figure 2.1. Schematic three of the parametric project.

It is important to note that the parametric project focuses on the most significant architectural design variables, i.e. those that are common to practically any actual building: shape, proportion of glazing, orientation, and composing of constructions and fenestration. The design variables that the buildings can optionally have were omitted (for example the use of shading devices). This criterion is intended mainly to avoid an excessive level of complexity, considering that the project can be extended in the future to include other kind of variables. In any case, a reasonably wide range of design options were defined for each variable, trying to generate a search space truly useful for designers.

2.3. Design options and parameters definition

This section offers a more detailed description of the parameters associated to the different design variables and options. Also, when required, explains the modeling criteria assumed during the development of the parametric project in EnergyPlus and jEPlus.

2.3.1. Geometric configuration

The parametric project includes 16 building shapes developed with basis on a modular scheme, as shown in Figure 2.2. Note that the first number in the building shape name corresponds to the height, the second to the length and the third to the width, expressed in meters. All the building shapes are composed of a certain number of square modules: 11 shapes have 36 modules (12m x 12m), four shapes have 18 modules (18m x 18m), and one shape has 25 modules (14.4m x 14.4m). Moreover, all shapes have 3m floor-to-ceiling height, a useful floor area of 5,184 m^2 and an internal volume of 15,552 m^3. The floor area is very close to the medium office building which is part of the DOE Commercial Reference Buildings [44] [45]. The basic idea of this approach is generating a relatively wide range of building shapes, some of them sharing certain parameter values (for instance, two shapes with the same compactness value), which can be useful for comparison.

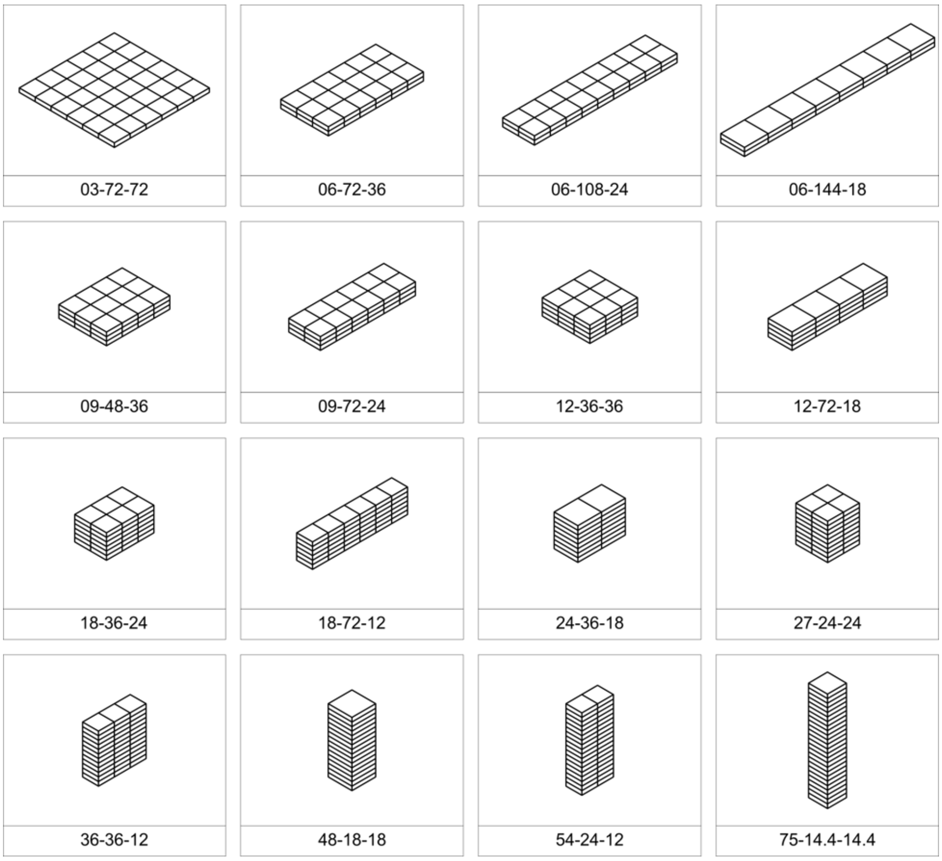

Figure 2.2. Modular definition of building shapes.

As part of the modeling criteria, when building shapes have three or less stories, each story is explicitly modeled. Shapes with four or more stories are modeled in a simplified way, including only the upper, the lower and one of the intermediate stories. A multiplier is assigned to the intermediate story in order to get the actual number of stories. In this case, surfaces between stories are considered adiabatic, i.e. thermal mass effect is considered, but not heat transfer between spaces. Regarding the internal space arrangement, each story is divided into five thermal zones, one central and four perimeter zones (see Figure 2.3). The internal walls that separate central from perimeter zones are always placed at 4.6 m from the external walls. This configuration, in line with ASHRAE modeling criteria [46], is primarily intended to accurately assess the influence of shape on daylighting potential, allowing to model light sensors in the perimeter zones but not in the central ones.

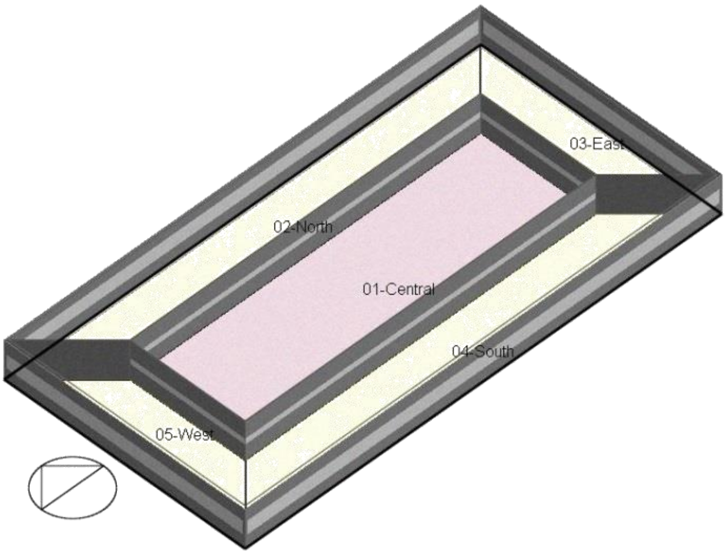

Figure 2.3. Example of building internal zoning.

Building shape options can be defined by a number of parameters. A preliminary analysis showed that the following parameters have some potential to determine the relationship between building shape and energy performance:

Vol / ExtSurf (Compactness) = *Internal volume* divided by *Total external surface area*.

ExtSurf / Vol (Form factor) = *Total external surface area* divided by *Internal volume*.

Glaz / ExtSurf = *Total glazing area* divided by *Total external surface area*.

Glaz / Vol = *Total glazing area* divided by *Internal volume*.

Wall / ExtSurf = *Total wall surface area* divided by *Total external surface area*.

Wall / Vol = *Total wall surface area* divided by *Internal volume*.

Roof / Vol = *Total roof area* divided by *Internal volume*.

Table 2.1 shows the values of these parameters for the 16 building shapes, as well as the number of stories and the external surfaces areas. Note that *Total external surface area* includes walls, roofs and external floors, while *Total wall surface area* includes glazing area. Note also that for the specified glazing-related parameters a WWR of 0.35 is considered.

In addition to general shape and WWR, the parametric project can easily include any **orientation angle** with respect to the geographical north (clockwise). In this study, for instance, 8 orientation angles were set, ranging from 0 to 157.5º. As the WWR is identical in all the facades, these options actually represent the 16 orientations produced if intervals of 22.5º are assumed.

Table 2.1. General areas and parameters of building shapes.

Name H-L-W (m)	No. of Stories	Wall (m^2)	Roof (m^2)	Floor (m^2)	ExtSurf (m^2)	Glaz (m^2)	Vol / ExtSurf	ExtSurf / Vol	Glaz / ExtSurf	Glaz / Vol	Wall / ExtSurf	Wall / Vol	Roof / Vol
		External surfaces areas					Shape parameters						
03-72-72	1	864	5,184	5,184	11,232	302	1.385	0.722	0.027	0.019	0.077	0.056	0.333
06-72-36	2	1,296	2,592	2,592	6,480	454	2.400	0.417	0.070	0.029	0.200	0.083	0.167
06-108-24	2	1,584	2,592	2,592	6,768	554	2.298	0.435	0.082	0.036	0.234	0.102	0.167
06-144-18	2	1,944	2,592	2,592	7,128	680	2.182	0.458	0.095	0.044	0.273	0.125	0.167
09-48-36	3	1,512	1,728	1,728	4,968	529	3.130	0.319	0.107	0.034	0.304	0.097	0.111
09-72-24	3	1,728	1,728	1,728	5,184	605	3.000	0.333	0.117	0.039	0.333	0.111	0.111
12-36-36	4	1,728	1,296	1,296	4,320	605	3.600	0.278	0.140	0.039	0.400	0.111	0.083
12-72-18	4	2,160	1,296	1,296	4,752	756	3.273	0.306	0.159	0.049	0.455	0.139	0.083
18-36-24	6	2,160	864	864	3,888	756	4.000	0.250	0.194	0.049	0.556	0.139	0.056
18-72-12	6	3,024	864	864	4,752	1,058	3.273	0.306	0.223	0.068	0.636	0.194	0.056
24-36-18	8	2,592	648	648	3,888	907	4.000	0.250	0.233	0.058	0.667	0.167	0.042
27-24-24	9	2,592	576	576	3,744	907	4.154	0.241	0.242	0.058	0.692	0.167	0.037
36-36-12	12	3,456	432	432	4,320	1,210	3.600	0.278	0.280	0.078	0.800	0.222	0.028
48-18-18	16	3,456	324	324	4,104	1,210	3.789	0.264	0.295	0.078	0.842	0.222	0.021
54-24-12	18	3,888	288	288	4,464	1,361	3.484	0.287	0.305	0.088	0.871	0.250	0.019
75-14-14	25	4,320	207	207	4,735	1,512	3.285	0.304	0.319	0.097	0.912	0.278	0.013

2.3.2. Constructions

One important aim of the parametric project is to allow evaluating how the composition of opaque constructions affects the energy performance of office buildings. In order to achieve this aim, 25 construction options were generated with basis on two parameters relatively easy to calculate and understand, the thermal mass level and the insulation level, which are expressed by the **global heat capacity**, C_G, and the **global thermal resistance**, R_G, respectively. These concepts, as well as the specific configuration of the constructions, are described below. Table 2.2 shows the 25 construction options, which result from the combination of five values of global heat capacity and five values of global thermal resistance. C_G values are from 62.3 to 377.3 kJ/m^2•K, while R_G values are from 0.7 to 3.5 m^2•K/W.

Table 2.2. Global heat capacity and thermal resistance values for the 25 constructions options.

		Very Low Mass **VLM**	Low Mass **LM**	Medium Mass **MM**	High Mass **HM**	Very High Mass **VHM**	
Very Low Insulation	**VLI**	62.1	129.2	223.7	300.0	373.8	C_G (kJ/m^2·K)
		0.7	0.7	0.7	0.7	0.7	R_G (m^2·K/W)
Low Insulation	**LI**	62.1	129.2	223.7	300.0	373.8	C_G (kJ/m^2·K)
		1.4	1.4	1.4	1.4	1.4	R_G (m^2·K/W)
Medium Insulation	**MI**	62.1	129.2	223.7	300.0	373.8	C_G (kJ/m^2·K)
		2.1	2.1	2.1	2.1	2.1	R_G (m^2·K/W)
High Insulation	**HI**	62.1	129.2	223.7	300.0	373.8	C_G (kJ/m^2·K)
		2.8	2.8	2.8	2.8	2.8	R_G (m^2·K/W)
Very High Insulation	**VHI**	62.1	129.2	223.7	300.0	373.8	C_G (kJ/m^2·K)
		3.5	3.5	3.5	3.5	3.5	R_G (m^2·K/W)

Global heat capacity

The thermal mass level is defined by the global heat capacity, concept similar to the thermal mass parameter (TMP) described in the standard ISO 13790-2008 [47]. It is the sum of the surface heat capacities, K_m, of all the constructions in the building, divided by the useful floor area:

$$C_G = \frac{\sum K_m}{S_F} \tag{1}$$

For external constructions (walls, roofs and exterior floors), it was considered only the internal surface heat capacity. In contrast, for internal constructions (partitions and internal floors) surface heat capacities of both sides were considered. Glazed surfaces were subtracted from the total wall area, assuming that their contribution to the building thermal mass is irrelevant. Surface heat capacities of the individual constructions were calculated according to the effective thickness method included in the simplified option of the standard ISO 13786-2007 [48]. In this method, the surface (areal) heat capacity, K_m (kJ/m^2·K), is calculated summing the heat capacities of the material layers included in the construction, until a maximum depth, it is, the effective thickness:

$$K_m = \sum_i \rho_i \ c_i \ d_i \tag{2}$$

$$\sum_i d_i = d_T \tag{3}$$

where:
ρ_i is the density of the layer i (kg/m^3)
c_i is the specific heat of the layer i (kJ/kg·K)
d_i is the thickness of the layer i (m)
d_T is the effective thickness assumed in the calculation (m)

The calculation begins on the surface exposed to the thermal zone, while the effective thickness is assumed always as the minimum of the following values: (1) a half of the construction total thickness; (2) the thickness of the material layers placed between the exposed surface and the first insulation layer; (3) a predetermined thickness, which depends on the temperatures variation period. In this case it was considered a thickness of 10 cm, corresponding to a variation period of 24 hours. The application of these criteria implies that the total thickness could cover only a part of one of the material layers. On the other hand, when it is an internal construction, for example a partition, it is necessary to calculate the surface heat capacity in both directions, since both surfaces provide thermal mass to the adjacent zones.

Global thermal resistance

The insulation level is defined by mean of the **global thermal resistance**. It is derived from the total thermal resistance, R_T, of external constructions, in this case walls, roofs and external floors. For simplicity, identical values of total thermal transmittance were assigned to all the external constructions with the same insulation level, avoiding the need to handle weighted values that take into account its relative area and/or orientation. In the case of the air gaps included in some constructions, simple resistance values were used. According to the standard ISO 6946-2007 [49], the total thermal resistance is defined as:

$$R_T = R_{si} + R_1 + R_2 \ ... \ R_n + R_{se} \tag{4}$$

where:
R_{si} is the internal surface resistance
$R_1, R_2 \dots R_n$ are the thermal resistances of the material layers
R_{se} is the external surface resistance

The thermal resistance of the material layers is defined as:

$$R = \frac{d}{\lambda} \quad (5)$$

where:

d is the thickness of the material layer (m)

λ is the thermal conductivity of the material (W/m·K)

Detailed characteristics of constructions

The building models include 5 construction types, according to their relative position: walls, partitions (internal walls), roofs, internal floors and external floors. In order to define the 25 construction options, firstly 5 sets of constructions types were developed, specifically configured to achieve the 5 global heat capacity values previously explained. Subsequently, five variations of each constructions set were developed by modifying only the insulation layer thickness in walls, roofs and external floors, in order to achieve the 5 global thermal resistance values. Thus, the 5 construction sets, multiplied by the 5 insulation levels, produce the 25 construction options. The following criteria were also assumed:

1. The insulation layer of external constructions (wall, roofs and external floors) is always located towards the outside. Thus, the layer providing thermal mass is in contact with internal spaces.
2. External insulation is never directly exposed to the environment. The external walls always include a perforated-brick layer in their outer side. The roofs always include a waterproofing layer (EPDM) in their outer side. The external floors always include a layer of plasterboard or plastering in their outer side.
3. External constructions were carefully configured to avoid that their surface heat capacity is changed by modifying the insulation layer thickness.
4. Roofs and internal floors always include an air cavity at the bottom part. This setting, besides being a common configuration in office buildings, which often have plenums, allows considering than the thermal mass is provided in each space mainly by walls, partitions and floors, and only to a lesser extent by ceilings.

Table 2.3 shows the constructions materials and their thermal properties. The sources are (1) CTE Constructive Elements Catalogue [50], (2) Standard ISO 10456 [51], (3) ASHRAE Handbook [52] and (4) CIBSE Guide A [53]. The CTE Constructive Elements Catalogue is part of the Building Technical Code [54], the regulatory instrument for environmental and energy characteristics of buildings in Spain. It provides information about thermal characteristics of many standardized materials and building products.

Figure 2.4, furthermore, shows the detailed arrangement of constructions, organized according to their type and thermal mass level. Note that the same wall and partition were used in the very low mass (VLM) and low mass (LM) construction options. This was for properly modulating the variations in global heat capacity values.

Table 2.3. Construction materials and their thermal properties.

			Thickness (*d*)	Conductivity (*k*)	Specific heat (*c*)	Density (*ρ*)
			m	W/m·K	J/Kg·K	Kg/m^3
A	Air 100mm-R=0.09	(1)	0.100	Thermal resistance (R) = 0.09 m^2·K/W		
B	Air 100mm-R=0.18	(1)	0.100	Thermal resistance (R) = 0.18 m^2·K/W		
C	Air 50mm-R=0.18	(1)	0.050	Thermal resistance (R) = 0.18 m^2·K/W		
D	Ceramic Tiles	(1)	0.015	1.000	800	2000
E	Concrete	(1)	Var.	1.900	1000	2400
F	Block-Hollow	(1)	0.100	0.625	1000	1210
G	Brick-Perforated	(1)	0.115	0.743	1000	1220
H	Brick-Solid	(1)	0.115	1.042	1000	2170
I	EPDM	(2)	0.003	0.250	1000	1150
J	Insulation	(3)	Var.	0.040	1400	15
K	Linoleum	(2)	0.003	0.170	1400	1200
L	Plasterboard	(2)	0.013	0.250	1000	900
M	Plastering	(1)	0.010	0.570	1000	1150
N	Slab01-Panels	(2)	0.038	0.250	1000	900
O	Slab02-Light	(1)	0.065	1.150	1000	1560
P	Slab03-Medium	(1)	0.250	1.064	1000	1180
Q	Slab04-Heavy	(1)	0.250	1.923	1000	1740
R	Slab05-VeryHeavy	(1)	0.200	2.300	1000	2400
S	Steel Sheet	(4)	0.001	45.000	480	7800

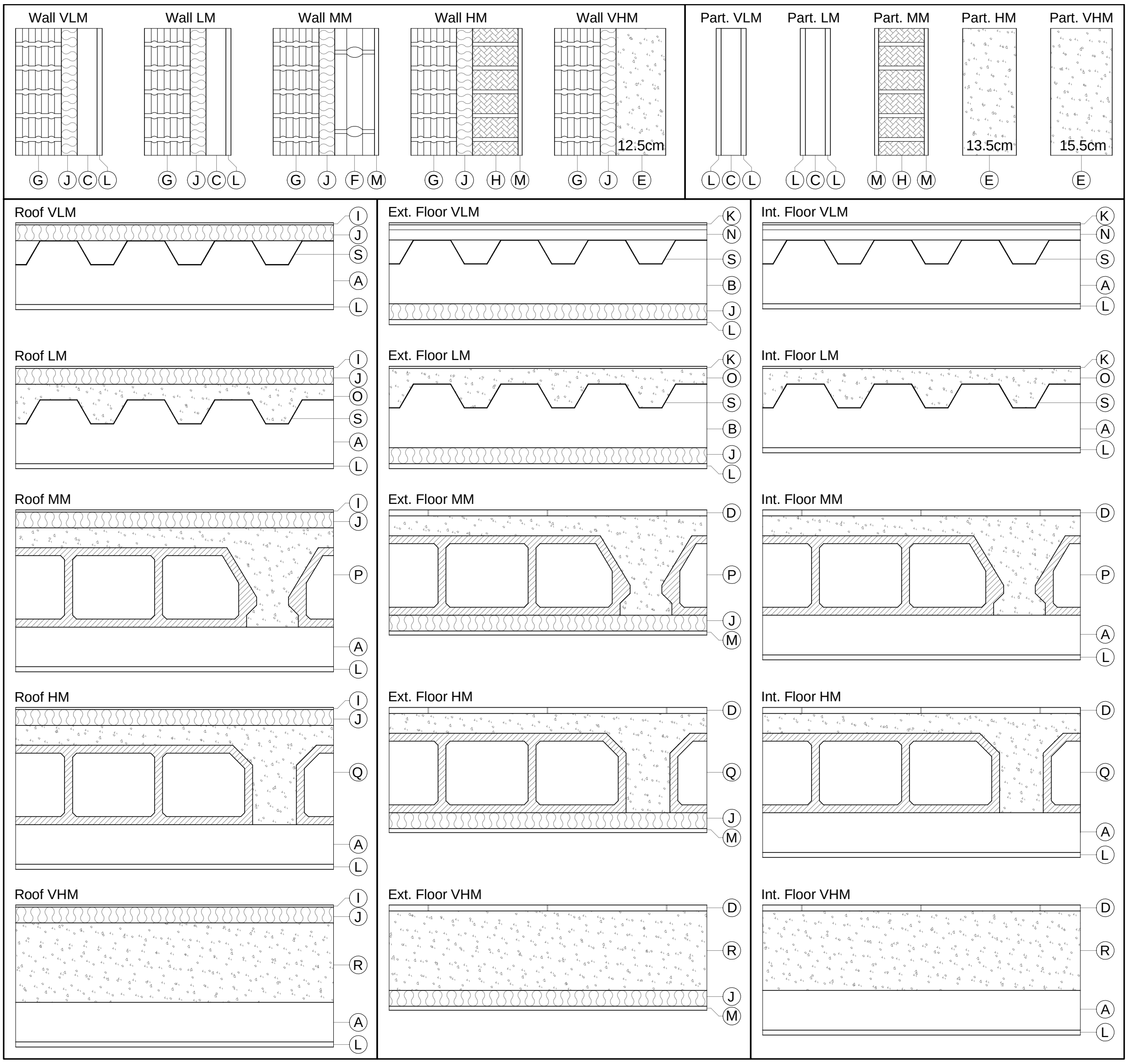

Figure 2.4. Detailed configuration of constructions, according to the different levels of thermal mass.

2.3.3. Glazing options

The parametric project includes 18 glazing options, illustrated in Figure 2.5. These options are generated by combining 3 quantities of panes (single, double and triple) and 6 types of 6 mm thick glass (clear, absorptive, reflective, absorptive-reflective, low emissivity and spectrally selective). In double and triple glazing, special glasses are located outside, while the internal ones are always clear glasses. In addition, when special glasses have a reflective coating, this coating is located at the surface No. 2, which corresponds to the inner surface of the outer glass. The gas layer is always considered an air layer with a thickness of 12mm. Note that air infiltration is not explicitly modeled as a parameter of the glazing, but as a parameter of envelope as a whole.

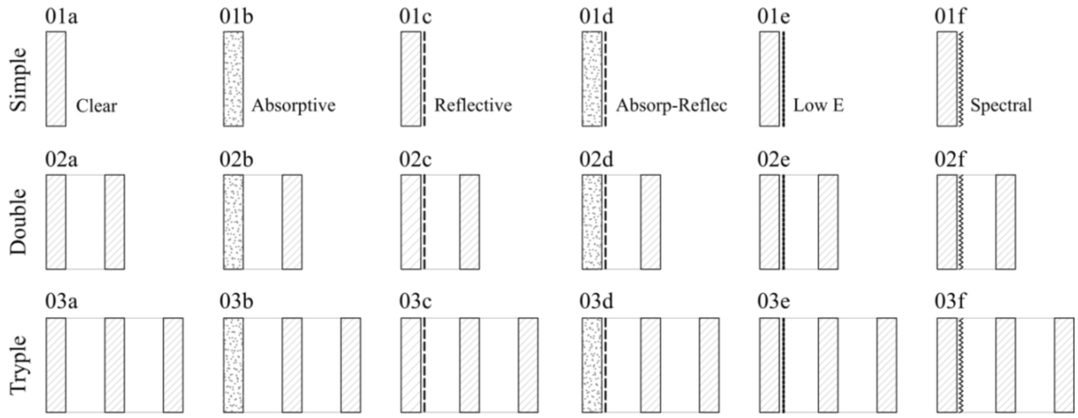

Figure 2.5. The 18 glazing options included in the parametric project.

Characteristics of glass types

The characteristics of the 6 glass types used in the study were taken from the data package *WindowGlassMaterials*, prepared by the EnergyPlus development team [55]. It includes thermal and optical properties of about 60 typical glasses. The selection is intended to offer a small but representative sample of the glasses commonly used in the building sector. Such simplification is important, because the current glass market is extraordinarily wide. For example, the International Glazing Database [56] includes over 4,700 glasses produced by manufacturers worldwide. Although each of these glasses has almost unique optical properties, in this study it is assumed that glasses with similar properties can be grouped, in order to simplify building energy analysis. The graph in Figure 2.6 shows the main optical properties of the 6 glass types. The stacked bars show the proportion of total solar radiation absorbed (A_s), reflected (R_{fs}) and transmitted (T_s), while solid line shows the level of light transmission (T_v) and dotted line shows emissivity (E_b).

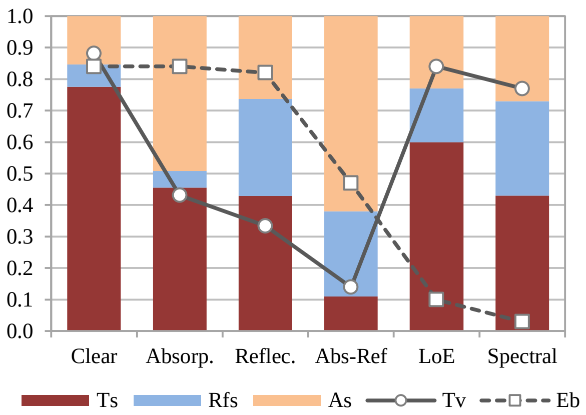

Figure 2.6. Optical properties of the 6 glass types.

Figure 2.7 illustrates how the six glass types reflect (1), absorb (2) and transmit (3) the total solar radiation, visible light and longwave radiation. In the case of total solar radiation, the diagrams also show the part of absorbed radiation that is re-emitted as heat to the indoor (4) and added to the overall solar heat contribution (5). The arrows thickness represents the corresponding fractions.

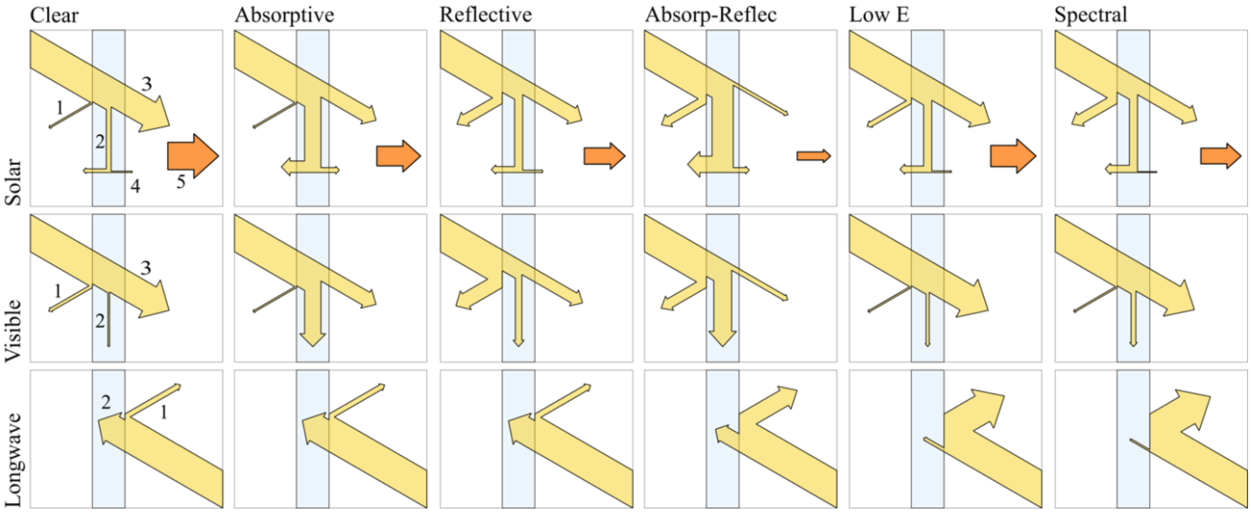

Figure 2.7. Response of each glass type to total solar radiation, visible light and longwave radiation.

The clear glass offers high transparency to solar radiation and visible light, while, due to its high emissivity, reflects only a small part of the long-wave radiation. The absorptive glass significantly reduces the transmission of solar and visible radiation, but maintains a low reflectivity and high emissivity. This behavior is due to the metal oxide particles incorporated into its internal structure, which increase heat absorption and give it the tinted appearance. Similarly, the reflective glass reduces the transmission of solar and visible radiation, but in this case incorporating a coating that instantly reflects much of the incident radiation. The different way absorptive and reflective glasses reduce the transmission of solar radiation can generate diverse performance patterns of the glazing system. The absorptive-reflective glass, as indicated by its name, combines the features of both glass types reducing even more the transmission of solar and visible radiation. This can be accomplished, for example, by adding a reflective coating to a tinted glass. Low emissivity glass, on the other hand, has a metallic coating which reflects most of the long-wave radiation (emitted by objects at terrestrial temperatures), making it particularly suitable for reducing heat loss to the outside without affecting light transmission too much. However, as shown in Figure 2.7, the low emissivity glass does not reduce solar transmission in a significant way. Finally, the spectrally selective, likely the most advanced of these glasses, has a metallic coating that reflects both shortwave and long-wave radiation, but remains very transparent to visible light. Thus, it reduces much of the total solar transmission and the outward heat loss, without excessively affecting the daylighting performance.

Glazing parameters

Glazing options can be characterized by three well-known parameters: overall thermal transmittance (U-factor), solar heat gain coefficient (SHGC), and visible transmittance (T_v). These values were calculated through the Window 7.3 software [57], with basis on the guidelines defined in the NFRC 100-2010 [58] and NFRC 200-2010 [59] documents, which in turn are based on the ISO 15099 standard [60]. Table 2.4 shows the design conditions used to calculate the U-factors and the SHGC. In this study, window frames and dividers are not considered, nor the effect of glass edges, so the values correspond to what is known as center of glass.

Table 2.4. Design conditions used for calculating glazing parameters.

Design condition	U-factor	SHGC
Inside air temperature (ºC)	21	24
Outside air temperature (ºC)	-18	32
Wind velocity (m/s)	5.5	2.75
Incident solar radiation (W/m^2)	0	783
Outside film coefficient (W/m^2-K)	26	15

The NFRC 100-2010 document defines the overall thermal transmittance (U-factor) as the heat transferred in a unit of time, through a unit area of the glazing (including the resistance of the surface air films), induced by a difference of one unit of temperature between the outdoor and indoor environment. Units are W/m^2·K. The U-factor, multiplied by the difference between indoor and outdoor environment, and by glazing area, determines the total heat transfer due to conductive, convective and radiant (longwave radiation) processes. Furthermore, according to the ISO 15099 standard, thermal transmittance is the inverse of the total thermal resistance (R_t), which is the sum of thermal resistances of the surface films, the gas layers and the glasses, as expressed in Equation (6); the thermal resistance of the gas layers is expressed according to Equation (7), where $T_{f,i}$ y $T_{b,i-1}$ are the surface temperatures of the glasses delimiting the cavity; and the thermal resistance of the glass panes is calculated according to Equation (8).

$$R_{\mathrm{t}} = \frac{1}{h_{\mathrm{ex}}} + \sum_{i=2}^{n} R_i + \sum_{i=1}^{n} R_{\mathrm{gv},i} + \frac{1}{h_{\mathrm{int}}} \tag{6}$$

$$R_i = \frac{T_{\mathrm{f},i} + T_{b,i-1}}{q_i} \tag{7}$$

$$R_i = \frac{d_{\mathrm{gv},i}}{\lambda_{\mathrm{gv},i}} \tag{8}$$

According to the NFRC 200-2010 document, the solar heat gain coefficient (SHGC) is the solar heat that passes through the glazing, divided by the incident solar radiation. The solar heat gain includes the direct transmission, as well as the portion of the solar heat absorbed by the glass and re-emitted into the space by conductive, radiant and convective processes. The ISO 15099 standard indicates that the solar heat gain can be determined by calculating the difference between the heat flow (in W/m^2) through the glazing, considering the incident solar radiation, and the heat flow without solar radiation, as expressed in Equation (9). This standard also proposes procedures for detailed calculations of all the heat transfer processes through the glazing.

$$\tau_{\mathrm{s}} = \frac{q_{\mathrm{int}} - q_{int}\,(I_{\mathrm{s}} = 0)}{I_{\mathrm{s}}} \tag{9}$$

The NFRC 200-2010 document defines the visible transmittance (T_v) as the visible light passing through the glazing and reaching the interior space, divided by the amount of incident visible light. In this case, the visible light entering the space is weighted by the photopic response of the human eye [61]. The ISO 15099 standard also provides procedures for the detailed calculation of these processes.

Figure 2.8 shows the values of SHGC, T_v and U-factor for the 18 glazing options. The number of glass panes (and therefore gas layers) has an important effect on heat transmission due to the difference between outdoor and indoor temperatures (U-factor), although low emissivity values have also a significant effect in this point. In contrast, the type of glass affects mainly the solar heat gain coefficient (SHGC) and the visible light transmission. All these features, however, perform simultaneously to determine the global properties of glazing.

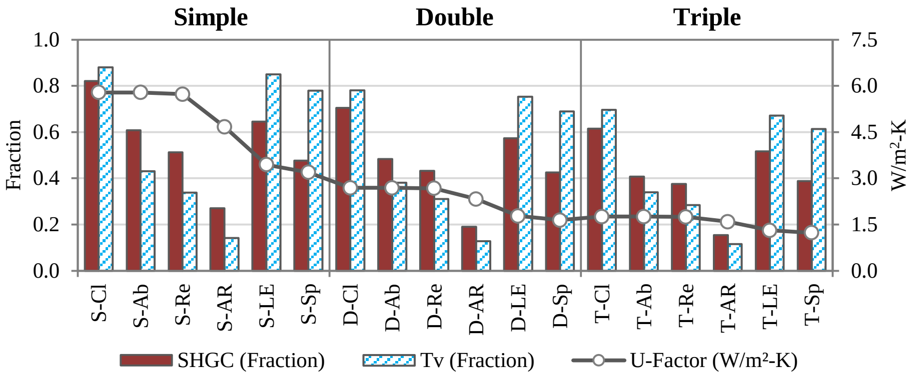

Figure 2.8. Parameters of the 18 glazing options.

2.3.4. Infiltration

Buildings infiltration mainly depends on the configuration and operation of openings, such as doors and windows, on the perforations made to the envelope, such as the insertion of ducts and pipes, and even on the porosity of constructions. According to various studies, infiltration can have a significant impact on the energy performance of office buildings, especially on heating demands [62] [63]. Furthermore, the level of infiltration may affect the impact of other design variables, such as building shape and insulation level. Due to this fact, it could be important to take into account the effect of this variable on the environmental and energy performance of buildings.

There are many methods to define the infiltration levels, although these can be grouped in two main categories: those that take into account the relationship between building volume and exposed surface, and those that do not [64]. The first approach was adopted in this study, defining the infiltration level with basis on two main criteria. One is related to the overall exposed building area, which means that buildings with higher relative area of external surfaces have higher total infiltration rates (assuming the same construction quality). The other is related to the proportional area of openings: as openings often represent weak points in terms of infiltration, it is assumed that walls have higher infiltration rates compared with other external surfaces. Based on these criteria and the guidelines given by the ASHRAE SSPC 90.1 Envelope Subcommittee [65], the infiltration rates per area of external surfaces shown in Table 2.5 were determined, including three infiltration levels: low, medium and high.

Table 2.5. Infiltration rates per area of external surfaces (m^3/h-m^2).

	Low	Medium	High
Wall	0.785	1.962	3.139
Roof	0.196	0.491	0.785
Ext. Floor	0.196	0.491	0.785

The values established in Table 2.5 are derived from the following criteria:

- Infiltration rates through roofs and external floors equal 25% of the infiltration rates assigned to walls. This ratio is derived, approximately, from values recommended by the ASHRAE SSPC 90.1 Envelope Subcommittee for different envelope items.

- The medium infiltration rates (1.962 m^3/h-m^2 for walls and 0.491 m^3/h-m^2 for roofs and external floors) were adjusted in such a way that, when applied to the building shape 09-48-36, the closest to the medium office building of the DOE CRB, generates a total infiltration rate of 0.30 ac/h.
- The low and high infiltration rates were established by reducing and increasing 60%, respectively, the medium level rates. This approach allows including a wide range of infiltration levels in the parametric project.

From the infiltration rates per surface area defined above, total infiltration rates (air changes per hour) were calculated for each building shape. These infiltration rates correspond to periods when HVAC systems are inactive (off). Following the criteria used in the DOE CRB [44], during periods when HVAC systems are active (on), infiltration rates are reduced by 75%. The resulting values, used to specify infiltration levels in EnergyPlus, are shown in Table 2.6.

Table 2.6. Total infiltration rates per building shape (ac/h), with HVAC systems off and on.

Shape	Low		Medium		High	
	Off	On	Off	On	Off	On
03-72-72	0.17	0.04	0.44	0.11	0.70	0.17
06-72-36	0.13	0.03	0.33	0.08	0.52	0.13
06-108-24	0.15	0.04	0.36	0.09	0.58	0.15
06-144-18	0.16	0.04	0.41	0.10	0.65	0.16
09-48-36	**0.12**	**0.03**	**0.30**	**0.07**	**0.48**	**0.12**
09-72-24	0.13	0.03	0.33	0.08	0.52	0.13
12-36-36	0.12	0.03	0.30	0.07	0.48	0.12
12-72-18	0.14	0.04	0.35	0.09	0.57	0.14
18-36-24	0.13	0.03	0.33	0.08	0.52	0.13
18-72-12	0.17	0.04	0.44	0.11	0.70	0.17
24-36-18	0.15	0.04	0.37	0.09	0.59	0.15
27-24-24	0.15	0.04	0.36	0.09	0.58	0.15
36-36-12	0.19	0.05	0.46	0.12	0.74	0.19
48-18-18	0.18	0.05	0.46	0.11	0.73	0.18
54-24-12	0.20	0.05	0.51	0.13	0.81	0.20
75-14-14	0.22	0.06	0.56	0.14	0.89	0.22

2.3.5. Usage intensity and internal gains

The type of activities and usage patterns strongly influence the amount of energy consumed by buildings [66]. In the first place, equipment and lights are directly associated to energy consumptions. Furthermore, these elements, together with people inhabiting the building, produce internal heat gains that reduce heating loads and increase cooling loads. Internal heat gains are especially important in office buildings, due to the relatively high occupancy densities and the large concentration of electric equipment. In temperate and cold climates, for example, internal heat gains could be the most influential factor in cooling energy consumptions [67].

In order to assess how the level of internal gains affects the impact of architectural design variables on building energy performance, the parametric project includes three usage intensities. Each intensity involves different rates of heat gains associated with occupancy, equipment and lighting, as shown in Table 2.7. Occupancy does not imply direct energy consumption, but affects internal heat gains, while equipment and lighting have impact in both components. In addition, unlike lighting energy consumptions, those associated to office equipment are considered constant and independent of the architectural characteristics of buildings.

Table 2.7. Heat gains rates derived from the usage intensity of the building, normalized by floor area.

Usage Intensity	Occupancy (W/m^2)	Equipment (W/m^2)	Lighting (W/m^2)	Total (W/m^2)
Low	4.6	4.9	7.5	**17.0**
Medium	9.2	9.9	12.4	**31.6**
High	13.9	14.8	17.4	**46.1**

Note that, while internal gains in actual buildings can differ significantly among the different spaces, depending on their specific usage conditions, the internal heat gains rates used in this project are the same for all zones. This approach is intended to simplify the definition of the parametric project, while still representing adequate values for office buildings. Thus, internal heat gains rates associated to occupancy, equipment and lighting were defined as weighted averages of the corresponding values for three space types, open offices, private offices and common areas, considering a distribution of floor areas of 25%, 57% and 18%, respectively. These values were defined with basis on the study of Korolija et al. [66], which in turn was based on a comprehensive study on non-domestic buildings in the UK, developed by Steadman et al. [68].

Occupancy, equipment and lighting heat gains

For the medium usage level, the heat gain rate associated to occupancy was established using a single occupancy density of 0.073 pers/m2. This is the weighted average value of the densities used by Korolija et al. [69] for open offices (0.111 pers/m^2), private offices (0.071 pers/m^2) and common areas (0.028 pers/m^2). Similarly, a single rate of metabolic heat was calculated based on the values of 125 W/pers for offices spaces and 145 W/pers for common spaces, resulting in a unique metabolic heat rate of 126.4 W/pers. Multiplying this value by the occupancy density produces an occupancy heat gain rate of 9.245 W/m^2, which fits between 6.5 W/m^2 used in the medium office building of the DOE Commercial Reference Buildings [44] and 10.2 W/m^2 which is the mean estimated by the British Council for Offices [70]. Occupancy heat gain rates for low and high levels were derived from the medium level by reducing and increasing the occupancy density by 50%.

The equipment heat gains were calculated by multiplying the occupancy densities by a typical equipment power consumption per person (140 W/pers in offices and 70 W/pers in common areas) and then applying the distribution of floor areas. The medium usage intensity rate is very near to the one used in the medium office building of the DOE Commercial Reference Buildings.

The artificial lighting heat gains of 12.4 W/m^2 for the medium usage level were calculated by assuming a lighting system efficiency of 3.5 W/m^2 per each 100 lux of required illuminance. The average illuminance was derived by using a weighted average of the required minimum illuminances for particular space types. A minimum illuminance of 400 lux is considered for office spaces according to the ASHRAE 90.1-2010 standard [46] which is consistent with EN 12464-1:2002 [71]. The common spaces require minimum illuminance of 150 lux [72]. The lighting heat gain rates for the low and high usage levels were established by reducing and increasing the efficiency assigned to the medium level by 40%. As part of the definition of lighting parameters, it is assumed that lighting is accomplished by unventilated recessed luminaires. Thus, approximately 37% of the heat is emitted as thermal radiation, 18% as visible radiation and the remaining 45% as convective heat exchange. Furthermore, it is considered that the entire energy consumption ends up as heat into the zones.

The artificial lighting heat gains are modulated in the perimeter zones by introducing a lighting control. It is assumed that, when zones are occupied, the artificial lighting increases if daylighting decreases, and vice versa, in order to ensure the required illuminance level. In other words, the artificial lighting is used in those zones to achieve a required illuminance when natural light is insufficient. Some design variables, such as WWR and glass type, may have impact on the potential use of daylighting and the corresponding energy consumption reduction.

Internal gains schedules

The internal gains in real buildings change throughout the day, depending mainly on occupancy patterns. In order to consider this point, the parametric project includes schedules that modify the maximum heat gain rates previously described. The fractional values of the schedules are shown in Figure 2.9. It is considered that the buildings are gradually occupied during the morning, partly occupied during lunch time, and gradually unoccupied during the afternoon. In the case of equipment and lighting, it is also considered a small fraction for unoccupied periods (generally nocturnal). This represents, for example, devices on standby and emergency lights. The values used in the schedules are based on sources such as the National Calculation Method [73] and DOE Commercial Reference Buildings [44], but have been modified to establish a closer relationship between the occupancy patterns and the equipment and lighting heat gain rates.

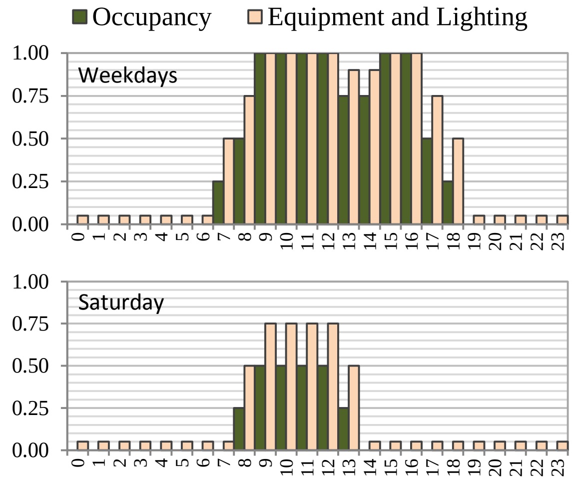

Figure 2.9. Fractional values used for adjusting internal gains.

2.3.6. HVAC Systems

The HVAC systems were modelled using the EnergyPlus's object *IdealLoadsAirSystem*. According to the EnergyPlus documentation [74], this object represents an ideal HVAC system modelled as a VAV terminal unit that supplies cold or hot air, at variable temperature and humidity, until the zone loads are met. The supply airflow rate can vary between zero and the maximum to meet the requirements of heating or cooling, humidity controls and minimum outside air supply, among others. In this case, it is assumed that the HVAC systems have no capacity restrictions, so they can meet any present load. The main HVAC settings are the following:

- During occupied periods, heating setpoint temperature is 21ºC, while cooling setpoint is 25ºC. These setpoints are within the ranges recommended by the standard EN 15251:2007. Setback temperature setpoints were set to 12°C and 30°C for heating and cooling respectively in order to avoid extreme conditions during unoccupied periods.
- The heating and cooling setpoints are assumed as operative temperatures. It means that heating and cooling systems have to meet both convective and radiant component of the global thermal balance. This approach avoids underestimating the thermal loads and offers greater sensitiveness to compare the effect of architectural characteristics on buildings energy performance [75].

- The models include humidity control based on hygrostats. The relative humidity setpoint for humidification is 30%, while for dehumidification is 60%. This is in line with Wang recommendation [76]: between 30% and 65% for summer and between 20% and 60% for winter.
- Regarding the mechanical ventilation, it is considered a minimum outside airflow rate of 10 l/s·person. According to the UK Building Regulations Approved Document F [77], this flow rate is necessary to achieve an adequate air quality in office buildings. The value is also within the range established by the European Standard EN 13779: 2007 for a mid-level air quality [78].

The parametric project includes three options for HVAC system configuration: a) *No free cooling, No heat recovery*, a) *Free cooling, No heat recovery*, c) *No free cooling, Heat recovery*. These options are aimed to evaluate two major energy-saving strategies directly associated with HVAC systems, and to study to what extent they influence the impact of architectural design variables.

The EnergyPlus free cooling (economizer) model allows 100% of outdoor air to be distributed to the space when there is cooling demand and external conditions are adequate (the outside air enthalpy is less than the return air enthalpy) [79]. However, the total airflow rate in cooling mode is limited to 10 ac/h in all zones in order to prevent unrealistic operation. Several studies indicate that free cooling can offer significant energy savings depending on the climate zone and building characteristics [80] [81].

On the other hand, the heat recovery model involves heat exchange between the exhaust air and the entering outdoor air. In this case it is considered an enthalpic model, coupled to both heating and cooling systems, which allows sensible and/or latent heat recovery when the outside air enthalpy is more favorable than the return air enthalpy [79]. The heat recovery system is assumed with an efficiency of 0.70 for sensible heat and 0.65 for latent heat. Several studies indicate that heat recovery can be a viable saving strategy, also depending on the climate zone and building characteristics [82] [83] [84] [85].

2.4. Application examples

As an application example, the parametric project was used to evaluate the energy impact of three variables that are not strictly associated to architectural design: the usage intensity, the level of infiltration and the saving strategy applied to HVAC system. A scenario with 729 design solutions was defined by combining the options listed in Table 2.8. They were simulated for cities representing the 12 climate zones defined by the Building Technical Code of Spain [54]. Figure 2.10 shows the cooling degree-days (base 20°C) and heating degree-days (base 18°C) calculated from the hourly weather data files corresponding to those cities.

Table 2.8. Design options used to define the 729 design solutions.

Variable	**Options**		
Building shape		09-48-36	
WWR	20	35	50
Orientation		0°	
Constructions	LM-VLI	LM-MI	LM-VHI
Glazing	S-Cl	D-Cl	T-Cl
Int. Gains Level	Low	Medium	High
Infilt. Level	Low	Medium	High
HVAC Strategy	None	Free C.	H. Recov.

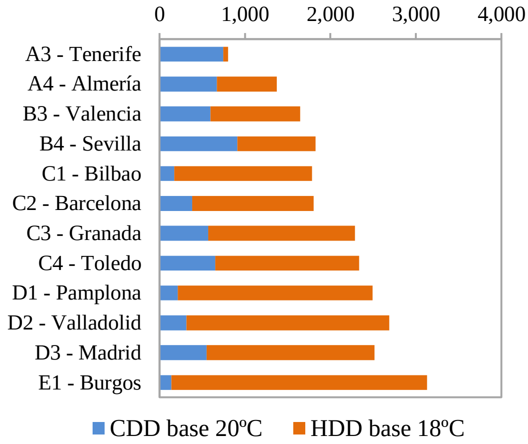

Figure 2.10. Cooling and heating degree-days for 12 cities representative of Spanish climate zones.

Simulation results are summarized in Figure 2.11, Figure 2.12 and Figure 2.13. The boxplot diagrams show the distribution of the sum of heating and cooling loads, calculated for the three variables and the 12 climate zones. The boxes in the diagrams cover interquartile ranges. The central line in each box indicates the median value. The lower and upper whiskers show the whole range of outputs. In addition, the blue and red circles indicate the average difference of the second and third options with respect to the first one, respectively. The values of average differences are shown in the scale at the right of the graph. Negative values imply a reduction of the loads.

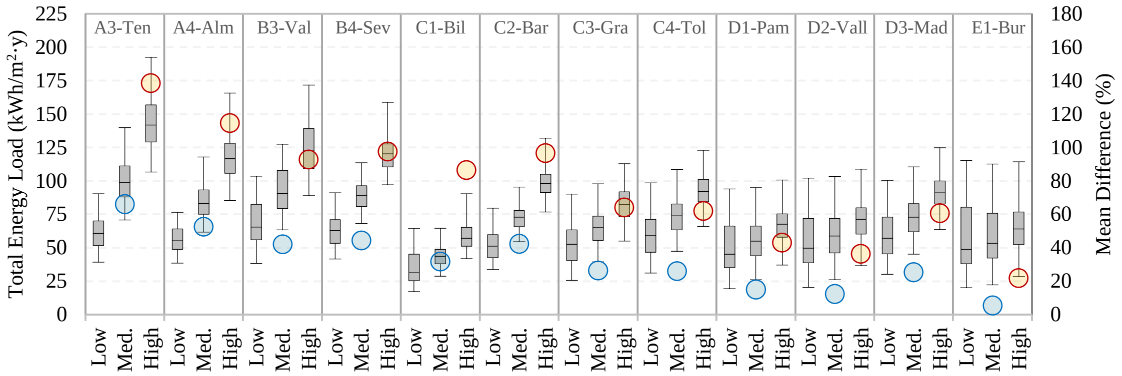

Figure 2.11. Distribution of total energy load values for the three levels of internal gains, and mean differences with respect to the low level.

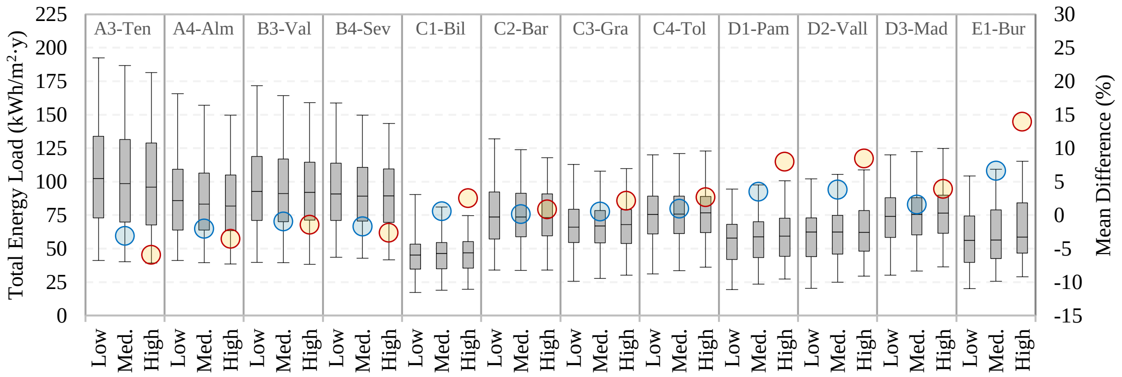

Figure 2.12. Distribution of total energy load values for the three levels of infiltration, and mean differences with respect to the low level.

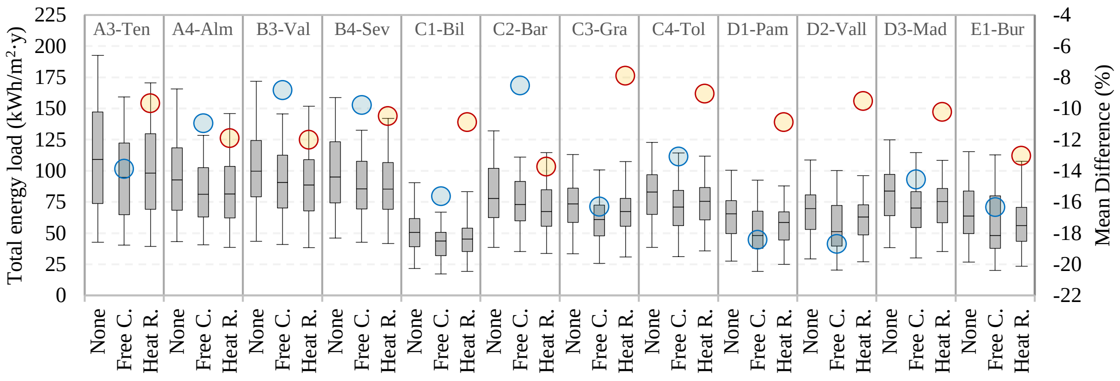

Figure 2.13. Distribution of total energy load values for the three options for HVAC system, and mean differences with respect to the first option.

Figure 2.11 shows that greater levels of internal gains consistently lead to greater energy loads. This trend is very marked in climate zones with high cooling demands (an average difference up to 138% in Tenerife, for example), while declines in climates with high heating demands. These results are reasonable, since internal heat gains derived from people, equipment and lighting increase cooling demand while decrease heating demand. It is evident that the level of internal gains can largely affect the energy performance of buildings, and perhaps the specific effect of design solutions. Regarding the infiltration level, Figure 2.12 shows that the heating + cooling energy loads tend to reduce in hot climates when this variable is increased, while augment in cold climates. However, the differences are relatively small, especially in warm climates. For example, in the climate zone *A3-Tenerife* a high infiltration level produces an average difference of -5.9% with respect to the lowest level. As expected, the biggest differences are found in cold climates such as *E1-Burgos*, where the difference between the highest infiltration level and the lowest one reaches a value of 14%. The results for HVAC options are much less regular and predictable than those for internal gains and infiltration levels, as can be seen in Figure 2.13. Although not using free cooling or heat recovery is consistently the worst option in all climate zones, it is important to note that the selection of one of these strategies is not always a straightforward task. The free cooling option produces the greatest negative average difference in eight climate zones, which reduces the heating + cooling energy loads. In the remaining four climate zones, the heat recovery option is the one that produces greatest negative mean differences, although in two of them the difference is small (*A4-Almeria* and *B4-Sevilla*). Furthermore, the position and length of interquartile boxes and whiskers do not clarify which is the ideal strategy in each case.

A more detailed analysis of the results allows identifying the insulation level as the variable that affects the impact of free cooling and heat recovery as energy-saving strategies the most, at least in this case. For example, when the 729 design solutions are grouped into 243 sets of three solutions, in which the HVAC option is the only parameter that is varied, the number of times each strategy is the best can be count and even associated to the insulation level. This information is presented in Table 2.9, showing that the free cooling strategy has better results in seven climate zones, while the heat recovery is more favorable in the remaining five zones. Excepting the climate zone *E1-Burgos*, these results are in line with the average differences shown in Figure 2.13. The most interesting aspect of the table, however, is that it clearly shows that the free cooling strategy is better in design solutions with medium or very high insulation level, while heat recovery is better in solutions with very low insulation. Although the experiment is not exhaustive, it indicates that the use of free cooling could have greater potential in buildings with higher insulation levels, or in other words, that the use of free cooling could enhance to some extent the positive effect of thermal insulation.

Table 2.9. Times free cooling and heat recovery are the best options, considering insulation level.

		A3 Ten	A4 Alm	B3 Val	B4 Sev	C1 Bil	C2 Bar	C3 Gra	C4 Tol	D1 Pam	D2 Vall	D3 Mad	E1 Bur	Mean
Times F.C. is better	VLI	35	0	0	0	0	0	14	0	1	2	0	0	4
	MI	81	43	20	44	57	9	78	73	68	76	73	51	56
	VHI	81	68	46	69	72	32	81	80	76	80	78	67	69
	Total	**197**	**111**	**66**	**113**	**129**	**41**	**173**	**153**	**145**	**158**	**151**	**118**	**130**
Times H.R. is better	VLI	46	81	81	81	81	81	67	81	80	79	81	81	77
	MI	0	38	61	37	24	72	3	8	13	5	8	30	25
	VHI	0	13	35	12	9	49	0	1	5	1	3	14	12
	Total	**46**	**132**	**177**	**130**	**114**	**202**	**70**	**90**	**98**	**85**	**92**	**125**	**113**

In order to further illustrating the potential of the parametric project, samples of 2,000 design solutions were simulated, considering four climate zones. They were chosen to represent some of the most characteristic climate zones of Spain: (a) A3-Tenerife: maritime, cooling dominated climate; (b) C2-Barcelona: Mediterranean, mild climate; (c) D3-Madrid: continental, warm/cold climate; and (d) E1-Burgos: continental, heating dominated climate. The design solutions were randomly selected by the Latin hypercube method, fixing only the variables of internal gains and infiltration, both settled at their medium level. The results are shown in the graphs in Figure 2.14, where X, Y and Z axis indicate the energy loads for heating, cooling and lighting, respectively (units are kWh/m^2-year). The results points are also colored according to the shape option of each design solution, allowing to visually exploring the impact of this variable on the energy performance of buildings.

Clearly, the result points are distributed through the three-dimensional graphs in accordance with the energy loads produced in each climate zone. Although the range of lighting loads, denoted by the position of points on the Z axis, is very similar in the four climates, the ranges of heating and cooling loads show important variations, which produce a different distribution of the cloud of points in each case. The range of heating loads, denoted by the position of points on the X axis, gradually increases from the climate zone A3-Tenerife to the climate zone E1-Burgos. On the other hand, the range of cooling loads, denoted by the position of points on the Y axis, shows the inverse pattern: it gradually decreases from the climate zone A3-Tenerife to the climate zone E1-Burgos. As a result, the cloud of points in the climate zone A3-Tenerife has a flatten shape that remains very close to the Y-Z plane. In this case the range of heating loads is quite narrow, while the range of cooling loads is very wide. The clouds of points in climate zones C2-Barcelona and D3-Madrid have similar shapes, which denote a decrease of the range of cooling loads and an increase of the range of heating loads (in comparison with climate zone A3-Tenerife). It can be stated that these climates have a more balanced distribution of heating and cooling loads, although the climate zone D3-Madrid shows slightly more extreme conditions. Finally, the cloud of points in the climate zone E1-Burgos clearly moves towards and along the X-Z plane. In this case the range of cooling loads decreases even more, while the range of heating loads increases markedly.

Regarding the distribution of points according to the building shape, the graphs of the four climates show similar patterns. Shapes with lower height (blue points) tend to have higher lighting loads and lower cooling loads, while shapes with greater height (yellow-red points) show the inverse trend, that is, lower lighting loads and higher cooling loads. The differences in heating loads are less evident, but it seems that shapes with lower height tend to have higher values. In any case, given that within the limits of this study cooling loads have greater weight than heating and lighting loads, it is very likely that increasing the height of the building may negatively affect its energy performance.

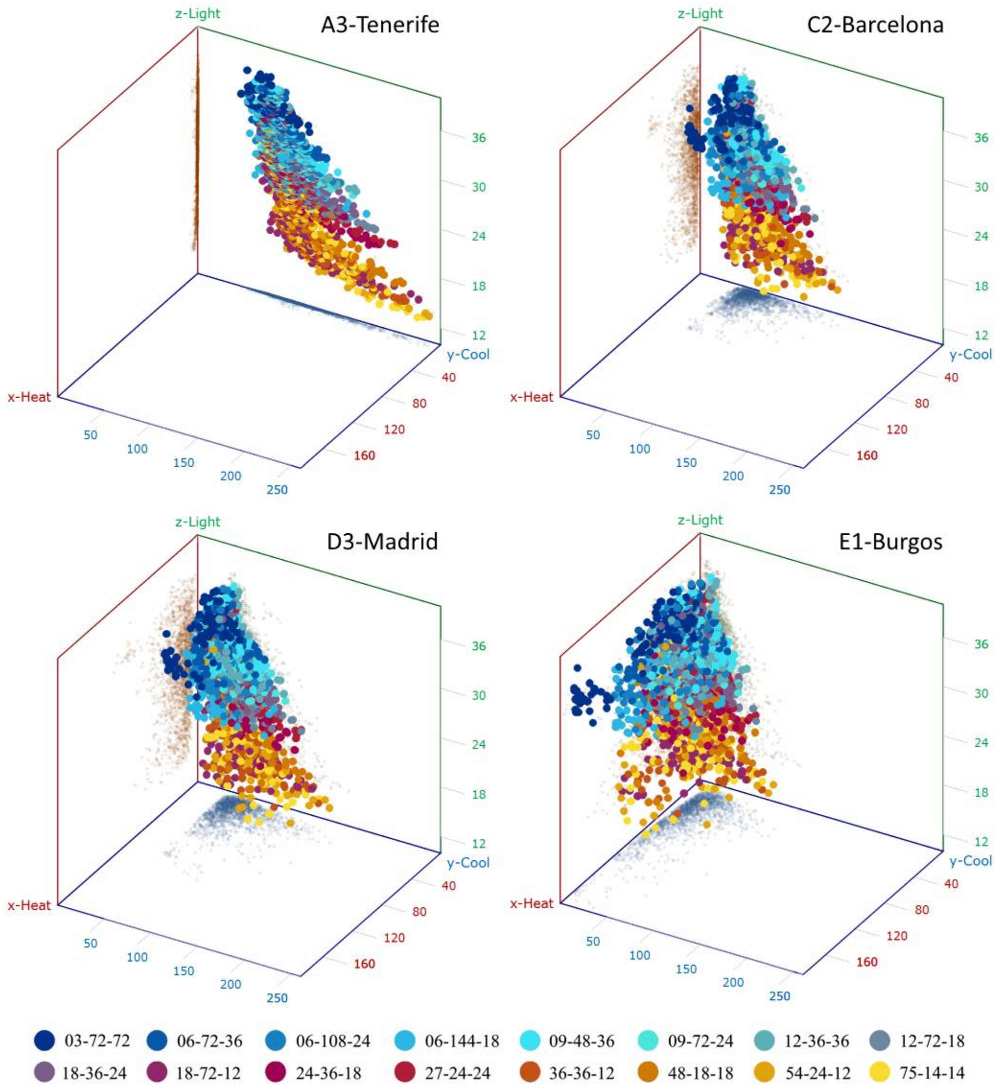

Figure 2.14. Parametric simulations of random samples for four Spanish climate zones.

Beyond the visual information provided by the graphs, it is important to note that parametric simulations of random samples like these can serve as a basis for analysis methods that do not require results of the whole space, such as data mining techniques, sensitivity analysis and implementation of artificial neural networks.

2.5. Conclusions

This chapter describes the development of a parametric simulation project, aimed to study the impact of main architectural design variables on energy performance of office buildings, considering different climate zones. The project is based on two main programs: EnergyPlus and jEPlus. The former is one of the most recognized software in the field of dynamic energy simulation of buildings, while the last one is conceived as a manager to facilitate parametric simulations with EnergyPlus.

The parametric project includes design variables related to the geometric configuration of buildings, as well as the detailed composition of opaque constructions and glazing. It also includes secondary variables associated to building usage intensity, air infiltration and the application of energy-saving strategies to HVAC systems. The parametric project, in its basic form, allows exploring a search space of 7,776,000 design solutions, but the variables and options can be easily reduced to focus on certain aspects of building performance, or to match specific research requirements.

The definition of design options and parameters was supported by the review of specialized scientific literature and diverse standards and codes related to energy efficiency of buildings. The main objective was to develop a parametric project within a solid conceptual framework, which allows consistently exploring the complex and nonlinear relationships of design variables.

A short study was conducted in order to show the potential of the parametric project. It consisted on the analysis of the energy impact of three secondary variables, considering all the Spanish climate zones: the usage intensity, the level of infiltration and the energy-saving option applied to the HVAC system. The results not only provided interesting information on the implications which these variables have on the energy performance of buildings, but also allowed to differentiate the effect that the main Spanish climate zones nay have on building energy performance. The parametric project formed the basis for more comprehensive studies, allowing the implementation of methods such as sensitivity analysis, computational optimization and artificial neural networks that can contribute to the goal of having a better understanding of design decisions on environmental and energy performance of buildings.

Chapter 3. Optimization of design variables

In recent decades, optimization has become a valuable method for finding, in a more efficient way, the solutions that best solve a particular design problem. This chapter describes an optimization analysis involving the simultaneous execution of whole-building energy simulations and evolutionary algorithms. The analysis is primarily intended to identify the architectural design options that offer the optimal energy, environmental and economic performance, considering a hypothetical medium size office building located in four Spanish climates. The optimization analysis is supported by an extensive parametric project, which includes all the basic design variables: shape, window area and orientation, as well as the detailed composition of glazing and opaque constructions. In addition, it considers the simultaneous effect of design variables on heating, cooling and lighting loads. The study includes and compares the results of three different optimization scopes, one single-objective and two multi-objective analyses. One of the main conclusions is that optimizing buildings exclusively based on its energy performance could lead to biased results. A more comprehensive set of metrics should be used where possible. The results of this research can be useful as guidance for the decision-making during the early architectural design stage, and could help to improve the existing building energy codes.

3.1. Introduction

Determining the best global solutions for architectural design variables, in terms of energy and environmental efficiency, is not an easy task, mainly because (1) the variables affect each other through processes that are often not linear, and (2) the relative weight of each variable can change significantly depending on the factors such as climatic conditions and usage characteristics. Furthermore, the concept of "efficient performance of buildings" has changed noticeably in recent years. The objectives for sustainability include not only reducing energy consumptions, but also conserving natural resources and minimizing the generation of harmful emissions and waste during the life cycle of buildings [86]. Additionally, it is important to include the economic aspect of the problem, covering the entire life cycle of buildings. Otherwise, the sustainable designs can be seen as infeasible, and the key design decisions may be abandoned on the ground of costs [87].

In recent years, many computational tools have been developed for the environmental and energy analysis of buildings. Perhaps the most important are the whole-building dynamic simulation programs such as EnergyPlus, TRNSYS, DOE-2 and IDA ICE [36], which are becoming more powerful, easier to use through graphical interfaces, and more integrated into the global design process by mean of standards like Building Information Modeling (BIM). When simulations are used together with methods such as parametric analysis, design of experiments or sensitivity analysis, they can provide very valuable information about the performance of buildings and their systems. However, these traditional methods are inefficient when the goal is to find optimal solutions for problems of great scale and complexity as described above. Parametric simulations, for example, allow finding the real optimum solutions if all the solutions in the design space are simulated (exhaustive search), but that is often not feasible due to the required amount of time and resources.

The limitations of traditional methods have led to the development of alternatives for identifying optimal solutions (or almost) in a faster and more efficient way. One important research line is the computational optimization. It involves the use of optimization algorithms through iterative computational processes for finding the minimum or maximum values of one or more performance objectives (e.g. minimize energy consumption and/or maximize comfort level) by evaluating a number of design variables (e.g. building shape and envelope insulation). The process can be subject to implicit or explicit constrains [88]. In the field of energy and environmental building optimization, the process often involves the coupled use of simulation programs to calculate the values of the performance objectives. This approach is known as simulation-based optimization.

3.1.1. Building optimization background

Besides confirming the significant growth that building energy optimization has had in recent years, a general study of the literature focused on this topic allows identifying some key aspects, which are explained below. Three extensive reviews recently conducted are especially relevant [88] [89] [90].

Optimization algorithms

Many different optimization algorithms have been used to solve engineering problems. The selection of an algorithm depends primarily on the nature of the problem to be solved, including the type of design variables, the characteristics of the performance objectives and the presence or absence of constrains [90]. In the field of building energy optimization, the simultaneously heuristic, stochastic and population-based methods have clear predominance. These methods does not guarantee that true optimal solution will be found, but offer an efficient alternative with good probabilities to find it, or at least to find a solution sufficiently close to the optimum [89]. Among the most common methods of this kind are (1) evolutionary algorithms, like Genetic Algorithms and Differential Evolution, which are based on the Darwinian principle of survival of the fittest individuals; (2) direct search algorithms, like the Pattern Search of Hooke and Jeeves, that compares a set of points around the current one to look for those in which the performance objective is better; and (3) other bio-inspired algorithms, such as the Particle Swarm Optimization.

Evolutionary algorithms are by far the most popular, especially the so called Genetic Algorithms. The review made by Evins [89] reveals that Genetic Algorithms were used in over 50% of specialized papers, while in the review by Nguyen et al. [90] the ratio exceeds 40%. According to these authors, the following are the reasons that make Genetic Algorithms so popular:

- They can handle continuous variables, discrete variables, or both, in the same optimization run.
- Being population-based and able to determine multiple Pareto optimal solutions, are especially suitable for solving multi-objective problems.
- They permit concurrent evaluation of *n* individuals in a population, allowing parallel simulations on computers with multiple cores.
- They are very robust when it comes to handling problems with discontinuities, multi-modal and/or highly constrained.
- They usually do not cause problems when simulation programs fail to evaluate specific solutions.

There are many alternatives among the Genetic Algorithms.. Probably the most widely used to date are variants of the Strength Pareto Evolutionary Algorithm (SPEA) and the Nondominated Sorting Genetic Algorithm (NSGA) [43]. Both are part of the group of algorithms known as Multi-Objective Genetic Algorithms (MOGA). In this research, we applied the optimization algorithm NSGA-II, which is described in more detail in the section **3.2**.

Single-objective vs. multi-objective analysis

Problems associated with the design of buildings often comprise conflicting or contradictory objectives, such as minimizing energy consumption while comfort levels are maximized, or reducing both CO_2 emissions and construction costs. As a result, in recent years the multi-objective optimization analysis has become more popular than the single-objective analysis [89]. It is also probable that the improvement of optimization algorithms and the availability of higher computation power have contributed to this trend.

There are two main approaches to include more than one objective in the optimization analysis [88]. The simplest one is to generate a unique objective by summing two or more sub-objectives, each multiplied by a weighting factor. Although it is easier to implement in optimization algorithms, this approach does not allow to discern how each sub-objective affects the others, unless several analyzes are made modifying the weighting factors. This option obviously will require more time and resources. The second approach, truly multi-objective, is based on the concept of Pareto frontier: a solution is optimal (i.e. non-dominated) when no other feasible solution improves one of the objectives without affecting at least one of the other. In that case the multi-objective algorithms generate a set of non-dominated solutions, known as the Pareto front. If the problem includes only two objectives, the Pareto front is a two-dimensional curve. This concept can also be applied to three or more objectives, although the results may be difficult to analyze. It is also important to note that this approach, rather than finding a single optimal solution, seeks to explore a set of optimal solutions and evaluate various trade-offs among them.

Definition of performance objectives

One key aspect to establish the purpose and scope of the optimization analysis is defining the performance objectives, also known as objective functions. They are the parameters used to measure the fitness of the design solutions. In the field of building optimization a variety of performance objectives have been used, although they can be classified into three main groups: environmental impact, economic impact and indoor environmental quality. The specific definition of the performance objectives has changed significantly over time, especially in the first two groups.

In its simplest form, the environmental impact has been assessed by energy loads or consumptions associated to HVAC and lighting systems. In the review made by Evins [89], about 60% of the optimization analyses included this parameter as performance objective, almost 30% as the unique one. A more explicit definition of the environmental impact has been through emissions of carbon dioxide (CO_2) [91] [92] [93], either associated to building operation (operational CO_2), to the construction process (embodied CO_2), or both. Some researchers have used the concept of carbon dioxide equivalent (CO2-eq) [87], which includes the global warming potential of other greenhouse gases such as methane, nitrous oxide and hydrofluorocarbons. Finally, in recent years the use of Life Cycle Assessment methodologies (LCA) has increased [94] [95], aiming to address the potential environmental impacts in a more complete way, due the consideration of the building whole life cycle and issues such as climate change, resource depletion, toxicity, eutrophication and acidification [34]. However it is important to note that the application of these methodologies to objects as complex as buildings, poses serious challenges. Among them are the complexity of the methodology itself and the lack of reliable data on many of the building components [35].

In early studies on building optimization, it was not common to include economic aspects, although it can be argued that they are considered implicitly when using performance objectives based on energy consumption: if it decreases, also the operating cost of the building decreases. However, in recent years economic aspects have become a fundamental part of optimization analysis, mainly because not including them can easily lead to unfeasible solutions from a financial point of view [87]. In the review made by Evins [89], at least 40% of papers involved some variation of cost as performance objective. The simplest way to include the cost factor into the optimization analysis is through the construction initial cost (capital cost), the cost of energy consumed during its lifetime (operational cost) or the sum of both [87] [93] [91]. As in the case of environmental impact, in recent years several authors have used more comprehensive analysis methods, such as Life Cycle Cost (LCC) [96] [97]. It represents the global costs of the construction, operation, maintenance and, sometimes, final disposing of the building, for a certain study period (usually life cycle), adjusting all these costs to reflect the value of money over time [98]. Although not as complex as the LCA, LCC methods imply empirically defining some critical parameters such as discount rates and increases in the cost of energy. Changes in these parameters can completely change the LCC analysis results.

The category of indoor environmental quality mainly includes analyses that use the comfort level as performance objective [99] [100] [101], although some researchers have addressed other objectives such as daylighting levels [102]. The comfort level is usually evaluated through the number of hours in discomfort, calculated according to a standard procedure. It can be used as a design objective when buildings operate in passive mode (without HVAC systems), or when it is aimed to assess the effect of different control strategies for HVAC systems (e.g. temperature setpoints) that could lead to discomfort conditions. In the review made by Evins [89] about 15% of the optimization analyses included parameters related to indoor environmental quality.

Definition of design variables

Design variables represent those aspects that can be adjusted to achieve optimal buildings from the energy, environmental and/or economic point of view. Their selection and definition is a crucial part in the optimization analysis. In line with Evins et al. [89], the design variables and options that are often addressed on building optimization analysis can be grouped into three main categories: the building, the systems and the energies.

The building category comprises those variables more closely linked to architectural design, variables in which architects can theoretically have a greater influence. It includes the characteristics of envelope constructions, both opaque (e.g. walls, roofs and floors) and transparent (e.g. windows and skylights), as well as the geometric configuration (e.g. shape, orientation and glazing distribution). The systems category includes variables associated with the building mechanical systems, mainly HVAC systems but also other such as domestic hot water (DHW) and artificial lighting. In this case the variables can focus on the systems design (e.g. configuration and components) and/or the application of control strategies (e.g. setpoints and fluids flow rates). Finally, energies category refers mainly to the use of renewable or residual energy sources. It includes technologies such as cogeneration, solar thermal and photovoltaic systems, site wind power, geothermal sources and heat storage systems. Generally, these energy systems are coupled to the mechanical systems, but in some cases can be attached directly to the building, as in the Canadian well system.

While optimization analysis often mix design variables from the categories previously defined, it is interesting to note that the review made by Evins [89] shows that, if the 74 analyzed papers are grouped according to predominant type of design variables, 59% corresponds to the Building category (38% focused on envelope constructions, 21% on geometry); 25% corresponds to the Systems category (17% focused on the design of HVAC systems, 7% in control and 1% in the lighting system); and 16% corresponds to the Energy category.

There are some important decisions about the way variables and design options will be represented in the optimization algorithms, for example if they are defined as continuous or discrete, or if they are coded in binary form, as integer numbers or by actual values [43]. Beyond these considerations, and assuming that the chosen algorithm can correctly handle the involved design variables, perhaps the main problem associated with the design variables is their influence on the size of the search space. The investigative nature of optimization analysis leads to include the biggest possible number of design variables and options, which can lead to excessively large and/or complex search spaces. In order to avoid this problem many researchers choose to focus on a small number of variables or to reduce the available options for each variable. Some authors [103] have explored the implementation of global sensitivity analysis, by methods such as Morris or Sobol, to identify the most relevant design variables. In any case, if the reduction of design variables and options is excessive the usefulness of the optimization analysis can also decrease dramatically. Consequently, it is important to pursue an appropriate balance between scope and viability. This is especially true when whole-building simulations are used as part of the optimization process.

Calculation of building performance

In the field of computational optimization, especially when using evolutionary algorithms, it is necessary to use some method or tool to iteratively assess the performance of buildings, according to the established design variables and performance objectives. As described by Machairas et al. [88] this task is often solved through three different strategies: simplified analytical methods, building simulation programs and surrogate models.

The use of simplified analytical methods involves describing a specific problem in mathematical terms. Its main advantage is that it allows researchers to address problems that cannot be adequately solved by existing simulation programs, for example some problems associated with the control of the building and its mechanical systems. Also make it possible to extract results almost instantly, facilitating intensive exploration of the search space. However developing such methods is not easy or practical in the professional field, so they are usually applied to relatively simple problems in certain research areas.

The second approach is coupling the optimization algorithms with simulation programs that are capable of modeling at least a significant part of the thermal and energy processes involved in the operation of buildings and their mechanical systems. To date, it is probably the most common choice. In the review made by Evins [89], for example, about 65% of the researchers used a building simulation program. One of the major advantages of using these programs is that they can offer detailed and precise information about building performance, including thermal loads, energy consumptions, daylighting levels, internal conditions and environmental data such as CO_2 emissions. However, they can be very demanding in terms of time and computational resources, especially when working with complex and highly detailed models. In addition, according to Wetter and Wright [104], the code of these programs can generate discontinuities in the performance objectives, which can cause failures of the optimization algorithms that require continuity. Nguyen et al. [90] investigated the usage intensity of 20 of the most popular building simulation programs in this area. The most commonly used were EnergyPlus (37.2%), TRNSYS (35.3%), DOE-2 (10.0%), and ESP-r (5.6%). According to the same authors, one of the main reasons why these programs are popular, in addition to their high-quality performance, is that they offer input and results data in text format, facilitating the coupling with the optimization algorithms.

A third alternative is the use of surrogate models, or meta-models, which are created using machine learning methods such as artificial neural networks (ANN), genetic programming, Bayesian networks or support vector machines (SVM). Generating the surrogate models usually involves three phases: (1) creating a detailed simulation model, for example using EnergyPlus or TRNSYS; (2) simulating multiple variants (design solutions) to produce a database with the results; and (3) using the database to train and validate the surrogate models by mean of one of the mentioned methods. The surrogate models are then used instead of simulation programs (hence its name), emulating their behavior [90] with the main objective of reducing the requirement of time and computing resources, eventually allowing to explore broader search spaces. When surrogate models are of good quality can facilitate the optimization analysis [99] [100] [105], but it is important to take into account that its creation is often quite demanding and may require knowledge of artificial intelligence methods. Also, using surrogate models rather than simulation programs can increase uncertainty and the risk of cumulative errors in the optimization process. When the performance objectives are very sensitive to changes on the design variables, surrogate models may even be unfeasible [90].

3.1.2. Purpose and scope of this study

Computational optimization methods offer great advantages to achieve high performance buildings, considering both the complex interrelations between its components and the difficulties to solve contradictory objectives. This study explores the use of a multi-objective genetic algorithm, coupled to a whole-building simulation program, in order to identify architectural design options that theoretically would optimize the performance of a medium size office building, reducing both environmental and economic impacts. The following are the main assumptions:

a) The analysis focuses on optimizing the architectural design variables. Although it is necessary to develop holistic optimization analyses that consider the synergies among buildings, their mechanical systems and renewable energies [89], it is also important to understand the particular implications of each of these fields. This is especially true about architectural design for several reasons. The first one is that optimizing the building *per se* should be a priority: even if renewable energies and high efficiency mechanical systems are available, using it in buildings that are inefficient from an architectural point of view is at least illogical and not effective. The second reason is that buildings often have a long life cycle, so it is not surprising that their mechanical systems will face major changes. Strongly associating building performance to a particular HVAC system could be risky in the long term. Finally, it is important to recall that some of the architectural design variables, such as geometry, can provide very good results with a very low or no cost. Knowing the optimal options for these variables, regardless of other non-architectural factors, is crucial in the early project stages.

b) The optimization analysis concentrates on the most significant design variables, those that are common to practically any building: shape, orientation, proportion of glazing, and composing of constructions and fenestration. Those variables that are optional (for example shading devices) have been omitted. However, a reasonably wide range of design options has been defined for each variable, trying to generate a search space that is truly meaningful and useful for designers.

c) The definition of the performance objectives includes the effect that architectural design variables have simultaneously in the three major energy components of buildings: heating, cooling and lighting annual loads. Energy consumption associated to equipment is not considered, because it is independent of the architectural features.

This research also aims to compare the effect of using performance objectives with different scopes, following three general lines: energy, environmental and economic impacts. The intention is to investigate how this aspect may influence optimization results and the decision-making on architectural design.

3.2. Methodology

The main part of this study relies on a method known as simulation-based building optimization, since it involves the concurrent use of a whole-building energy simulation program and an optimization algorithm. The process involved three general stages [90]: the preprocessing, the optimization (execution) and the post-processing phases. Although the analysis process is not always lineal, these phases are critical in the researching process.

The preprocessing phase represents the conceptual and practical statement of the optimization problem. Among other tasks, it includes the selection of the appropriate calculation algorithms and tools, the definition of design variables, performance objectives and constraints, as well as the formulation of the scenarios covered by the study. These points are described with detail in the sections 3.2.1 to 3.2.3. In the optimization phase, the most relevant tasks are the “tuning” of the optimization settings (such as population sizes, crossover rate and mutation rate), the execution of the simulations, the identification of calculation errors or failures, as well as controlling the termination criteria. Although in the building performance field it is almost impossible to determine if a global optimum has been reached, the main goal of this phase is to guarantee that results are good enough for the objectives of the study. The post-processing phase comprises the arrangement and analysis of the results. It involves, among other tasks, placing the data into tables, charts and diagrams that facilitates its reading and interpretation. In this study, an effort was made to generate graphical material that facilitates the understanding of the results.

3.2.1. Coupled simulation and optimization approach

The coupled process of simulation and optimization was implemented through the programs EnergyPlus and jEPlus+EA. As previously stated, EnergyPlus is one of the most utilized programs in this research area, being well known by its capability for iteratively modeling the thermal and energy flows taking place in buildings and its mechanical systems [39]. On the other hand, jEPlus+EA is an extension of jEPlus, a program originally focused on parametric simulations with programs such as EnergyPlus and TRNSYS [40]. It performs optimization analysis by integrating the simulation engines with Evolutionary Algorithms (EA). In order to accomplish this task, jEPlus+EA aims to simplify three key tasks: encoding building design problems in terms of "genes", converting new design solutions to simulation models, and controlling the execution of simulation jobs and its results [43].

In its current version jEPlus+EA employs the optimization method Nondominated Sorting Genetic Algorithm II, best known by its acronym NSGA-II. It has been adapted to use integer encoding, hybrid crossover-mutation operators, as well as Pareto achieving techniques. As many of the most advanced Genetic Algorithms (GA), the NSGA-II represents a multi-objective, population-based, elitist, stochastic global search method. This algorithm and its variants have been used in numerous studies, and are recognized by its robustness and versatility. For instance, Magnier and Haghighat [99] combined the algorithm NSGA-II with a simulation-based Artificial Neural Network in order to optimize the thermal comfort and the energy consumption of a typical 2-storey house. Evins and collaborators developed several optimization studies coupling the NSGA-II algorithm to different calculation tools, mainly EnergyPlus, and addressing problems such as the optimal configuration and control strategies for a double-skin façade, the decision-making about the operation of Combined Heat and Power (CHP) and Combined Cooling, Heat and Power (CCHP) installations [92], as well as the optimum solutions of a modular hotel unit, considering seven ASHRAE climate zones [91]. Gossard et al. [100] coupled an artificial neural network to the algorithm NSGA-II, in order to optimize the annual energy consumption and the summer comfort degree of a dwelling in two French climates. Ascione et al. [106] coupled EnergyPlus to a variant of the optimization algorithm NSGA-II, through the computing environment of MatLab, in order to develop a method to identify cost-optimal solutions for energy refurbishment of existing buildings, considering different budget levels. Finally, Carreras et al. [95] presented a methodology for evaluating the optimal insulation thickness in buildings envelope, minimizing simultaneously the cost and environmental impacts derived from both the energy consumed along its lifespan and the constructions materials.

The simulation-optimization process implemented in this study, through the coupled execution of EnergyPlus and jEPlus+EA, is illustrated in Figure 3.1. The steps are further explained below.

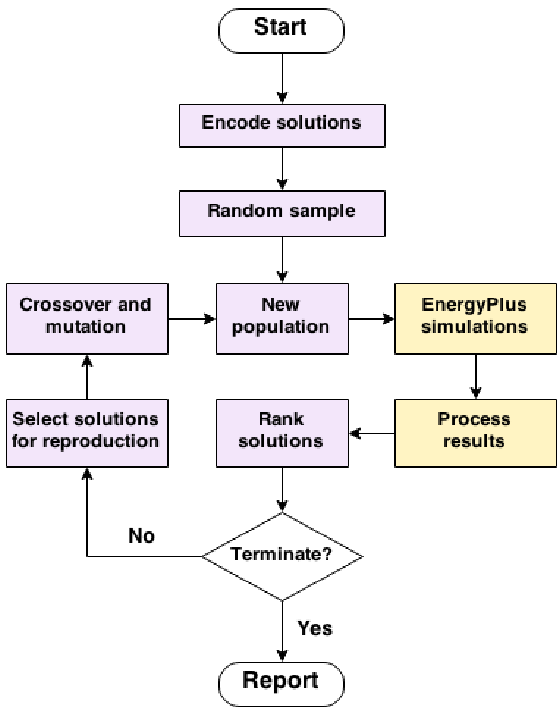

Figure 3.1. Flowchart of the implemented simulation-optimization process.

a) The design options and solutions are encoded to be represented numerically, so they can be processed by the optimization algorithm. jEPlus+EA uses an integer encoding scheme which discretizes the continuous variables into finite and indexed values, reducing the solution space to a finite scope. Although some potentially optimum solutions can be lost due to the discretization procedure the integer encoding scheme has shown better performance compared to a typical binary encoding scheme, at least in the field of building performance analysis [43]. In this context, the encoding of a design solution is named a “chromosome”, while the encoding of a design option is called a “gene”.

b) From all the design solutions that can be generated by combining the variables and options included in the optimization analysis, that is, the solution space, it is taken a random sample to produce the initial population. The process is handled by mean of the Latin Hypercube method, while the number of selected solutions (chromosomes) depends on the population size parameter defined as part of the analysis settings.

c) jEPlus+EA converts the chromosomes in the current population to a set of simulation jobs, then compiles and calls all the input files required by EnergyPlus, including the model files (IDF/IMF), the weather file (EPW) and the results extraction file (RVX), and triggers the execution of this program. EnergyPlus runs independent annual simulations of the design solution and generates the results specified by the RVX file.

d) Following the criteria explained in section **3.2.3**, the results obtained from the EnergyPlus simulations are processed in order to calculate the values corresponding to the performance objectives for all the current design solutions.

e) The solutions are ranked according with its fitness, that is, to what extent they meet the performance objectives. The ranking method involves two strategies. Firstly, the design solutions (chromosomes) are sorted into non-domination Pareto fronts. Less dominated fronts get better ranking position. After that, within each Pareto front the chromosomes are rated according to Euclidian distances between them. Solutions that are more separated from other solutions get better ranking position. This approach helps to create more distributed (less crowded) solution sets.

f) The design solutions that will be the “parents” of the next generation are selected using a process called tournament. This process is stochastic but clearly influenced by the fitness values: two (or more) chromosomes are selected randomly from the current population and the best one, according to its ranking position, is chosen as parent. The tournament selection pushes the process for quality improvements, but its probabilistic nature avoids the entire search becoming too aggressive and being trapped in a local optimum: high quality solutions have higher chance to become parents, but even low quality solutions have small possibilities.

g) The selected design solutions, i.e. the parents, are processed by two variation operators, crossover and mutation, in order to create new solutions, the offspring. Crossover operator merges two parent solutions into some offspring solutions. It is a stochastic process because the parents and their combined parts are selected randomly. The mutation operator, furthermore, is applied just to one solution, generating a modified mutant child. This operator is also stochastic: the parts of the solution that are changed depend also on random choosing.

g) The offspring solutions constitute the new population and are simulated by mean of EnergyPlus. The new results are extracted and the corresponding performance objective values are calculated.

h) Parents and offspring are put together and the ranking process is executed again, proceeding to the selection of the parents that will form the next generation. This is an elitist strategy: creating a “mating pool” by combining parents and offspring, and applying again the tournament selection procedure, guarantees that best solutions tends to be kept during the optimization process.

i) The optimization process continues the same way and finishes once the predefined number of generations (iterations) is reached, or if it is canceled manually. The optimum solutions are those in the highest ranked non-dominated set, considering all generations.

Due the random component of the optimization algorithm employed, it is difficult to ensure that all possible optimal solutions are found, even if only discrete variables are used. In order to reduce this risk, optimization process was repeated two times in each case, and subsequently parametric simulations were performed considering the options identified in the Pareto fronts. In this way, there is more confidence that the real optimum solutions have been found.

3.2.2. Design variables and options

The design variables and options included in the optimization analyses are derived from the parametric project described in chapter 2. Some minor adjustments were made to the project in order to accomplish the specific goals of this research. A brief description of the parametric project is included here for facilitating the interpretation of the optimization analyses.

Figure 3.2 shows the schematic tree of the parametric project. Note that two variables, usage intensity and infiltration, have been fixed at their medium level. This criterion is intended to simplify the optimization analysis to some extent, considering that, although these variables can have a significant impact on buildings performance, they are not design decisions in a strict sense. In this case the variables over which the designer has greater control have preponderance. Therefore, the optimization analyses are based on modifications to 6 design variables, which together comprise 78 options: 16 building shapes, 8 glazing ratios, 8 orientations, 5 thermal mass levels, 5 insulation levels, 3 numbers of glass panes, 6 glass types and 3 HVAC options. Each unique path in the parametric tree, considering from top to bottom, represents a different design solution. The total quantity of different solutions is 1,382,400, which represents the global search space of the optimization analysis in each climate zone. Assuming a running time of 10 seconds per solution, simulating the entire search space would require near 3,804 hours (160 days). It is clear that finding the optimal solutions through a typical parametric approach would be impractical.

The synthetic description of the design variables and their design options is as follows:

Shape. The parametric project includes 16 modular shapes, for an office building with a useful floor area of 5,184 m^2 and an internal volume of 15,552 m^3. The name of each building shape derives from its height, length and width dimensions (in meters). These shapes can be described by a number of geometric parameters. For instance, the range of compactness values (volume divided by external surface) goes from 1.38 for the shape 03-72-72 to 4.15 for the shape 27-24-24.

WWR. The original parametric project included window to wall ratios from 0.20 to 0.80, with increments of 0.15. Three other options were also considered in this study, 0.25, 0.30 and 0.40, offering a finer resolution in the zone of low WWR's, which in preliminary analysis shown the best overall performance.

Orientation. The orientation of buildings with respect to the cardinal axes can be easily changed in the parametric project, and could even be described as a continuous parameter. As a variable for the optimization analysis, here orientation has eight values. The values have finer resolution near orientation 0º, which in preliminary analysis offered the best overall performance. Due the fact that glazing is uniformly distributed in all the facades of the building, this range represents 16 orientation angles.

Thermal mass. It is one of the variables describing the characteristics of opaque constructions in the parametric project. It covers five levels of thermal mass, from very low to very high. It is described by means of the parameter global heat capacity ($kJ/m^2 \cdot K$), which is calculated with basis on standards

ISO 13790-2008 and ISO 13786-2007. The complete set of values is as follows: 62.1, 129.2, 223.7, 300.0 and 373.8.

Insulation. It is the second variable describing opaque constructions in the parametric project. Also covers five insulation levels, from very low to very high. Insulation value is defined by means of the parameter global thermal resistance (m^2•K/W), which is calculated according to the standard ISO 6946-2007. The complete set of values is as follows: 0.7, 1.4, 2.1, 2.8 and 3.5.

Panes. It is one of the variables describing the characteristics of glazing in the parametric project. Represents the number of panes glazing is composed of, with three options: one, two and three panes. The number of panes mainly influences the U-factor values of the glazing. For instance, with clear glass the U-factor values are of 5.786 (1 pane), 2.689 (2 panes) and 1.775 (3 panes).

Glass type. It is the second variable describing the characteristics of glazing. Represents the type of glazing, which covers six options: clear, absorptive, reflective, absorptive-reflective, low emissivity and spectrally selective. These glass types produce a wide range of values for parameters such as SHGC and visible transmittance. For instance SHGC and visible transmittance values, considering two panes glazing, range from 0.190 to 0.705 and from 0.128 to 0.781, respectively.

HVAC. The parametric tree also includes three options concerning the energy-saving strategy of the HVAC system: (a) *No free cooling / No heat recovery*, (b) *Free cooling / No heat recovery*, (c) *No free cooling / Heat recovery*. The free cooling (economizer) model operates allowing as far as 100% of outdoor air when there is cooling demand and external conditions are satisfactory. The heat recovery model, furthermore, involves a heat exchange between the exhaust air and the entering outdoor air.

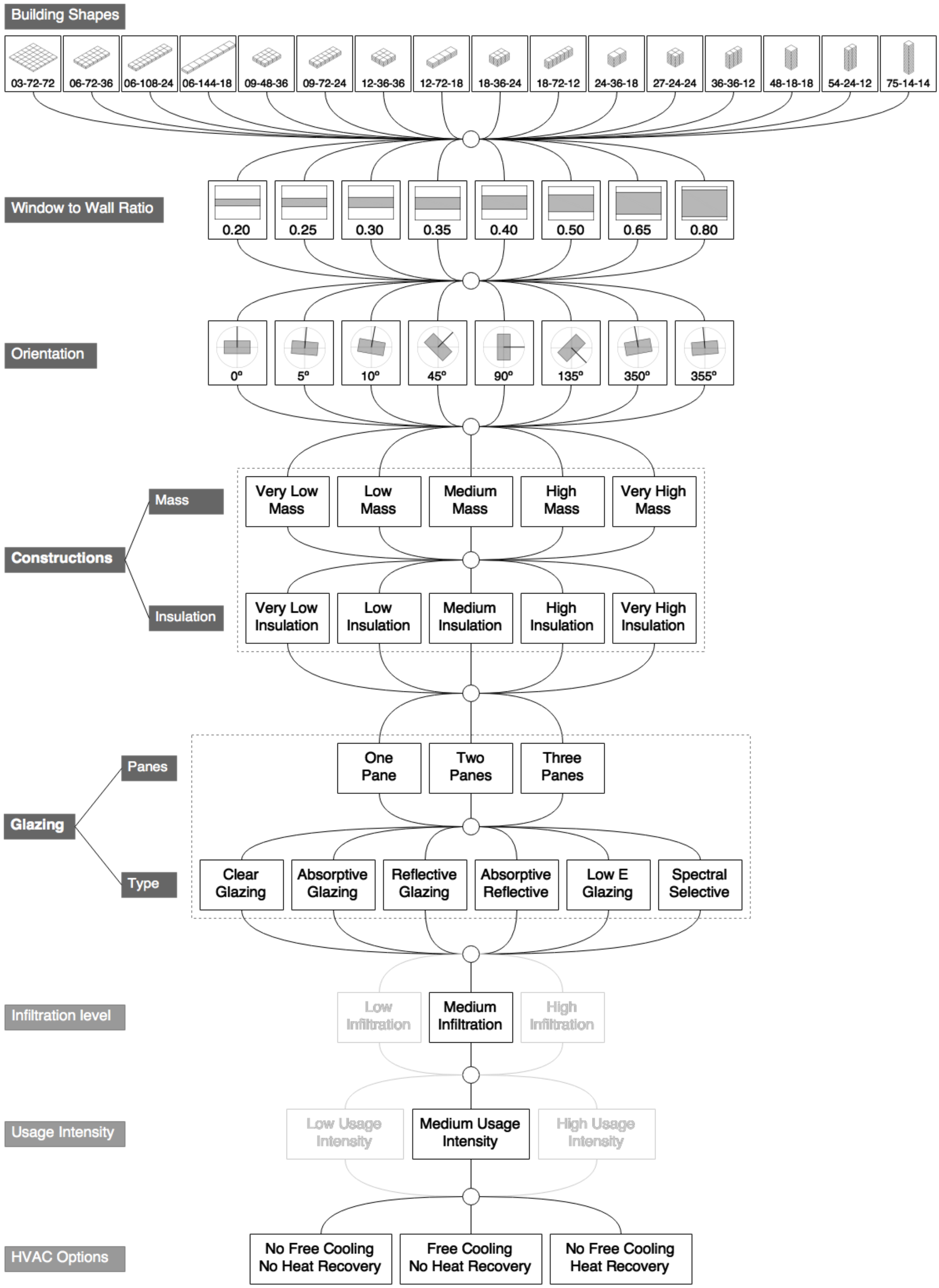

Figure 3.2. Schematic tree of the parametric project used for optimization analyses.

3.2.3. Performance objectives

One important goal of this research is to compare optimization results produced with performance objectives having different scopes in terms of energy, environmental and economic impacts. To achieve this goal, it was defined a set of performance objectives organized into three different analysis scopes (see Table 3.1):

Scope A. It addresses a single performance objective: to minimize the annual energy load associated with heating, cooling and lighting systems (total energy load). It is not a common objective in optimization analysis nowadays, but allows assessing the consequences of selecting an objective with a reduced scope.

Scope B. It includes two performance objectives. The first one focuses on the environmental impact and consists on minimizing operational CO_2 emissions associated to heating, cooling and lighting systems. The second one focuses on the economic impact and consists on minimizing the initial construction cost. Both items are relatively easy to calculate and provide a more comprehensive building performance assessment.

Scope C. It is similar to the Scope B, but significantly expands the scope of the performance objectives. The environmental impact is reduced by minimizing the global CO_2 emissions, that is, the sum of operational and embodied CO_2 emissions. Embodied CO_2 is associated to the constructive elements of the building, in this case opaque constructions and glazing. The economic impact is reduced by minimizing the global cost, that is, the sum of both initial and operational cost. The operational cost is derived from energy consumption during the study period. Below are explained the main criteria applied to calculate each of the performance objectives along the optimization analyses.

Table 3.1. Performance objectives and optimization scopes.

	Scope A	Scope B	Scope C
Objective 1	Total energy load	Operational CO_2	Global CO_2 (Operational + Embodied)
Objective 2	N/A	Initial cost	Global cost (Initial + Operational)

Total energy load

The total energy load (TL), in kWh/m^2-y, is the sum of the loads provided by the heating and cooling systems, in addition to the energy consumed by the lighting system, to maintain environmental conditions required during occupied periods over one year:

$$TL = Q_h + Q_c + E_l \quad (10)$$

where Q_h is the annual heating load, Q_c is the annual cooling load and E_l is the annual lighting energy consumption. These loads are directly calculated by the simulation program.

Operational CO_2

The operational CO_2 (OE), in kgCO$_2$/m^2, represents the carbon emissions associated to primary energy consumed by the heating, cooling and lighting systems through life span (30 years):

$$OE = \left(EF_g \times \frac{Q_h}{\eta_h}\right) + \left(EF_e \times \frac{Q_c}{\eta_c}\right) + (EF_e \times E_l) \quad (11)$$

where EF_g y EF_e are the CO_2 emission factors of natural gas and electricity, respectively, Q_h and Q_c are the heating and cooling loads along the study period, η_h and η_c are the seasonal coefficients of performance of the heating and cooling systems, and E_l is the electricity consumption of the lighting system along the study period. The CO_2 emission factor considered for natural gas is 0.252, while for electricity is 0.399. These emission factors are recommended by the Spanish Institute for Energy Diversification and Savings (IDAE) [107]. Regarding the coefficients of performance of heating and cooling systems, standard values of 0.8 and 2.5 were used, respectively. Note that in the Scope B optimization analyses the operational CO_2 values are not for the entire life span but for one year.

Embodied CO_2

The embodied CO_2 (EE), in $kgCO_2/m^2$, represents the carbon emissions associated to the production of materials and components of opaque constructions and glazing. Similar to the initial construction cost, the embodied emissions mainly depends on the type of opaque constructions and glazing but are also affected by geometric variables such as shape and glazing ratio. The embodied CO_2 can be expressed by the equation:

$$EE = \sum_i A_c\,(i) \times C_c(i) + \sum_j A_g(j) \times C_g(j) \qquad (12)$$

where A_c *(i)* is the area of the opaque construction type *i*, C_c *(i)* is the unitary embodied carbon of the opaque construction type *i*, A_g *(j)* is the area of the glazing type *j* and P_g *(j)* is the unitary embodied carbon of the glazing type *j*. Opaque constructions are external walls, partitions, roofs, internal floors and external floors, while glazing is constituted by external and internal windows.

The unitary embodied carbon (Kg/m^2) is the sum of the carbon emissions associated to the materials and components that constitute opaque constructions and glazing. It was calculated primarily from data contained in the BEDEC database, offered by the Catalonian Institute of Construction Technology (ITeC) [108]. According to the ITeC, their embodied carbon values were initially obtained from the Catalonian Institute of Energy (ICAEN) and the Polytechnic University of Catalonia [109]. They also consulted data from manufacturers in order to contrast and complement the values. Recently the ITeC contrasted its data with sources focused on Life Cycle Assessment methodologies, like Ecoinvent 1.3, the Inventory of Carbon and Energy (ICE), the Construction Industry Research and Information Association (CIRIA) and the Institute for Energy Diversification and Saving (IDAE).

Figure 3.3 shows the embodied CO_2 of the 25 opaque construction options, considering the building shape 09-48-36 and a WWR of 0.35. The embodied CO_2 increases gradually from the low to the high levels of both thermal mass and insulation. Likewise, Figure 3.4 shows the embodied CO_2 of the 18 glazing options, considering the same building shape and WWR. In this case the embodied CO_2 does not increase as linearly as with opaque constructions, but also increases from one to three panes and, to less extent, from low performance to high performance glasses.

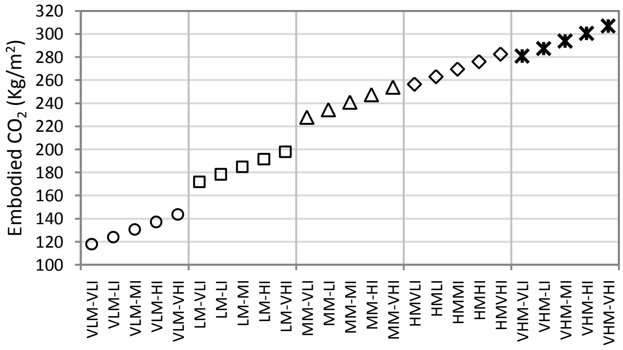

Figure 3.3. Example of embodied CO_2 of opaque constructions, normalized per floor area.

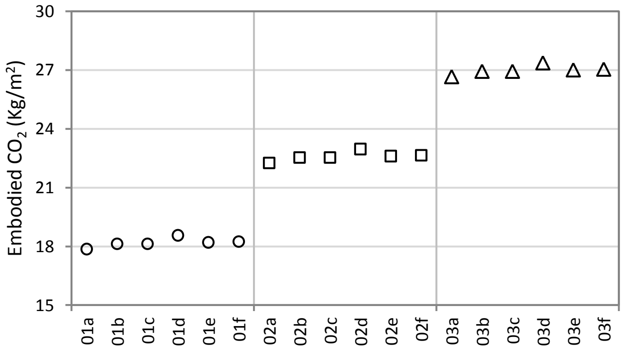

Figure 3.4. Example of embodied CO_2 of glazing, normalized per floor area.

Initial cost

The initial cost (IC), in €/m^2, represents in this case the simple cost of main building constructive elements. It depends mostly on both opaque constructions and glazing options, but is also affected by building shape and the proportion of glazing, since these geometric variables modify the area of every type of surface. The initial cost can be expressed by the following equation:

$$IC = \sum_i A_c\,(i) \times P_c(i) + \sum_j A_g(j) \times P_g(j) \qquad (13)$$

Where A_c *(i)* is the area of the opaque construction type *i*, P_c *(i)* is the unitary price of the opaque construction type *i*, A_g *(j)* is the area of the glazing type *j* and P_g *(j)* is the unitary price of the glazing type *j*. Opaque constructions are constituted by the external walls, partitions, roofs, internal floors and external floors, while glazing is constituted by the external and internal windows.

The unitary price (€/m^2) of each construction and glazing type includes all the components necessary for its execution, such as materials, labor, machinery and auxiliary equipment, but does not include indirect costs nor taxes. Unitary prices were calculated mainly from information contained in the BEDEC database, offered by the Catalonian Institute of Construction Technology [108]. It was also used complementary data from the Preoc Prices Database [110] and the CYPE Construction Prices Generator [111].

As an example, the Figure 3.5 shows the costs of the 25 opaque construction options, considering the building shape 09-48-36 and a WWR of 0.35. The costs increase gradually from the low to the high levels of both thermal mass and insulation. Similarly, the Figure 3.6 shows the costs of the 18 glazing options, considering the same building shape and WWR. In this case, the costs do not increase as linearly as with opaque constructions, but also increase from one to three panes and from low performance to high performance glasses.

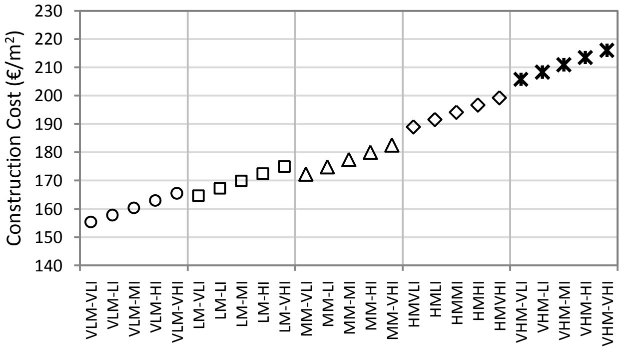

Figure 3.5. Example of initial costs of opaque constructions, normalized per useful floor area.

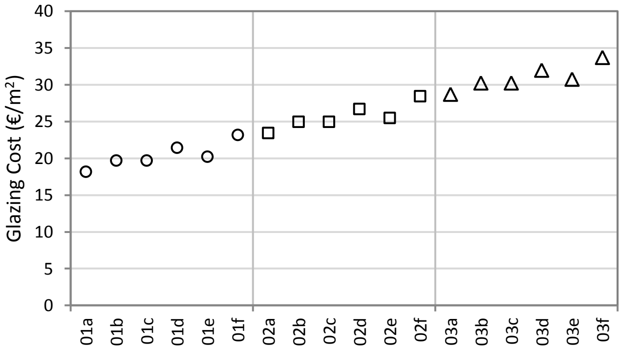

Figure 3.6. Example of glazing initial costs, normalized per useful floor area.

Operational cost

The operational cost (OC), in €/m^2, represents the present value of the energy consumed by the heating, cooling and lighting systems during the 30 years life span. It has been calculated according to the criteria established in the NIST Handbook 135 [98], as adapted by Hasan et al. [96]:

$$OC = \sum_k a\,(i) \times e_p(i)\ \times E(i) \tag{14}$$

where $a(i)$ is the discount factor of the energy type *i*, which takes into account the effect of inflation and price escalation, $e_p(i)$ is the current price of the energy type *i* (€/kWh), and $E(i)$ is the quantity of energy type *i* consumed per year. The types of energy included are natural gas (heating) and electricity (cooling and lighting). The discount factor for each energy type, furthermore, can be calculated by the following equations:

$$a\ = \frac{1 -\ (1 +\ r_e)^{-n}}{r_e} \tag{15}$$

$$r_e\ = \frac{r -\ e}{1 + e} \tag{16}$$

$$r\ = \frac{i - f}{1 + f} \tag{17}$$

where r_e is the real interest rate including the effect of energy price escalation, *n* is the number of years under study (30), *r* is the real interest rate, *e* is the energy price escalation, *i* is the nominal interest rate and *f* is the inflation rate.

Table 3.2 shows the values used for operational cost calculations, which have been adapted from several sources, such as the European Central Bank [112], The World Bank [113], Eurostat [114] and the Institute for Energy Diversification and Saving (IDAE) [107]. The values used in the calculations correspond to a relatively conservative approach, particularly with regard to the increasing of energy prices. It is important to note that this research is not intended to explore the effect that can have different scenarios for inflation, interest rates or energy prices.

Table 3.2. Values used and calculated (bold text) for operational cost calculations.

Gas price, $e_{p\text{-}gas}$ (€/kWh)	0.050
Electricity price, $e_{p\text{-}elec}$ (€/kWh)	0.120
Number of years, *n*	30
Inflation rate, *f*	0.025
Nominal interest rate, *i*	0.050
Gas price escalation, e_{gas}	0.015
Electricity price escalation, e_{elec}	0.020
Real interest rate *r*	**0.024**
RIR with escalation - Gas, $r_{e\text{-}gas}$	**0.009**
RIR with escalation - Elec, $r_{e\text{-}elec}$	**0.004**
Discount factor - Gas, a_{gas}	**26.09**
Discount factor - Electricity, a_{elec}	**28.09**

3.2.4. Selected climate zones

The optimization analysis was performed for four of the twelve climate zones defined by the Building Technical Code in Spain [54] represented by the following cities: A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos. These climate zones were selected intending to cover adequately the different climates of Spain. Figure 3.7 shows monthly profiles of cooling degree days (base 20°C) and heating degree days (base 18°C) for these cities. Also shows the mean maximum and mean minimum relative humidity (circles and short lines, respectively) with the scale on the right. These data offer an idea about the air conditioning requirements that could be present in each climate zone.

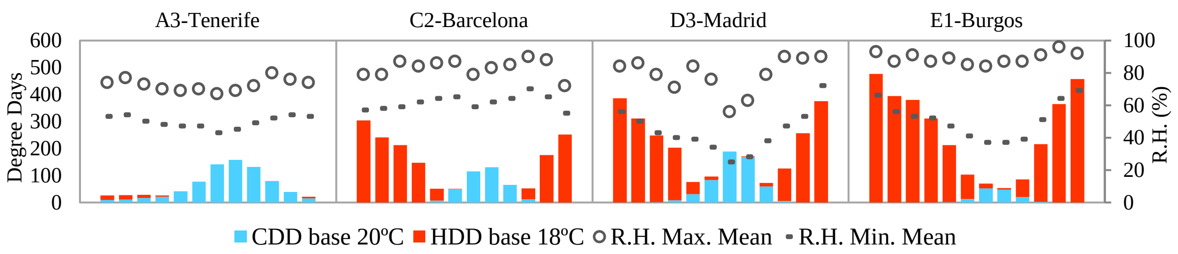

Figure 3.7. Cooling and heating degree days, as well as mean RH in the four climate zones.

3.3. Results

The general results of the three different optimization scopes are synthetized in the graphs of Figure 3.8, Figure 3.9, Figure 3.10 and Figure 3.11, as well as Table 3.3, Table 3.4, Table 3.5 and Table 3.6. In each case, the graph designated with the letter "a" shows the values of operational CO_2 and initial cost (corresponding to the Scope B) for the Scopes A, B and C. The graph designated with the letter “b”, on the other hand, shows the values of global CO_2 and global cost (corresponding to the Scope C) also for the Scopes A, B and C. These graphs allow visualizing the effect that optimizing within the Scopes A and C can have in the context of the Scope B, as well as the effect that optimizing within the Scopes A and B can have in the context of the Scope C. This information could be of interest in order to take more appropriate design decisions. In order to facilitate the understanding of the results, the solutions of Scope B Pareto fronts have been divided into groups, according to their performance and design options.

The tables are a complement of the graphs. They show some of the most efficient solutions of the optimization Scope A, some representative solutions of each group identified in the Pareto fronts of the Scope B analyses, and some or all the solutions of the optimization Scope C. The data include the options corresponding to the design variables (shape, WWR, orientation, opaque constructions, glazing and HVAC), as well as the results for the different performance objectives. Each solution is identified with a code derived from the optimization scope letter (A, B or C) and the number corresponding to its rank position. Some cells are shaded to emphasize performance values directly associated with each optimization scope. It is also possible to identify the solutions that are identical for two of the optimization scopes, as both codes are included in the appropriate column.

3.3.1. Detailed results per climate zone

Climate zone A3-Tenerife

Figure 3.8 and Table 3.3 summarize the results for the climate zone A3-Tenerife. The orientation is the only design variable having the same option in all solutions, with a value of 0º. Other two variables have very similar values along the different analysis scopes: WWR, which is usually 0.20 (just in one case the value is 0.25), and the HVAC option, which is mostly the heat recovery. Of 41 solutions found, only five have free cooling, the three solutions of the Scope A and two solutions of the Scope B. Other characteristics of the solutions found in the analyses are pointed out below.

A) Three design solutions were selected to represent the best options in the context of the **Scope A** optimization analysis. They all have the building shape 06-144-18, as well as spectrally selective glazing with two or three panes. The main difference is about constructions. Although all solutions here have a very low insulation level, their thermal mass level varies from medium to very high.

B) The **Scope B** optimization analysis produced 35 solutions, which can be divided into four groups principally differentiated by their shapes, constructions and glazing options:

- **Group B-I** comprises 6 solutions, they all with the building shape 18-72-12. Constructions have from medium to very high thermal mass level, but the insulation level is always very low. All the glazing options have spectrally selective glass with 1, 2 or 3 panes.
- **Group B-II** includes 5 solutions. They are identical to Group I in terms of building shape, while constructions have always medium thermal mass and very low insulation levels. Glazing options have spectrally selective, low-e or clear glass, with 1 (predominant), 2 or 3 panes.
- **Group B-III** comprises 15 solutions, which have a wider range of building shapes: 09-72-24, 12-72-18, 18-36-24, and 24-36-18. All the constructions have also medium thermal mass and very low insulation levels. Glazing is mainly composed of 1 pane (only one solution has 2 panes), with clear, reflective, low E or spectrally selective glass.
- **Group B-IV** includes 9 solutions with two building shapes, 12-36-36 and 18-36-24. All the constructions have very low thermal mass, while almost always have very low insulation levels (only one solution has low insulation level). Glazing options has always 1 pane, with clear, reflective, low E or spectrally selective glass types.

C) The Pareto front of the **Scope C** optimization analysis has only 3 solutions. All of them have the building shape 18-72-12, very low insulation level and spectrally selective glass type. The thermal mass level is low (2 solutions) or very low. The number of glass panes is 2 (2 solutions) or 1.

Comparing the performance of solutions from to the different optimization scopes, graph 3.8a shows that solutions of Scope A are placed near the solutions of Group B-I. However, none of the solutions coincide, because in this case the building shape is a differentiating variable. Additionally, the solutions of Scope C are very close to the solutions of Group B-II. In fact, there are two matching solutions in this case.

Graph 3.8b shows that solutions of Group B-II remain very close to the Pareto front of Scope C, while the other solutions tend to move away. Specially the solutions of Scope A and Group B-I decrease their performance markedly regarding both objectives global CO_2 and global cost.

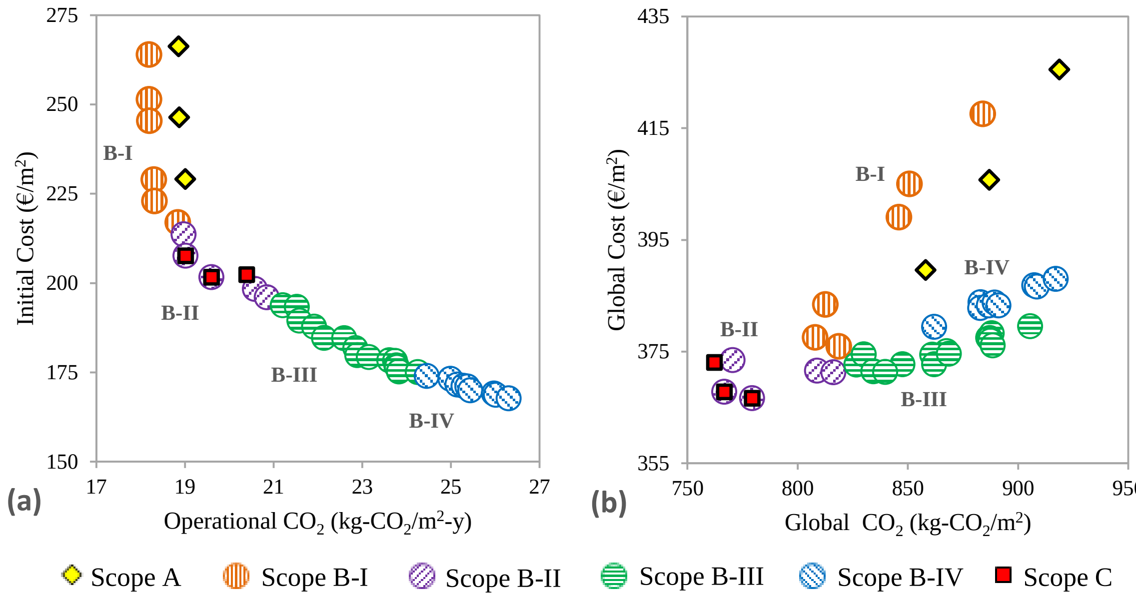

Figure 3.8. Results of optimization scopes A, B and C, for climate zone A3-Tenerife.

Table 3.3. Design options and performance objectives values for solutions selected from Figure 3.8.

Solutions			Design Options						Performance Objectives				
Scope	**Id.**	**Group**	**Shape**	**WWR**	**Orient.**	**Constructions**	**Glazing**	**HVAC**	**TLoad**	**OCO_2**	**ICost**	**GCO_2**	**GCost**
A	A-01	N/A	06-144-18	0.20	0°	05A_VHM-VLI	02f_D-SP	HR	79.54	18.86	266.2	918.8	425.5
	A-02		06-144-18	0.20	0°	04A_HM-VLI	02f_D-SP	HR	79.62	18.87	246.4	887.0	405.7
	A-03		06-144-18	0.20	0°	03A_MM-VLI	03f_T-SP	HR	80.16	19.01	229.1	858.2	389.6
B	B-01	**I**	18-72-12	0.20	0°	05A_VHM-VLI	02f_D-SP	FC	85.17	18.19	264.0	884.2	417.5
	B-03		18-72-12	0.20	0°	04A_HM-VLI	02f_D-SP	FC	85.22	18.20	245.4	846.1	399.0
	B-04		18-72-12	0.20	0°	03A_MM-VLI	03f_T-SP	FC	85.38	18.30	229.0	812.7	383.4
	B-06		18-72-12	0.20	0°	03A_MM-VLI	01f_S-SP	FC	88.34	18.84	216.9	818.8	375.9
	B-07	**II**	18-72-12	0.20	0°	02A_LM-VLI	03f_T-SP	FC	89.28	18.97	213.7	770.6	373.4
	B-10		18-72-12	0.20	0°	02A_LM-VLI	01e_S-LE	FC	99.46	20.59	198.3	808.9	371.5
	B-11		18-72-12	0.20	0°	02A_LM-VLI	01a_S-Cl	FC	101.26	20.85	196.0	816.3	371.3
	B-13	**III**	36-36-12	0.20	0°	02A_LM-VLI	01a_S-Cl	FC	104.63	21.53	193.3	830.1	374.4
	B-14		12-72-18	0.20	0°	02A_LM-VLI	01f_S-SP	FC	96.91	21.59	189.5	834.5	371.4
	B-17		09-72-24	0.20	0°	02A_LM-VLI	01a_S-Cl	HR	99.62	22.60	184.5	867.8	375.1
	B-20		18-36-24	1.20	0°	02A_LM-VLI	01f_S-SP	FC	103.91	23.16	179.3	868.8	374.6
	B-18		24-36-18	0.20	0°	02A_LM-VLI	01e_S-LE	FC	105.89	22.85	181.8	861.1	374.4
	B-24		18-36-24	0.20	0°	02A_LM-VLI	01c_S-Re	FC	104.71	23.79	176.5	887.6	376.9
	B-26		12-36-36	0.20	0°	02A_LM-VLI	01a_S-Cl	FC	108.28	24.26	175.0	905.6	379.5
	B-27	**IV**	18-36-24	0.20	0°	01A_VLM-VLI	01f_S-SP	FC	111.19	24.46	174.0	862.1	379.4
	B-30		18-36-24	0.20	0°	01A_VLM-VLI	01c_S-Re	FC	113.07	25.29	171.2	886.9	383.2
	B-31		12-36-36	0.20	0°	01A_VLM-VLI	01f_S-SP	FC	113.43	25.38	171.0	889.5	383.7
	B-33		12-36-36	0.20	0°	01A_VLM-VLI	01e_S-LE	FC	117.61	25.98	169.1	907.5	386.8
	B-35		12-36-36	0.20	0°	01A_VLM-VLI	01a_S-Cl	FC	119.69	26.31	167.7	917.3	388.0
C	C-01	N-A	18-72-12	0.20	0°	01A_VLM-VLI	02f_D-SP	FC	97.55	20.39	202.4	762.4	373.0
	C-02 / B-08		18-72-12	0.20	0°	02A_LM-VLI	02f_D-SP	FC	89.95	19.02	207.7	766.8	367.8
	C-03 / B-09		18-72-12	0.20	0°	02A_LM-VLI	01f_S-SP	FC	92.74	19.61	201.7	779.4	366.6

Climate zone C2-Barcelona

Results for the climate zone C2-Barcelona are summarized in Figure 3.9 and Table 3.4. There are three design variables whose solutions are very similar along the analysis scopes. One is the WWR, which is consistently 0.20 (just in two cases the WWR is 0.25). Other variable is orientation, which has only three values: 0º (77% of the solutions), 355º (16%) and 350º (7%). The last one is the HVAC energy saving option, which is always the heat recovery. The main differences among the solutions in each analysis scope are as follows:

A) The best design options of the **Scope A** are represented by three selected solutions. All of them have the building shape 18-72-12, double spectrally selective glazing and high insulation level. However, they differ regarding their thermal mass, which range from medium to very high level.

B) The 57 solutions of **Scope B** can be divided into four groups, differentiable mainly by their shape, constructions and glazing options:

- **Group B-I** comprises 8 solutions having exclusively the building shape 18-72-12. Constructions have from medium to very high thermal mass level, and from medium to very high insulation level. All the glazing options have spectrally selective glass and 2 or, predominately, 3 panes.
- **Group B-II** includes 12 solutions having also the building shape 18-72-12. Here, however, all the constructions have low thermal mass, with medium to high insulation level. Glazing solutions have spectrally selective or low-e glass, with 1 to 3 panes (the 2 panes option predominates).
- **Group B-III** comprises 26 solutions, which contains a wider range of building shapes: 12-72-18, 18-36-24, 24-36-18 and 27-24-24. All the constructions have low thermal mass, with low to high insulation level (prevailing the latest). Glazing is composed of 1 or 2 panes, with clear, low-e or spectrally selective glass.
- **Group B-IV** includes 11 solutions with two building shapes: 12-36-36 and 18-36-24. Constructions have all very low thermal mass level, with insulation from very low to medium level. Glazing is composed always of 1 pane, with predominance of clear and low-e glass types.

C) Eight solutions were found in the Pareto front of the **Scope C** analysis. All of them have the building shape 18-72-12. Constructions have very low or low thermal mass level, while the insulation level ranges from low to high. The glazing options have always the spectrally selective glass type and 2 or 3 panes.

The comparison of results among the three analysis scopes is quite similar to the one for the climate zone A3-Tenerife. Graph 3.9a shows that solutions of Scope A are very close to the solutions of the Group B-I, with one solution belonging to both categories. Likewise, solutions of Scope C are very close to the Group B-II, having 5 solutions belonging to both categories.

The differences with respect to the climate zone A3-Tenerife are more evident in the graph 3.9b. Here, the solutions of the Group B-II also remain very close to the Pareto front of Scope C optimization analysis, while the other groups tend to diverge. However, the solutions of Scope A and Group B-I tend to move away more in terms of global cost than in terms of global CO_2. Also, the solutions of Group B-II remain relatively close to the Pareto front of the Scope C analysis.

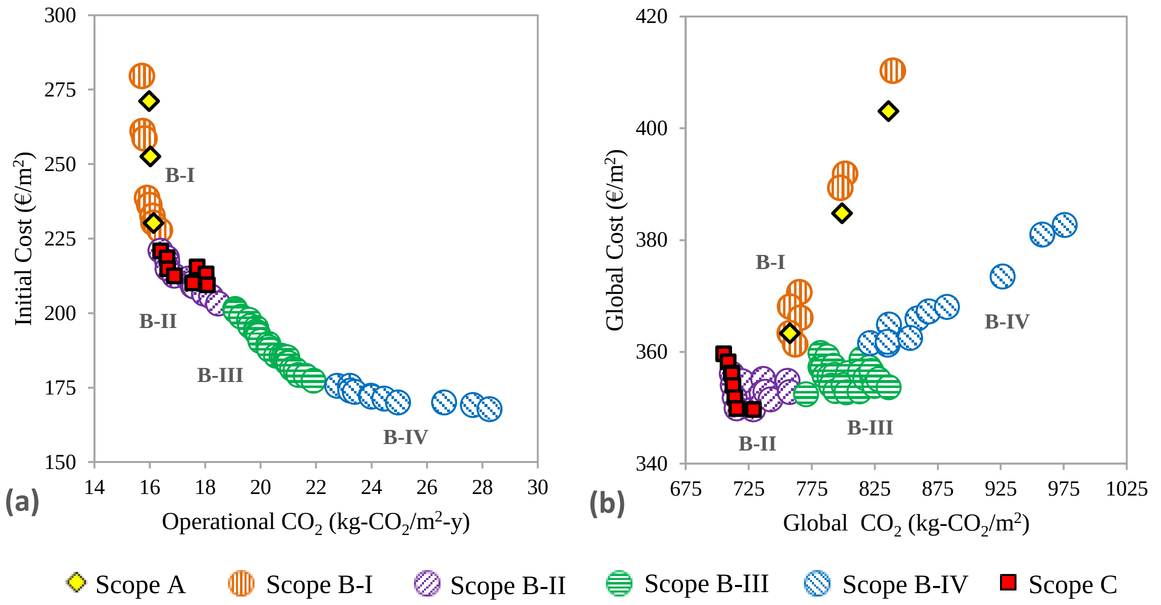

Figure 3.9. Results of optimization scopes A, B and C, for climate zone C2-Barcelona.

Table 3.4. Design options and performance objectives values for solutions selected from Figure 3.9.

Solutions			Design Options						Performance Objectives				
Scope	**Id.**	**Group**	**Shape**	**WWR**	**Orient.**	**Const.**	**Glazing**	**HVAC**	**GLoad**	**OCO_2**	**ICost**	**GCO_2**	**GCost**
	A-01		18-72-12	0.20	0°	05D_VHM-HI	02f_D-SP	HR	68.07	15.98	271.2	836.1	403.0
A	A-02	N/A	18-72-12	0.20	0°	04D_HM-HI	02f_D-SP	HR	68.28	16.03	252.6	799.1	384.8
	A-03 / B-07		18-72-12	0.20	0°	03D_MM-HI	02f_D-SP	HR	68.97	16.15	230.2	757.8	363.3
	B-01		18-72-12	0.20	355°	05E_VHM-VHI	03f_T-SP	HR	67.65	15.73	279.6	839.5	410.2
	B-03	I	18-72-12	0.20	355°	04D_HM-HI	03f_T-SP	HR	67.49	15.82	258.6	797.9	389.3
	B-05		18-72-12	0.20	355°	03D_MM-HI	03f_T-SP	HR	68.33	15.99	236.2	758.1	368.0
	B-08		18-72-12	0.20	0°	03C_MM-MI	02f_D-SP	HR	69.00	16.38	227.8	762.1	361.3
	B-09 / C-04		18-72-12	0.20	355°	02D_LM-HI	03f_T-SP	HR	70.71	16.40	220.9	711.7	356.0
	B-12 / C-06	II	18-72-12	0.20	0°	02D_LM-HI	02f_D-SP	HR	71.69	16.65	214.9	714.1	351.8
	B-16		18-72-12	0.20	0°	02C_LM-MI	02e_D-LE	HR	76.76	17.57	209.1	735.5	352.5
	B-20		18-72-12	0.20	0°	02C_LM-MI	01e_S-LE	HR	79.49	18.48	203.1	757.8	352.8
	B-21		12-72-18	0.20	0°	02D_LM-HI	02f_S-SP	HR	79.16	19.09	201.3	782.1	359.7
B	B-25		24-36-18	0.20	350°	02D_LM-HI	02f_S-SP	HR	79.99	19.63	195.7	783.7	357.0
	B-29		24-36-18	0.25	0°	02D_LM-HI	01f_S-SP	HR	82.21	19.91	193.2	789.3	355.6
	B-35	III	24-36-18	0.20	0°	02C_LM-MI	01e_S-LE	HR	84.14	20.57	185.7	802.8	352.7
	B-38		27-24-24	0.20	0°	02D_LM-HI	01e_S-LE	HR	88.53	20.92	185.2	815.0	358.7
	B-42		18-36-24	0.20	0°	02D_LM-HI	01a_S-Cl	HR	87.09	21.15	181.2	823.4	355.4
	B-46		18-36-24	0.20	0°	02B_LM-LI	01a_S-Cl	HR	87.87	21.92	177.2	836.5	353.6
	B-47		18-36-24	0.20	0°	01C_VLM-MI	01e_S-LE	HR	95.06	22.78	175.5	821.6	361.5
	B-50	IV	18-36-24	0.20	0°	01B_VLM-LI	01e_S-LE	HR	96.09	23.41	173.5	835.6	361.7
	B-54		12-36-36	0.20	0°	01B_VLM-LI	01a_S-Cl	HR	100.03	24.97	169.9	882.6	368.0
	B-57		12-36-36	0.20	0°	01A_VLM-VLI	01a_S-Cl	HR	110.31	28.27	167.7	976.0	382.6
	C-01		18-72-12	0.20	0°	01D_VLM-HI	03f_T-SP	HR	76.88	17.72	215.5	705.3	359.6
	C-03		18-72-12	0.20	0°	01D_VLM-HI	02f_D-SP	HR	78.42	18.09	209.5	711.3	356.2
C	C-05 / B-10	N-A	18-72-12	0.20	355°	02C_LM-MI	03f_T-SP	HR	70.62	16.63	218.5	712.5	353.9
	C-07 / B-13		18-72-12	0.20	0°	02C_LM-MI	02f_D-SP	HR	71.69	16.90	212.5	715.5	349.8
	C-08 / B-15		18-72-12	0.20	0°	02B_LM-LI	02f_D-SP	HR	72.66	17.55	210.1	728.9	349.6

Climate zone D3-Madrid

Figure 3.10 and Table 3.5 synthetize the results obtained for the climate zone D3-Madrid. The options for WWR, orientation and HVAC saving alternative are also quite constant along the different analysis scopes. The WWR is always 0.20, with no exception in the entire analysis space. An orientation of 0º is almost the unique alterative, with only one solution with a value of 350º and two solutions with a value of 355º. Finally, the HVAC free cooling option prevails clearly, as just in three solutions the best option is heat recovery. Other important highlights:

A) The three solutions that represent the best design options of the Scope A have the building shape 18-72-12, triple spectrally selective glazing and very high insulation level. The only difference among them is the thermal mass level, which ranges from medium to very high.

B) The Scope B analysis provided 44 Pareto front solutions, which can be classified in four groups characterized primarily by their shape, constructions and glazing options:

- **Group B-I** includes 6 solutions, all with the building shape 18-72-12. Here constructions have always very high insulation level, while thermal mass level varies from medium to very high. Glazing options are composed of low-e or spectrally selective glass, predominately with 3 panes (only one solution has 2 panes).
- **Group B-II** comprises 6 solutions with the building shape 18-72-12, while constructions have low thermal mass level with high or very high insulation level (mostly the last one). Glazing solutions have mostly 2 panes (just two solutions have 3 panes) with spectrally selective or low-e glass.
- **Group B-III** includes 22 solutions with two building shapes, 12-72-18 and 18-36-24. All the constructions have low thermal mass, with medium to very high insulation level. Glazing is composed of 1, 2 or 3 panes, with low-e or spectrally selective glass.
- **Group B-IV** comprises 10 solutions with two building shapes: 12-36-36 and 18-36-24. Constructions have always very low thermal mass level, with very low to medium insulation level. Glazing options have always 1 pane, but the glass type is clear, low-e or spectrally selective.

C) The Scope C optimization analysis generated a Pareto front with 9 solutions. In this case, unlike the previous climate zones, they include two building shapes: 18-36-24 and 18-72-12. Constructions have very low or low thermal mass level, while their insulation level is high or very high. Glazing is composed of 1 or 2 panes, as well as low-e or spectrally selective glass type.

As in the previously analyzed climate zones, graph 3.10a shows that solutions of Scope A are very close to the solutions of the Group B-I. Furthermore, the three solutions of the Scope A coincide with three solutions of that group. Here, however, there is an important difference regarding the solutions of the Scope C. They are divided into two sets, one located near the Group B-II and the other located near the Group B-III. There are three coincidences in each case. This happens mainly because solutions of the Scope C include two building shapes, as highlighted above.

Graph 3.10b shows that, unlike the preceding climate zones, both Group B-II and Group B-III remain quite near to the Pareto front of the Scope C analysis. Furthermore, solutions of the Scope A and the Group B-I spread away from the previous solutions, but more in terms of their global cost than the global CO_2. Finally, it is important to note that solutions of the Group B-IV move markedly away from the optimum zone, both in terms of global CO_2 and global cost.

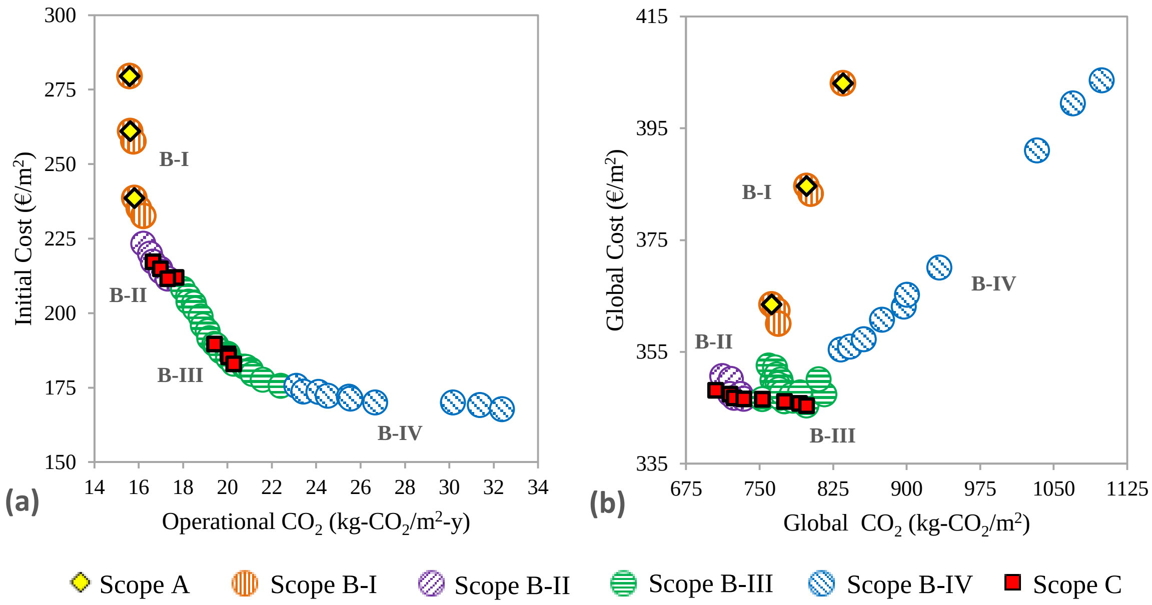

Figure 3.10. Results of optimization scopes A, B and C, for climate zone D3-Madrid.

Table 3.5. Design options and performance objectives values for solutions selected from Figure 3.10.

Solutions			Design Options						Performance Objectives				
Scope	Id.	Group	Shape	WWR	Orient.	Const.	Glazing	HVAC	GLoad	OCO_2	ICost	GCO_2	GCost
A	A-01 / B-01	N/A	18-72-12	0.20	0°	05E_VHM-VHI	03f_T-SP	FC	61.04	15.59	279.6	835.5	403.0
	A-02 / B-02		18-72-12	0.20	0°	04E_HM-VHI	03f_T-SP	FC	61.16	15.62	261.0	798.1	384.6
	A-03 / B-04		18-72-12	0.20	0°	03E_MM-VHI	03f_T-SP	FC	62.04	15.82	238.6	762.6	363.5
B	B-03	I	18-72-12	0.20	0°	04E_HM-VHI	02f_D-SP	FC	63.46	15.77	257.6	802.3	383.2
	B-05		18-72-12	0.20	0°	03E_MM-VHI	02f_D-SP	FC	64.52	16.02	235.2	768.5	362.4
	B-06		18-72-12	0.20	0°	03E_MM-VHI	02f_D-SP	FC	63.68	16.21	232.6	769.3	360.0
	B-07	II	18-72-12	0.20	355°	02E_LM-VHI	03f_T-SP	FC	63.77	16.22	223.3	712.2	350.6
	B-09 / C-02		18-72-12	0.20	0°	02E_LM-VHI	02f_D-SP	FC	65.51	16.65	217.3	720.1	347.4
	B-10 / C-03		18-72-12	0.20	0°	02D_LM-HI	02f_D-SP	FC	66.53	16.99	214.9	724.3	346.7
	B-13	III	12-72-18	0.20	0°	02E_LM-VHI	03f_T-SP	FC	68.02	18.01	208.1	759.5	352.5
	B-16		12-72-18	0.20	0°	02D_LM-HI	03e_T-LE	FC	70.80	18.50	203.2	767.9	350.9
	B-19		12-72-18	0.20	0°	02D_LM-HI	02e_D-LE	FC	72.15	18.81	198.9	773.6	348.8
	B-22		18-36-24	0.20	0°	02E_LM-VHI	02f_D-SP	FC	72.26	19.20	191.6	773.9	347.0
	B-29		18-36-24	0.20	0°	01E_VLM-VHI	01f_S-SP	FC	78.12	20.76	182.0	771.4	346.8
	B-34		18-36-24	0.20	0°	01C_VLM-MI	01e_S-LE	FC	85.05	22.41	175.5	810.7	350.0
	B-36	IV	12-36-36	0.20	0°	01C_VLM-MI	01e_S-LE	FC	87.67	23.43	173.6	842.6	355.9
	B-39		18-36-24	0.20	0°	01B_VLM-LI	01a_S-Cl	FC	95.92	25.48	171.9	897.4	363.0
	B-41		12-36-36	0.20	0°	01B_VLM-LI	01a_S-Cl	FC	99.23	26.67	169.9	933.7	370.1
	B-42		18-36-24	0.20	0°	01A_VLM-VLI	01a_S-Cl	HR	116.11	30.18	169.9	1033.3	391.0
	B-44		12-36-36	0.20	0°	01A_VLM-VLI	01a_S-Cl	HR	123.16	32.38	167.7	1099.4	403.5
C	C-01	N-A	18-72-12	0.20	0°	01E_VLM-VHI	02f_D-SP	FC	69.42	17.69	211.9	705.4	348.1
	C-04 / B-12		18-72-12	0.20	0°	02D_LM-HI	02e_D-LE	FC	69.54	17.32	211.5	734.2	346.6
	C-05 / B-26		18-36-24	0.20	0°	01E_VLM-VHI	02f_D-SP	FC	75.43	20.04	186.2	753.2	346.5
	C-07 / B-23		18-36-24	0.20	0°	02D_LM-HI	02f_D-SP	FC	72.89	19.42	189.6	775.5	346.1
	C-09 / B-28		18-36-24	0.20	0°	02D_LM-HI	01e_S-LE	FC	77.31	20.29	182.9	798.0	345.3

Climate zone E1-Burgos

The optimization results for the climate zone E1-Burgos are summarized in Figure 3.11 and Table 3.6. Here the only design variable that remains constant is the WWR, with a value of 0.20. Unlike the previous climate zones, orientation and HVAC alternative have significant variations.

A) The results for Scope A are again represented by three solutions. They all have the building shape 18-72-12, an orientation of 0º, triple spectrally selective glazing and heat recovery as HVAC saving alternative. They all have also constructions with very high insulation level. The only difference is the thermal mass, which varies from medium to very high level.

B) In this case, the Scope B optimization analysis generated a Pareto front with 39 solutions. It was not possible to classify these solutions into four groups, as in the previous climate zones. Instead, three groups were defined.

- **Group B-I** comprises 9 solutions. All these solutions have the building shape 18-72-12, an orientation of 0º, and the heat recovery HVAC alternative. Constructions have mostly very high insulation level (there is just one exception having high level), with low to high thermal mass level. Glazing options are composed of low-e or spectrally selective glass, with 2 or 3 panes.
- **Group B-II** includes 23 solutions. They have three building shapes, 12-36-36, 18-36-24 and 27-24-24, while the constructions have from very low to medium thermal mass level and from medium to very high insulation level. Glazing options have 1, 2 or 3 panes, as well as low-e or spectrally selective glass. Unlike the Group I, here all the solutions have the free cooling HVAC alternative.
- **Group B-III** comprises 7 solutions which have two building shapes: 12-36-36 and 18-36-24. Constructions have always very low thermal mass level, but very low to medium insulation level. All the glazing options have 1 pane, with clear or low-e glass type.

C) The Pareto front of the Scope C optimization analysis has in this case 5 solutions. Likewise the climate zone D3-Madrid, these solutions present two building shapes, 18-36-24 and 18-72-12, but here the former one clearly prevails (4 solutions). All the constructions have very low thermal mass and very high insulation levels, while the glazing options are composed of 2 or 3 panes, with low-e or spectrally selective glass type. Finally, all the optimal solutions in the Scope C have the free cooling HVAC alternative.

Graph 3.11a shows again that the solutions of Scope A remain very close to the solutions of the Group B-I. In this case there are two solutions belonging to both categories. Furthermore, four solutions of the Scope C analysis are located near the central part of the Group B-II (with three coincidences). On the other hand, one solution of the Scope C is located near the frontier between Groups B-I and B-II. This solution is the only one having the building shape 18-72-12.

Regarding the graph 3.11b, it is evident that all the solutions in Group B-II, as well as most of the solutions in Group B-I, remain close to the Pareto front of the Scope C analysis. In fact, the solutions of Scope A do not move away from the Pareto front of Scope C as markedly as in the other climate zones. This means that although they increase the global cost still can be feasible solutions in terms of global CO_2. On the other hand, solutions of the Group B-II move away from the optimum zone in a more remarkable way, in terms of both global CO_2 and global cost.

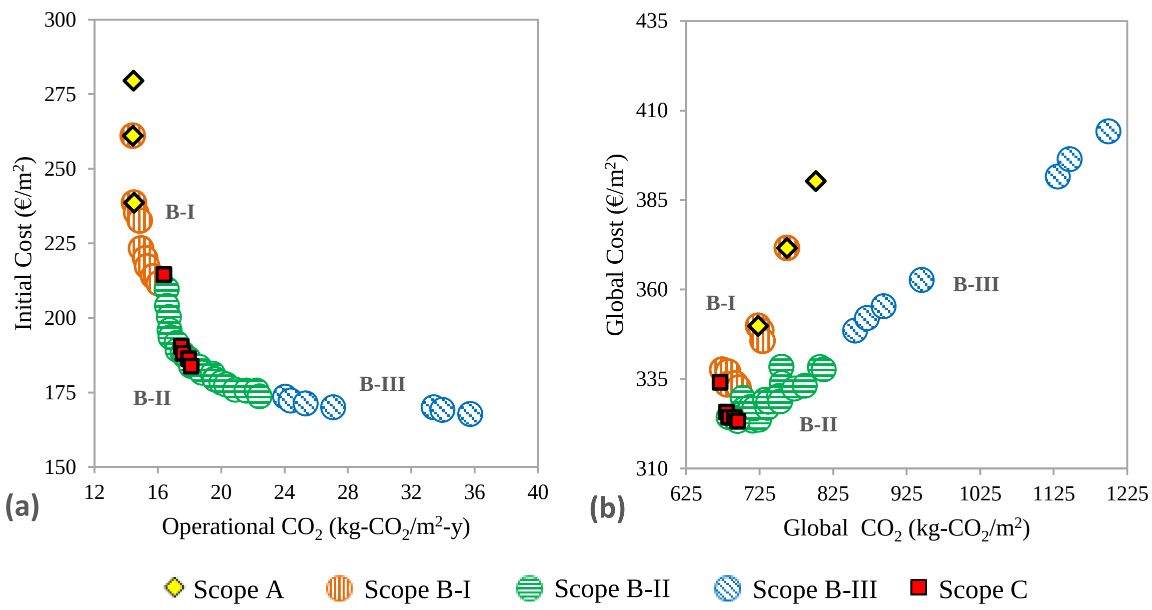

Figure 3.11. Results of optimization scopes A, B and C, for climate zone E1-Burgos.

Table 3.6. Design options and performance objectives values for solutions selected from Figure 3.11.

Solutions			Design Options						Performance Objectives				
Scope	**Id.**	**Group**	**Shape**	**WWR**	**Orient.**	**Const.**	**Glazing**	**HVAC**	**GLoad**	**OCO_2**	**ICost**	**GCO_2**	**GCost**
A	A-01 / B-01	N/A	18-72-12	0.20	0°	04E_HM-VHI	03f_T-SP	HR	48.61	14.44	261.0	762.4	371.5
	A-02		18-72-12	0.20	0°	05E_VHM-VHI	03f_T-SP	HR	48.69	14.47	279.6	801.9	390.2
	A-03 / B-02		18-72-12	0.20	0°	03E_MM-VHI	03f_T-SP	HR	49.14	14.52	238.6	723.4	349.8
B	B-03	I	18-72-12	0.20	0°	03E_MM-VHI	03e_T-LE	HR	51.58	14.66	235.2	727.8	348.5
	B-05		18-72-12	0.20	0°	02E_LM-VHI	03f_T-SP	HR	51.24	14.97	223.3	674.8	337.6
	B-07		18-72-12	0.20	0°	02E_LM-VHI	02f_D-SP	HR	52.55	15.35	217.3	681.0	333.4
	B-09		18-72-12	0.20	0°	02D_LM-HI	02e_D-LE	HR	56.52	16.08	211.5	696.9	332.5
	B-10	II	27-24-24	0.20	350°	03E_MM-VHI	03e_T-LE	FC	53.09	16.59	209.6	755.4	338.4
	B-12		18-36-24	0.20	350°	03E_MM-VHI	03e_T-LE	FC	52.40	16.60	204.0	755.8	333.8
	B-16		18-36-24	0.20	350°	02E_LM-VHI	02f_D-SP	FC	54.16	17.21	191.6	714.2	324.9
	B-23		12-36-36	0.20	355°	01E_VLM-VHI	02e_D-LE	FC	60.13	18.80	181.6	718.3	326.7
	B-28		18-36-24	0.20	0°	01D_VLM-HI	01e_S-LE	FC	65.57	20.33	177.5	753.4	328.6
	B-32		12-36-36	0.20	350°	01C_VLM-MI	01e_S-LE	FC	71.49	22.43	173.6	812.7	337.6
	B-33	III	18-36-24	0.20	0°	01B_VLM-LI	01e_S-LE	HR	81.70	24.07	173.5	855.2	348.5
	B-35		12-36-36	0.20	0°	01B_VLM-LI	01e_S-LE	HR	85.14	25.34	171.3	894.1	355.2
	B-36		12-36-37	0.20	0°	01B_VLM-LI	01a_S-Cl	HR	90.58	27.09	169.9	946.2	362.6
	B-37		18-36-24	0.20	0°	01A_VLM-VLI	01a_S-Cl	HR	109.93	33.44	169.9	1131.3	391.5
	B-39		12-36-36	0.20	350°	01A_VLM-VLI	01a_S-Cl	HR	117.18	35.73	167.7	1200.0	404.1
C	C-01	N-A	18-72-12	0.20	355°	01E_VLM-VHI	03e_T-LE	FC	54.47	16.39	214.5	671.5	334.0
	C-02		18-36-24	0.20	350°	01E_VLM-VHI	03f_T-SP	FC	55.63	17.49	190.5	680.4	325.7
	C-03 / B-18		18-36-24	0.20	350°	01E_VLM-VHI	03e_T-LE	FC	56.75	17.60	188.1	683.5	324.3
	C-04 B-20		18-36-24	0.20	350°	01E_VLM-VHI	02f_D-SP	FC	57.25	17.96	186.2	690.9	324.2
	C-05 / B-21		18-36-24	0.20	0°	01E_VLM-VHI	02e_D-LE	FC	58.55	18.12	183.8	695.7	323.2

3.3.2. General discussion about design variables

As seen in the previous section, lot of information can be generated from the results obtained in this study. However, one of the most important questions in this research is about the design options that can be defined as optimal for each design variable, depending on the optimization scope and the climate zone. This kind of data can be especially useful as guideline for the decisions making during the early phases of architectural design process, as well as to focus normative criteria in the field of buildings energy and environmental performance. The present section addresses with more detail the implications of the different design variables and their optimal design options.

Building shape

Regarding the building shape, of the 16 options included in the study only 9 appear at least once among the optimal solutions, as can be seen in Table 3.7. The most numerous, from high to low relevance, are the 18-72-12, 18-36-24, 12-36-36, 24-36-18 and 12-72-18. Among these options, the building shape 18-72-12 appears as the one with the highest energy, environmental and economic performance. It is evident that, in the context of this study, that building shape offers the best trade-off among energy consumptions, initial cost and embodied CO_2:

- It is the only shape in the solutions of the Scope A for climate zones C2-Barcelona, D3-Madrid and E1-Burgos. The only exception is climate zone A3-Tenerife, where solutions have the shape 06-144-18.
- It is the only shape in the solutions of the Group B-I in all the climate zones. It is also the only shape in the solutions of the Group II of the Scope B in the climate zones A3-Tenerife, C2-Barcelona and D2-Madrid.
- It is the only shape in optimal solutions of the Scope C analysis for the climate zones A3-Tenerife and C2-Barcelona. Also appears in the solutions for the climate zones D3-Madrid and E1-Burgos, although in the last one this shape is not predominant.

The second more relevant building shape is the 18-36-24, slightly more compact and with lower aspect ratio than the previous one. It is the predominant shape in the optimal solutions of the Scope C analysis for the climate zone E1-Burgos, and has an important role in the same scope for the climate zone D3-Madrid. Furthermore, this shape appears many times in the optimal solutions of the groups B-II, B-III and B-IV of the Scope B optimization analysis, in all the climate zones.

The third more relevant building shape is the 12-36-36, which is more compact than the previous ones. This shape is not part of the most efficient solutions in terms of energy, environmental and economic performance, but appears frequently in groups B-III and B-IV of the Scope B optimization analysis, for all the climate zones. That means that this building shape offers a good performance mainly from the economic point of view.

Another important point is that the higher the predominance of cooling loads the wider range of building shapes that can be part of the optimal solutions, as can be seen in the Table 3.7. In the climate zone A3-Tenerife there are 8 optimal building shapes, while this number is reduced to 6 shapes in C2-Barcelona and to 4 shapes in D3-Madrid and E1-Burgos. This may be because in hot climates the less compact forms can provide significant thermal advantages, as they facilitate the dissipation of heat from the building to the outside, although it is difficult to demonstrate this hypothesis within the limits of this study.

Table 3.7. Times building shapes appear in optimal solutions.

Building Shape	Climate zones A3-Ten	C2-Bar	D3-Mad	E1-Bur	Total
06-144-18	3	0	0	0	**3**
09-72-24	2	0	0	0	**2**
12-36-36	6	6	7	13	**32**
12-72-18	2	2	7	0	**11**
18-36-24	10	12	23	18	**63**
18-72-12	14	32	19	13	**78**
24-36-18	3	13	0	0	**16**
27-24-24	0	3	0	3	**6**
36-36-13	1	0	0	0	**1**
Total:	41	68	56	47	212

Orientation

The most common orientation in the optimal solutions among the different analysis scopes and climate zones is 0º, although there are some solutions with orientations of 350º and 355º. The only climate zone that does not show clearly this trend is the E1-Burgos, where the orientations of 350º and 355º appear in about the half of the optimal solutions, including all the solutions of the Scope C analysis. In any case, the optimization results confirm the findings of previous studies, which define the optimal orientation as close to 0º.

Window to wall ratio

The WWR is the most constant variable in this study. Of the 212 optimal solutions obtained in all the analysis scopes and climate zones, 209 solutions have a WWR of 0.20. Only 3 solutions, 1 in the climate A3-Tenerife and 2 in the climate C2-Barcelona, have a WWR of 0.25. It simply means that reducing the amount of glazing as much as possible is crucial for producing optimal solutions, regardless of the optimization scope or the climate zone.

Thermal mass and insulation levels

The effect of thermal mass level on energy, environmental and economic performance of buildings is very similar in the four climate zones. High levels of thermal mass improve the energy performance. With exception of the climate zone E1-Burgos, the most efficient solution in the Scope A analysis has very high thermal mass level. In addition, optimal solutions in the Group B-I for climate zones A3-Tenerife, C2-Barcelona and D3-Madrid include levels of thermal mass from medium to very high. However, the increase in initial cost and embodied CO_2 associated to high thermal mass makes this design variable to have low values when more comprehensive optimization objectives are pursued. For instance, all the optimal solutions in the Scope C analysis, in all the climate zones, have low or very low thermal mass level.

The insulation design variable shows a different behavior. It is evident that the higher the heating demand in the site, the higher benefits of increased insulation. However, it is also evident that the benefits of insulation have a limit, and furthermore, that higher insulation levels could be detrimental under certain conditions. These are the main findings regarding this variable:

- Practically all the optimal solutions in all the optimization scopes for the climate zone A3-Tenerife have very low insulation level. This means that, within the limits of this research, increasing the insulation level could be a bad strategy in climate zones where cooling loads are high and heating loads are very low.

- Apart from the climate zone A3-Tenerife, in the other climate zones the results for the Scope B analysis show that insulation level tend to be higher in the first groups, where solutions are more efficient in terms of operational CO_2, and lower in the last groups, where solutions are more efficient in terms of cost.
- The results for the Scope C optimization analysis, the most comprehensive in terms of economic and environmental performance, show that in the climate zone A3-Tenerife all the optimal solutions have very low insulation level, in the climate zone C2-Barcelona they have from low to high insulation level, in the climate zone D3-Madrid they have high (predominately) or very high insulation level, and finally the climate zone E1-Burgos is the only one where all the optimal solutions have very high insulation level.

Number of panes and type of glass

The number of panes that define the optimal glazing options is quite irregular, although it is possible to affirm that a number of 2 panes is the best overall option, according with the following findings:

- The optimal solutions of the Scope A analysis have 2 or 3 panes in the climate zone A3-Tenerife, 2 panes in the climate C2-Barcelona, and 3 panes in the climate zones D3-Madrid and E1-Burgos.
- The optimal solutions of the Scope B analysis, in the four climate zones, tend to have 3 panes in the first groups (higher efficiency in terms of operational CO_2) and 1 pane in the last ones (higher efficiency in terms of cost).
- The optimal solutions of the more comprehensive Scope C analysis have 1 or 2 panes in the climate zones A3-Tenerife and C2-Barcelona, as well as 2 or 3 panes in the climate zones D3-Madrid and E1-Burgos.

Regarding the glass type, it is remarkable that of the six options included in this study, only four are part of the optimal solutions along the different analysis scopes and climate zones: the clear, reflective, low-e and spectrally selective glasses. The absorptive and absorptive-reflective glass types, thus, do not appear in any of the solutions. Furthermore, only the low-e and the spectrally selective glass types, and especially the last one, appear consistently in the optimal solutions of the Scope A and Scope C analyses. The clear glass type appears mainly in the solutions of the groups III and IV of the Scope B analysis, that is, the more efficient solutions in terms of initial cost.

In any case, it is important to take into account that the type of glass and the number of panes found in the optimal solutions are associated to a very low WWR. Also, that the glazing surface is uniformly distributed in all the facades of the building.

HVAC saving option

The free cooling HVAC saving option is the most common in the optimal solutions found in this study, especially for the Scope C analysis. The only clear exception is the climate zone C2-Barcelona, where the heat recovery option forms part of all the optimal solutions. It is also remarkable the case of climate zone E1-Burgos, where both options are almost equally distributed.

3.4. Conclusions

This study addresses a broad optimization analysis, primarily focused on identifying the architectural design options that, applied to a medium size office building, produce lower energy, environmental and economic impacts. The optimization method is based on the simultaneous execution of dynamic whole-building simulations and evolutionary algorithms, supported by an extensive parametric project. Three different optimization scopes were included in the study. The more basic optimization scope covers a single performance objective, which consists on the total energy load (sum of heating, cooling and lighting loads). The intermediate optimization scope covers two commonly used performance objectives, the operational CO_2 and the initial cost (or capital cost). The more comprehensive optimization scope covers also two performance objectives, the global CO_2 (operational CO_2 plus embodied CO_2) and the global cost (initial cost plus operational cost). The three different optimization scopes were applied to four Spanish representative climate zones.

One of the most important conclusions of the study is that optimizing office buildings exclusively based on its energy performance could lead to sub-optimal solutions from a more comprehensive point of view. Here, optimizing the architectural design variables taking the total energy load as the unique performance objective generates solutions that tend to have a relatively poor performance in terms of global CO_2 and global cost. This tendency is because energy optimal solutions include design options that significantly increase the initial cost and the embodied CO_2, especially the amount of thermal mass. It is also clear that this tendency becomes stronger as cooling demand increases, as can be deduced by comparing the results for the four climate zones.

On the other hand, it is evident that choosing solutions with low initial cost leads to extremely bad solutions in terms of global CO_2 and global cost. This trend is the opposite of the one explained above, as the more comprehensive performance objectives deteriorates significantly when heating demand increases. The rising energy consumptions, in turn, generate higher operational CO_2 and operational cost.

The results also support the rule of thumb indicating that, if the optimization process has been done with basis on the operational CO_2 and the initial cost, it is better to choose solutions located near the central part of the Pareto front. In this way, it is less probable to select a solution apparently optimal but which in fact offers a poor performance from a more comprehensive performance point of view.

Regarding the role of the design variables included in the optimization analyses, it is convenient to highlight the following aspects as guidelines for design decisions:

- Building shapes with medium-low height and high aspect ratio offer the best overall performance through the different optimization scopes and climate zones. Within the limits of this study the shape 18-72-12, and secondly the shape 18-36-24, offer the best trade-off among energy, environmental and economic impacts.
- Reducing the amount of glazing as much as possible seems to be an important strategy to optimize the energy, environmental and economic performance of buildings. In this study the lowest WWR, 0.20, appears in practically all the optimal solutions through the different optimization scopes and climate zones. This strategy is frankly contradictory with current architectural trends, but should be taken into account if looking for real optimal solutions.
- Coinciding with other studies, the optimal orientation along the different optimization scopes and climate zones is close to 0º, i.e. larger façades oriented to north and south. However, some small variations are interesting to be taken into account. For instance, in the climate zone E1-Burgos orientations of 350º and 355º are common among the optimal solutions.
- High levels of thermal mass show favorable effects in terms of energy performance. However the increase in cost and embodied CO_2 associated to high levels of thermal mass lead to low values when more comprehensive optimization objectives are pursued, for example global CO_2 and global cost.
- Envelope insulation offers clear benefits when heating demand is high. However, according to the results, it is evident that the advantages of high insulation levels have a limit and, furthermore, they could be detrimental under certain conditions. For instance, optimal solutions for the climate

zone A3-Tenerife, where cooling demand clearly dominates, have always very low insulation level. On the other hand, the climate zone E1-Burgos, the coldest in this study, is the only one where the highest level of insulation appears consistently in optimal solutions.

- Results regarding the optimal number of panes are somewhat irregular, although 2 panes can be considered a good overall choice along the different optimization scopes and climate zones.
- The spectrally selective in the first place, and the low-e in the second one, are the glass types which offer the best overall energy, environmental and economic performance. It is important to take into account that these options are associated, due the limits of this study, to very low WWR.

The results of this study offer a better understanding of the effect that architectural design variables have on energy, environmental and economic performance of office buildings. These results cannot answer all the possible questions, since the study focuses on exploring the optimal design options. However, they could be useful as guideline for the decision-making during the early architectural design stages. Also can help to improve or fine-tune the normative criteria in the field of building energy performance. In the future, it would be desirable to extend the scope of this study, for example covering other usage conditions, more complex building shapes and more wide range of climate conditions. The usefulness of the optimization analysis can then increase substantially.

Chapter 4. Relative importance of design variables

Sensitivity analysis represents an effective approach to understand the impact that, in a given system, inputs have on the outputs. The Morris and Sobol sensitivity analysis methods were applied here to investigate the impact of the main architectural design variables on energy, environmental and economic performance of office buildings. Four representative Spanish climate zones were considered. The analyses were based on a large simulation parametric project, previously developed with EnergyPlus and jEPlus, and addressed the effect of eight input factors on eight outputs. The input factors mainly comprise the geometric configuration of the building and the composition of its opaque/translucent envelope, while the output variables include energy loads, operational and global CO_2, as well as initial and global costs. The results suggest that, in the context of this study, building shape and window to wall ratio (WWR) are the most important design variables, followed by the insulation and thermal mass levels of opaque envelope. The number of panes and the type of glass show low relative importance, while both orientation and HVAC saving strategy show the lower overall effect. This kind of information can be useful to improve building energy codes, as well as to support decisions making in architectural design processes, especially during the initial phases.

4.1. Introduction

Although energy efficiency of buildings is clearly affected by the way they are used and controlled along its lifespan, many of the characteristics which greatly determine their performance are decided from the design phases and are difficult or even impossible to amend once the building has been built. One example is the building general shape, often recognized as a factor that strongly affects its thermal behavior [115]. Other example is the selection of construction materials, which evidently affects the building total emissions of CO_2 and other harmful gases, as well as its role in the depletion of non-renewable resources. In general, it is widely accepted that addressing the energy and environmental performance of buildings from early design phases is the best practice, and the earlier the better: this is the design stage in which the most important energy savings and environmental impact mitigations can be addressed. However, the designer's decisions related to energy efficiency are often based only on previous experience, rules of thumb and/or general normative criteria.

The sensitivity analysis is a methodological approach that can be very useful during early architectural design stages, although should be considered as a complementary resource. If properly applied, it can help to identify the relative impact and importance that design variables can have on buildings energy and environmental performance. Having consistent sensitivity information could help focusing on the most relevant design variables, as well as identifying opportunities for improving building performance at the lowest cost. This study explores the use of sensitivity analysis methods making strong emphasis on architectural design variables.

4.1.1. Background on sensitivity analysis methods

Sensitivity analysis has been extensively used in diverse fields related to energy and environmental performance of buildings, including both theoretical and observational studies. Among these fields we can find building design, building energy simulation, building retrofit, energy auditing and management, and even the impact of climate change on building energy performance [116]. In general, the objective of sensitivity analysis is to determine the impacts that, in a given system, inputs have on the outputs. In the context of this study, the sensitivity analysis represents a method to determine the effect that the main architectural design variables have on building energy and environmental performance. These methods allow assessing which variables and parameters have the highest influence on the variance of building performance, and even to what extent [117].

There is a wide range of sensitivity analysis methods. According to Tian et al. [116] those methods can be differentiated in the first place as local or global methods. The latter includes regression, screening-based and variance-based methods. The general characteristics of some of the most common sensitivity analysis methods are described below.

Local sensitivity analysis

Local sensitivity analysis, also known as a differential sensitivity analysis, is often defined as one-factor-at-a-time approach. It is because sensitivity measures are generally calculated changing one factor at a time while all the other factors are fixed. Due to this approach, the choice of the base case is especially relevant. Among its advantages, this method is very straightforward compared to global sensitivity analysis and it is easy to implement and understand. It also requires less simulation runs. However, as downsides, this method only explores a reduced space of the input factors around the base case, cannot address the interactions and does not admit self-verification [118] [119].

Global sensitivity methods

Global sensitivity methods evaluate the variation of outputs due to each design parameter by varying all the other parameters simultaneously, considering their probability density function [120]. It is assumed that the whole behavior of the building is influenced by all the design variables at the same time, and thus the sensitivity of each design variable depends on the interaction with all the other design variables. In general, randomly selected design solutions and their associated outputs are used to estimate the sensitivity of design variables. Among the most common approaches for global sensitivity analysis, it can be mentioned the regression, the screen-based and the variance-based methods [116].

Regression/Correlation based methods

Due to its low computing cost and relatively easy understanding, regression/correlation methods are among the most used for sensitivity analysis in the field of building energy performance. They include indicators such as Pearson Correlation Coefficients (PEAR), Standardized Regression Coefficients (SRC) and Partial Correlation Coefficients (PCC), as well as their rank transformation Spearman Rank Correlation Coefficients (SPEA), Standardized Rank Regression Coefficients (SRRC) and Partial Rank Correlation Coefficients (PRCC) [121]. The capability and usefulness of these indicators varies widely. In general, PEAR, SRC, and PCC methods are considered suitable just for linear models. PCC method is also adequate when correlated input exists, because provides a measure of variable importance that tends to exclude the effect of other variables [116] [121].

The limitations related to linearity can be avoided with the use of rank transformations, which is the case of SPEA, SRRC and PRCC methods. Thus, these methods can be used with non-linear models. However, the rank transformation approach is still not fully satisfactory when relationships among inputs and outputs are non-monotonic [116]. Another problem associated to the ranking strategy is that transformations create in fact a new model, and thus the sensitivity measures are not exactly for the original one. The new model is more linear and more additive than the original one, which means that more variation can be explained as the sum of elementary effects.

Screening-based methods

This approach, mainly represented by the Morris method, is a global sensitivity analysis because the baseline changes in every step and the final sensitivity indexes are calculated by averaging at different points of the input space. However, unlike other global methods in which input values are taken directly from distributions, input factors here are taken as a discrete number of values, also called “levels”. Morris method offers two sensitivity indexes, Mu (μ) and Sigma (σ). The first one indicates the impact of the input factor on the outputs, while the second one offers an overall measure of the interactions with other factors and the nonlinear effects [122]. The most common objective of screening-based methods is to fix some input factors from a group of factors, but without reducing the output variance. The method could be more appropriate when the project include a majority of non-influential factors and few influential factors.

The principal advantage of the screening-based methods is the low computational cost, compared with other global methods such as the Sobol. The main disadvantage is that it offers qualitative measures by ranking input factors but cannot quantify the effect of different factors on outputs [123]. Thus, it is not possible to know how much of the total variances of outputs have been considered in the analysis and, in consequence, this method does not permit self-verification. Other disadvantage is that the mean of the output variable values of the sample does not converge to the population mean of the output, and thus cannot offer uncertainty analysis for building energy performance.

Variance-based methods

Variance-based methods work by decomposing the variance of the output [122]. They are capable of quantify all the variance of the output due to every input in the model, also considering the effect of interactions of inputs. The variance-based methods are considered as a model free approach, because they are suitable for complex nonlinear and non-additive models. The first order effect and total effect are the main sensitivity indices used in this approach. The first order effects account for the outputs variations associated to the corresponding inputs. The total effects measure the total contributions of the corresponding input to the output variance, including both first order and higher order effects due to interactions between variables. Thus, the difference between the first order effects and total effects can uncover the influence of interactions between variables. It can be stated that the first order effects are a good option if the objective is to prioritize energy saving measures. Instead, the total effects should be used if the main objective is to fix the factors which are not important in the energy models [116].

The most common variance-based methods are FAST (Fourier Amplitude Sensitivity Test) and Sobol [124]. The classical FAST method takes into account the nonlinear effects, but not the effect of interactions. On the other hand, the Sobol method is much more computationally expensive, compared to other global sensitivity methods, but can decompose all the output variance. This means that no variance of the outputs is left out in the analysis.

Sensitivity analysis based on meta-models

One recent trend in the field of sensitivity analysis is the use of meta-models [116]. This approach usually implies two steps. The first one consists of creation of a meta-model by using non-parametric regression methods with non-predetermined form, i.e. linear or non-linear, in such a way that it can be used for complex models. The second step consists of calculation of the sensitivity measures by mean of the meta-model. The main advantage of these methods is that they require much less computing power, allow exploring wider solution spaces and/or use more exhaustive sensitivity analysis approaches like the variance-based methods. Among the most common meta-model approaches are the Multivariate Adaptive Regression Splines (MARS), Adaptive Component Selection and Smoothing Operator (ACOSSO), Support vector machine, Gaussian Process (GP), Treed Gaussian Process (TGP) and Artificial Neural Networks (ANN).

4.1.2. Objectives and scope of this study

In this study, the Morris and Sobol global sensitivity analysis methods were implemented and compared. They are two of the most utilized and recognized methods not only in the field of building energy efficiency but also in many other disciplines. Those methods are applied to an extensive parametric simulation project, in order to investigate the effect and importance that the main architectural design variables have on energy, environmental and economic performance of office buildings, considering four representative Spanish climates. In addition to this central objective, the study aims to comply with the next ones:

- To identify the input factors that are more suitable to describe the architectural design variables in the context of sensitivity analysis.
- To explore the differences among a wide range of output variables, assumed as indicators of buildings performance.
- To compare the implemented sensitivity analysis methods, in terms of their performance and computational cost, as well as to evaluate their potential for future studies.

Some authors have used sensitivity analysis mainly to identify input factors that have no important effects on the output, and thus can be eliminated to reduce the complexity of the problem. In this study, however, it is assumed that all the design variables are important to some extent, and not necessarily have to be omitted from the global analysis. It is also assumed that sensitivity analysis represents just a part of the process of understanding the complex relationships underlying buildings performance. Note also that the study focuses on understanding the sensitivity of architectural design variables. Although in fact the overall energy and environmental performance of buildings depends also on the characteristics of their mechanical systems and on the source of energies, it is essential to understand the implications of each of these components independently. This is particularly true for architectural design variables, as once the building is built they are very difficult, if not impossible, to change.

4.2. Methodology

The sensitivity analyses in this study were performed using the Morris and the Sobol methods, which were selected from the literature review synthetized in the previous section. They are very different in terms of their conceptual and methodological approach to sensitivity analysis, as well as in their computational cost, but have been identified by other researchers as two of the most suitable methods when complex building energy-related problems are being addressed [116] [103].

There are two main purposes for using two sensitivity analysis methods. One is to contrast and validate to some extent the sensitivity results. It is expected that both methods offer, if not identical, at least similar results. Very different or even contradictory results could mean that there are problems with the setting and/or execution of the analyses. The other purpose is to test the performance and reliability of both methods and to determine their potential application in future studies.

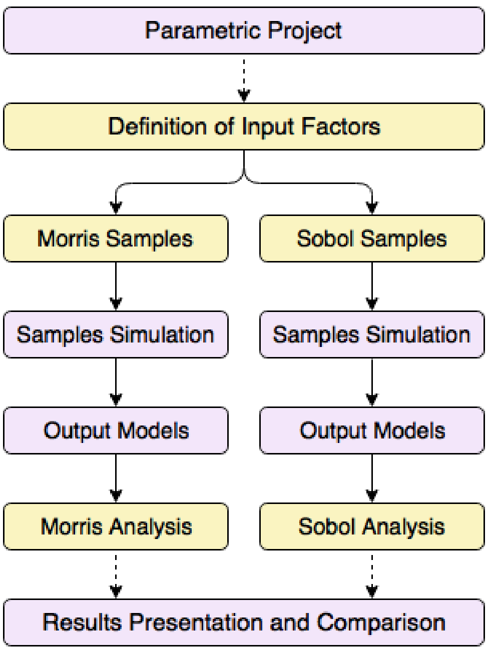

Figure 4.1. Sensitivity analyses workflow. Yellow fields are run in Simlab.

The workflow implemented to execute the sensitivity analyses implied the usage of three main programs: Simlab, EnergyPlus and jEPlus. Simlab is a modular desktop application provided by the European Commission and primarily designed for Monte Carlo based uncertainty and sensitivity analysis [125]. EnergyPlus is a widely recognized program used for the iterative and dynamic modeling of the most significant thermal and energy flows taking place on buildings and its mechanical systems [39]. jEPlus is an application mainly focused on parametric simulations within programs such as EnergyPlus and TRNSYS [40]. The process included the following main steps (see Figure 4.1):

a) **Definition of input factors**. The first step is done in the Statistical Pre-Processor module of Simlab. It consists of defining the range and probability distribution of the input factors, which are derived from the design variables of the parametric project. The type of probability distribution depends on the nature of the analysis, for example if it is focused on building design problems or on the evaluation of existing buildings.

b) **Generation of solutions sample**. In the second step, a solutions sample is generated by combining values of the previously defined input factors. The sampling strategy depends on the specific sensitivity analysis method to be used. This step is also done in the Statistical Pre-Processor module of Simlab.

c) **Simulation of solutions sample**. In this step the design solutions included in the sample are parametrically simulated with EnergyPlus through the interface of jEPlus. To do that it is necessary to translate again the input factors into the design variables and options of the parametric project, so they can be read by jEPlus.

d) **Creation of output model**. The simulation results are compiled as the values of the output variables to be used in the sensitivity analysis. The task consists simply on creation of a text file with a specific structure which can be read by Simlab.

e) **Execution of sensitivity analysis**. The solutions sample and the output model are coupled in the Model Execution module of Simlab. The sensitivity analysis is then performed through the Statistical Post-Processor module of the program.

f) **Interpretation and comparison of sensitivity analysis results**. In the last step the results of the sensitivity analyses are extracted and interpreted. Both Morris and Sobol methods are compared in terms of performance and computational requirements.

The next sections offer a more detailed description of the setting used for the sensitivity analysis methods, as well as the definition of the input factors and the output variables. A brief description of the selected Spanish climate zones is also included.

4.2.1. Settings of the sensitivity analysis methods

Morris and Sobol methods are both considered global sensitivity analysis methods, as they assess the variation of the outputs associated to one input factor (or design variable) by changing the other inputs simultaneously. It is assumed that the overall performance of buildings is affected by all the input factors at the same time, and thus the sensitivity of an input factor depends also on its interaction with all the other input factors [120]. Likewise, both methods use a sampling-based strategy, also known as Monte Carlo-based approach [103]. Monte Carlo methods offer statistical answers to a problem by executing multiple model evaluations with an input sample generated in a probabilistic way. Morris and Sobol methods use the results of these evaluations to calculate the sensitivity indexes [126].

Beyond these similarities, Morris and Sobol methods have important differences in terms of their conceptual and methodological approach. They also have very divergent computational costs, as has been observed by other researchers. The specific characteristics of both methods are explained in the next sections, together with the settings assumed for their implementation.

Morris method

The experimental strategy of Morris method consists on generating individually randomized "one-factor-at-a-time" experiments, each of which aims to evaluate the effect of changing the value of one of the input factors. Thus, it calculates the main effect of each input factor by computing a certain number of local measures at different points of the search space. Then it takes their average, reducing the dependence that a local experiment has on the specific point. The number of local measures is defined in such a way that each factor is varied over its interval of experimentation [121]. As a result, the method offers two sensitivity indices, Mu (μ) and Sigma (σ). The first one indicates the impact of the input factor on the outputs, while the second one offers an overall measure of the interactions with other factors and the nonlinear effects [121] [124].

The number of model executions, or simulations, required for implementing the Morris method is calculated as $r \times (k + 1)$, where r is the number of trajectories (successions of points starting from a random base vector in which two consecutive elements differ only for one component) and k is the number of input factors [121]. 10 trajectories were considered in this study, which are the maximum allowed by the method. Thus, considering that there are 8 input factors, samples of 90 model simulations were generated. Furthermore, for each input factor the Morris method operates on a certain number of levels, which correspond to the quantiles of the input factor distribution. 8 levels were assumed in this study, which take the quantiles 6.25th, 18.75th, 31.25th, 43.75th, 56.25th, 68.75th, 81.25th and 93.75th.

Sobol method

The Sobol sensitivity analysis is aimed to establish the contribution of each input factor to the whole model output variance, as well as its interactions with the other inputs [127]. The method consists on decomposing the model output variance into summands of variances of the input factors with increasing dimensionality. The decomposition of the output variance follows the classical analysis of variance in a factorial design. In order to establish accurately how the output variance relates to individual input factors and its interactions the first order, second order and higher order sensitivity indexes can be calculated. However, in this way the number of indexes increases exponentially and thus the computational cost. In practice, only the first order indexes and the total effects indexes are calculated, as they give good enough information about the model sensitivities [128]. The total effects indexes were introduced by Homma and Saltelli [129] to account for all the possible synergetic terms among a given input factor and all the others. A complete description of the mathematical implementation of Sobol method can be found in the Simlab manual [121].

The Sobol method requires the solutions sample to be generated by the Sobol sequence [130]. The adequate sample size depends on the model complexity and the number of input factors [103]. The minimum sample size for calculating both first and total order indexes is $n\ (2k + 2)$, where k is the number of input factors and n is the required model executions for estimating one individual effect. The predetermined n values of 16, 32, 64 and 128 were tested in this study. Considering that the analysis includes 8 input factors, those values produce sample sizes of 288, 576, 1152 and 2304. According to the tests, only the last option offered stable results. For example, n values of 1152 or lower produced sensitivity indexes with relatively high negative values. Such negative values are only acceptable when the sensitivity indexes are very close to zero. In any case, increasing the size of the sample reduces the possibility of having negative values [124]. Thus, a sample size of 2304 was used in this study for all the sensitivity analyses with the Sobol method.

4.2.2. Definition of input factors

The sensitivity analyses performed in this research are based on the parametric project explained in Chapter **2**. The parametric project, constructed around the programs EnergyPlus and jEPlus, is the source to define the input factors and the output variables used in the sensitivity analyses. Here it is included a short description of the parametric project, while the complete details can be consulted found in the mentioned chapter.

The schematic tree of the parametric project is shown in Figure 4.2. Note that it includes 10 design variables, although infiltration level and usage intensity are both fixed at their medium level. Thus, the parametric project comprises 8 active design variables, which together contain 55 design options: 16 building shapes, 5 WWR, 12 orientations, 5 thermal mass levels, 5 insulation levels, 3 numbers of glass panes, 6 glass types and 3 HVAC saving strategy options. Each unique path in the parametric tree, from top to bottom, represents a different design solution, so the total quantity of solutions is over 1.3 million. This quantity represents the global search space of the sensitivity analysis in each climate zone.

The eight design variables from the parametric project were translated into the input factors synthesized in Table 4.1. Although some design variables can be described with two or more parameters, one input factor per design variable is required by the implemented sensitivity analysis methods, which do not allow correlated parameters [121]. All the input factors are described by means of discrete distributions, although not always these distributions are uniform. In addition, the values of the distributions are equally weighted when possible (the sum of the values weights has to be 1, and thus small adjustments are required when the number of values in a distribution is odd).

Table 4.1. General definition of input factors.

Input factor	Parameter	Units	Steps	Increment	Minimum	Maximum
Shape	Wall/Ext.Surf.	N/A	16	Uneven	0.077	0.912
WWR	WWR	N/A	5	15	0.20	0.80
Orientation	Orientation angle	Degree	12	15	0	165
Thermal mass	Global capacity	$kJ/m^2 \cdot K$	5	Uneven	62.1	373.8
Insulation	Global resistance	$m^2 \cdot K/W$	5	0.7	0.7	3.5
Panes	Averaged U-factors	$W/m^2 \cdot K$	3	Uneven	1.57	4.77
Glass type	Averaged SHGC & T_{vis}	N/A	6	Uneven	0.17	0.75
HVAC	HVAC options	N/A	3	1	0	2

The main criterion behind the definition of the input factors is that there are no preconceptions about the probability or fitness of different design options. For each design variable, every design option has the same chance to be used by the designer. This approach is intended to avoid the interference of preconceived ideas and better understand the real impact of using different design options.

Shape. The parametric project includes 16 modular shapes, for a hypothetic office building with a useful floor area of 5,184 m^2 and an internal volume of 15,552 m^3. The name of each building shape derives from its height, length and width dimensions (in meters). These shapes can be described by a number of geometrical parameters, such as the compactness or the form factor, commonly used in the field of building energy analysis. However, the parameter *Wall Surface / Total External Surface* was selected in this case to define the associated input factor. From a set of tested parameters, this is the single one which better describes, without any repetition, the variations of building shapes. The complete set of values is as follows: 0.077, 0.200, 0.234, 0.273, 0.304, 0.333, 0.400, 0.455, 0.556, 0.636, 0.667, 0.692, 0.800, 0.842, 0.871 and 0.912.

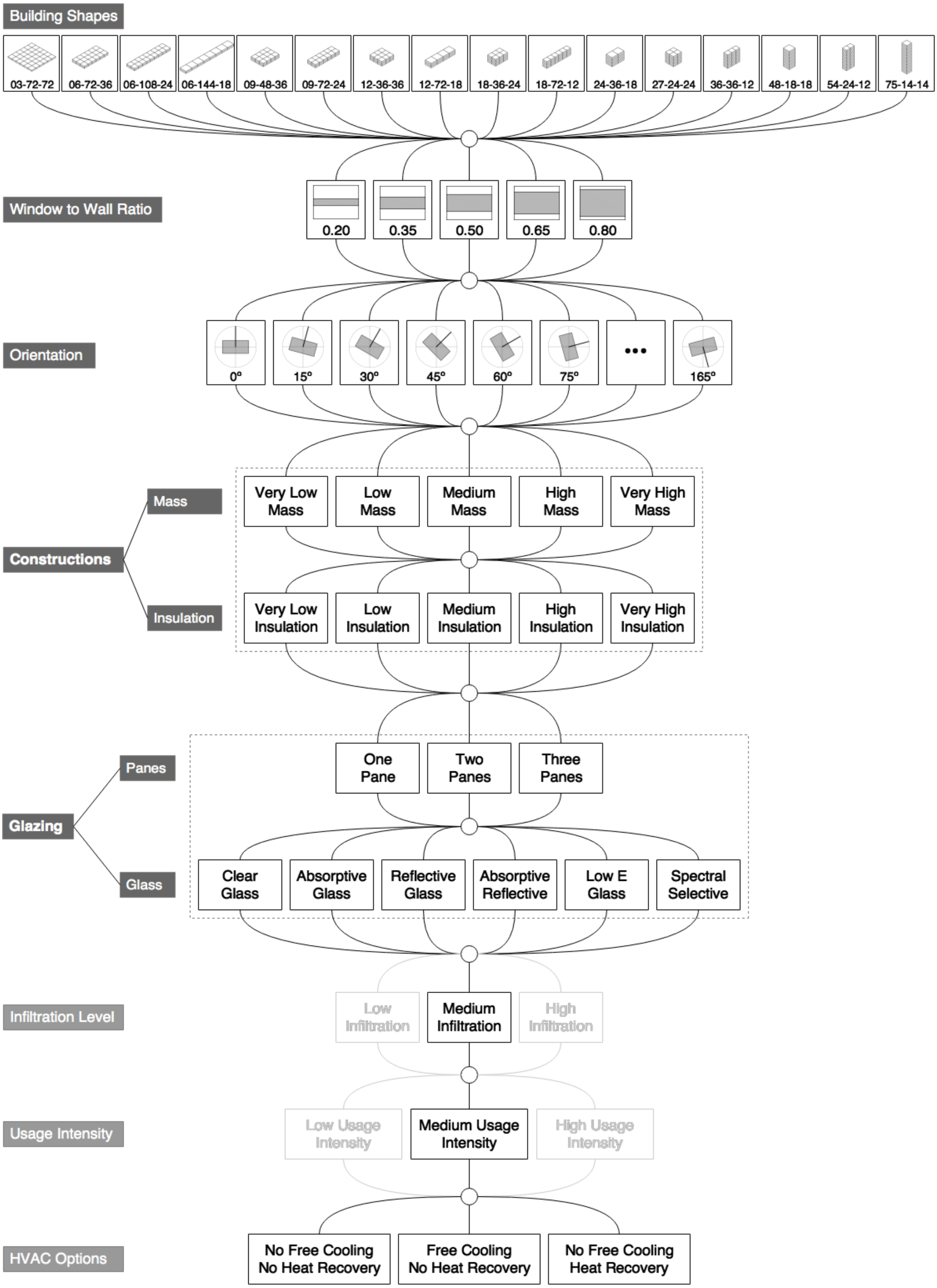

Figure 4.2. Tree of the parametric project used as a basis for sensitivity analyses.

WWR. The parametric project includes window to wall ratios from 0.20 to 0.80, with increments of 0.15. As it is very straightforward, the same parameter has been used for the corresponding input factor.

Orientation. The orientation of the building with respect to the cardinal axes can be easily changed in the parametric project, and could be even described as a continuous parameter. Here, as input factor for the sensitivity analysis, it is defined with increments of 15º, starting from 0 up to 165. Note that, as the glazing is uniformly distributed in all the facades of the building, this range is enough to represent 24 orientation angles covering the 360º.

Thermal mass. Thermal mass level is one of the variables which describe the characteristics of opaque constructions in the parametric project, covering five levels from very low to very high thermal mass. Here, it is described by means of the parameter global Heat Capacity (kJ/m^2•K), which is calculated with basis on standards ISO 13790-2008 and ISO 13786-2007. The complete set of values is as follows: 62.1, 129.2, 223.7, 300.0 and 373.8.

Insulation. Insulation is the second variable used to describe the characteristics of opaque constructions in the parametric project. It also covers five levels, from very low to very high insulation. Insulation input factor is defined by mean of the parameter global Thermal Resistance (m^2•K/W), which is calculated according to the standard ISO 6946-2007. The complete set of values is as follows: 0.7, 1.4, 2.1, 2.8 and 3.5.

Panes. One of the variables used to describe the characteristics of glazing in the parametric project is the number of panes, with three options: one, two and three panes. The associated input factor was defined as the average U-factor (W/m^2•K) of the six glass types (see below) for each number of panes. The U-factors were calculated through the Window 7.3 software, with basis on the guidelines defined in the NFRC 100-2010 and NFRC 200-2010 documents. The complete set of values is as follows: 1.57, 2.30 and 4.77.

Glass type. The other variable used to describe the characteristics of glazing in the parametric project is the type of glazing, which covers six options: clear, absorptive, reflective, absorptive-reflective, low emissivity and spectrally selective. It is a design variable quite more difficult to translate to an input factor, because is strongly associated to two parameters: SHGC and visible transmittance. In this case an approximate parameter was used to describe simultaneously both characteristics. It was calculated first averaging both parameters for each glass type with one, two and three glass panes, and then averaging the corresponding values for each number of panes. The complete set of values is as follows: 0.75, 0.67, 0.56, 0.44, 0.38 and 0.17.

HVAC. The parametric tree includes three options concerning the energy-saving strategy of the HVAC system: (a) *No free cooling / No heat recovery*, (b) *Free cooling / No heat recovery*, (c) *No free cooling / Heat recovery*. The economizer model operates allowing until 100% of outdoor air when there is cooling demand and external conditions are satisfactory. The heat recovery model, furthermore, involves a heat exchange between the exhaust air and the entering outdoor air. In order to define the associated input factor, these options were quantified as 0, 1 and 2, respectively.

4.2.3. Definition of output variables

Eight output variables were included in the sensitivity analysis, covering a wide range of performance criteria, from simple energy loads to life cycle assessment indicators. These output variables are explained in Chapter 3. A short description of each output variable is included here to facilitate the understanding of this part of the research.

Heating load (kWh/m^2-y). It is the thermal load covered by the ideal heating system to maintain the required internal environmental condition during occupied periods, per floor area and per year.

Cooling load (kWh/m^2-y). It is the thermal load covered by the ideal cooling system to maintain the required internal environmental condition during occupied periods, per floor area and per year.

Lighting load (kWh/m^2-y). It is the energy load associated to the artificial lighting system used to maintain required iluminance during occupied periods, per floor area and per year. It takes into account the potential for light energy savings of the building, since the energy models include daylighting sensors.

Total load (kWh/m^2-y). It is the sum of loads associated to the heating, cooling and lighting systems described above. This output variable is intended to evaluate the effect of design variables on the overall energy efficiency of buildings.

Operational CO_2 (KgCO_2/m^2-y). Represents the CO_2 emissions associated to primary energy consumed by the heating, cooling and lighting systems over the life span of the building, in this case 30 years.

Initial cost (€/m^2). Represents the simple cost of main building constructive elements. It depends mostly on both opaque constructions and glazing options, but is also affected by the building shape and the proportion of glazing, since these geometric variables modify the area of the different surface types.

Global CO_2 (KgCO_2/m^2). It is the sum of the operational CO_2 (described above) and the embodied CO_2, which represents the CO_2 emissions associated to the production of materials and components of opaque constructions and glazing. Similar to the initial construction cost, the embodied emissions mainly depend on the type of opaque constructions and glazing but are also affected by geometric variables such as shape and glazing proportion.

Global cost (€/m^2). It is the sum of the initial cost (described above) and the operational cost, which is the present value of the energy consumed by the heating, cooling and lighting systems during the considered life span of 30 years. The values used in the calculations correspond to a relatively conservative approach, particularly with regard to the increasing of energy prices.

Note that some output variables are not affected by the all the input factors, and thus will serve to test the reliability of the sensitivity analysis algorithms. For example, the orientation does not affect the initial cost and consequently the sensitivity measure should be zero in this case.

4.2.4. Selected climate zones

The two previously described sensitivity analysis methods were performed for four of the twelve climate zones defined by the Building Technical Code in Spain [54] represented by the following cities: A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos (E1). These climate zones were selected intending to cover adequately the different climates of Spain. Figure 4.3 shows monthly profiles of cooling degree days (base 20°C) and heating degree days (base 18°C) for these cities. Also shows the mean maximum and mean minimum relative humidity (circles and short lines, respectively) with the scale on the right. These data offer a good idea about the air conditioning requirements that could be present in each climate zone.

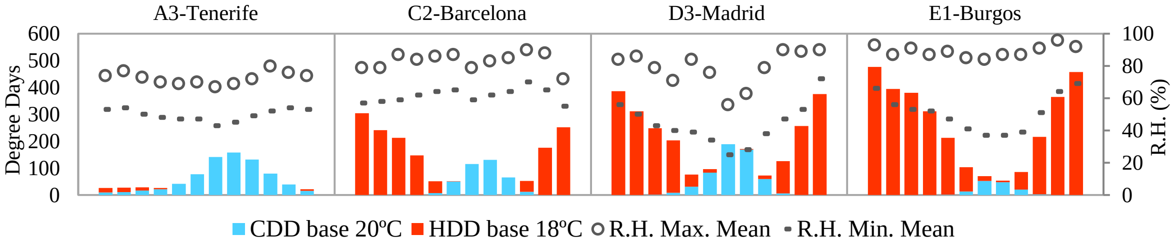

Figure 4.3. Cooling and heating degree days, as well as mean RH in the four climate zones.

4.3. Results

The results of the sensitivity analyses are shown and discussed in the next sections. First, results for Morris and Sobol methods are presented separately. After that, a section is dedicated to compare the results of both methods in terms of performance and computational cost.

Results for Morris sensitivity analysis method

The groups of graphs in Figure 4.4, Figure 4.5, Figure 4.6 and Figure 4.7 show the results of Morris method for the selected climate zones of Spain, considering the effects of the eight input factors (design variables) over the eight output variables. Each individual graph shows the indexes μ (Mu) and σ (Sigma) for the eight input factors, calculated for one output variable. As explained above, the index μ represents a measure of the influence of each input on the output. The higher the value is, the greater the contribution of the input to the variation of the output. The index σ, moreover, is a measure of the non-linear and/or interactive effects of each input. Low σ values indicate linear relationship among the input and the output, while high values indicate that the input has non-linear effects and/or has strong interaction with one or more of the other inputs. Thus, the inputs can be differentiated according to their level of influence and their level of linearity or interactivity. Note that for output variables lighting and initial cost there are some input factors which are not included in the graphs, as they have no influence at all (i.e. indices values have been correctly calculated as zero). For instance, insulation and thermal mass do not affect lighting output, and orientation does not affect initial cost.

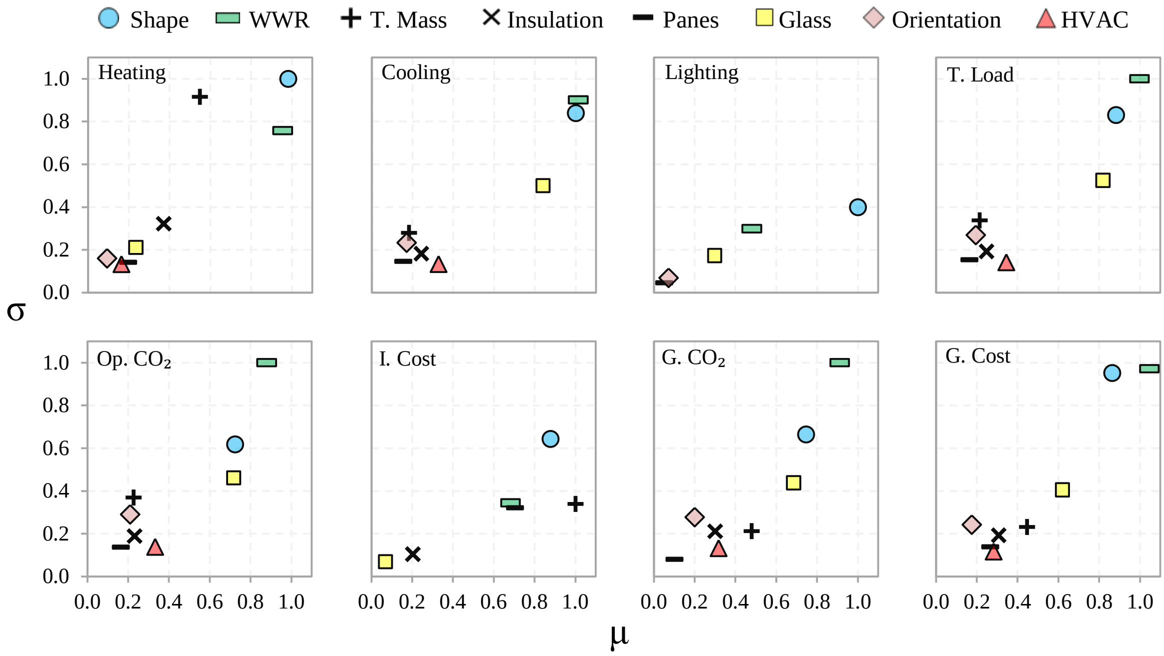

Figure 4.4. Results of Morris method for climate zone A3-Tenerife.

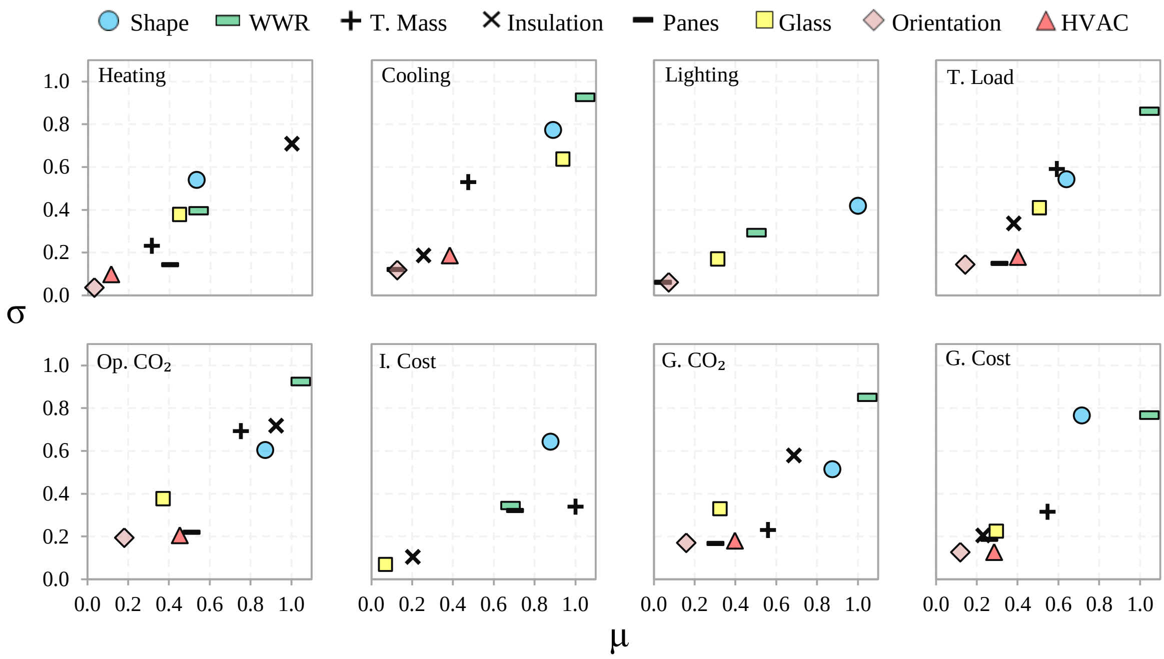

Figure 4.5. Results of Morris method for climate zone C2-Barcelona.

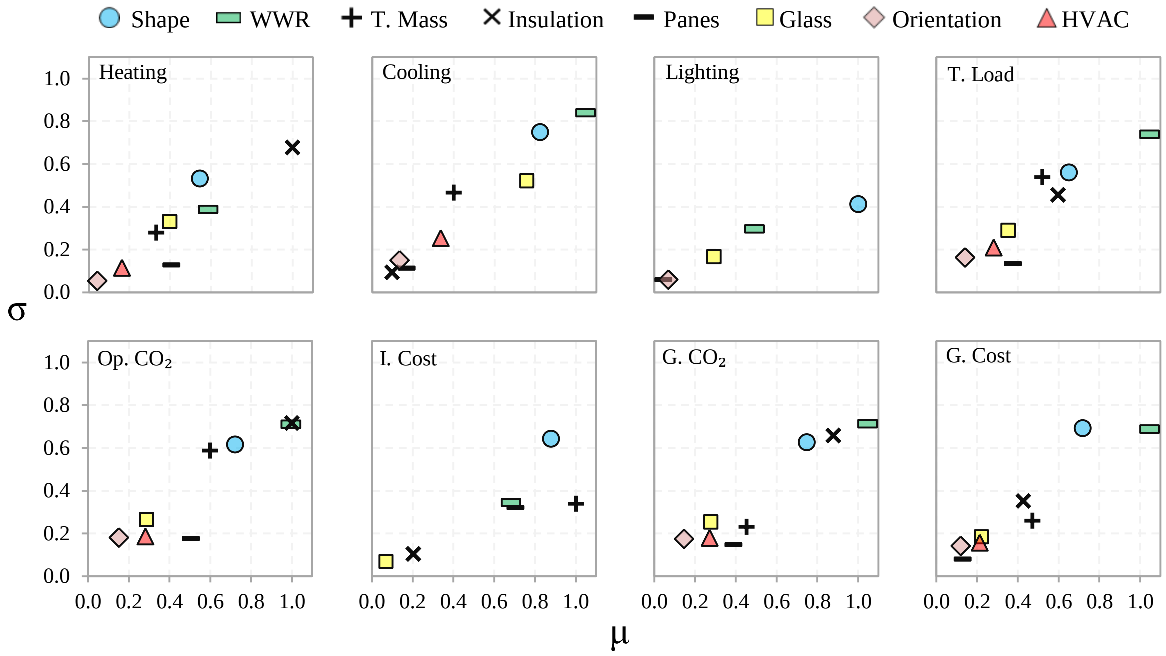

Figure 4.6. Results of Morris method for climate zone D3-Madrid.

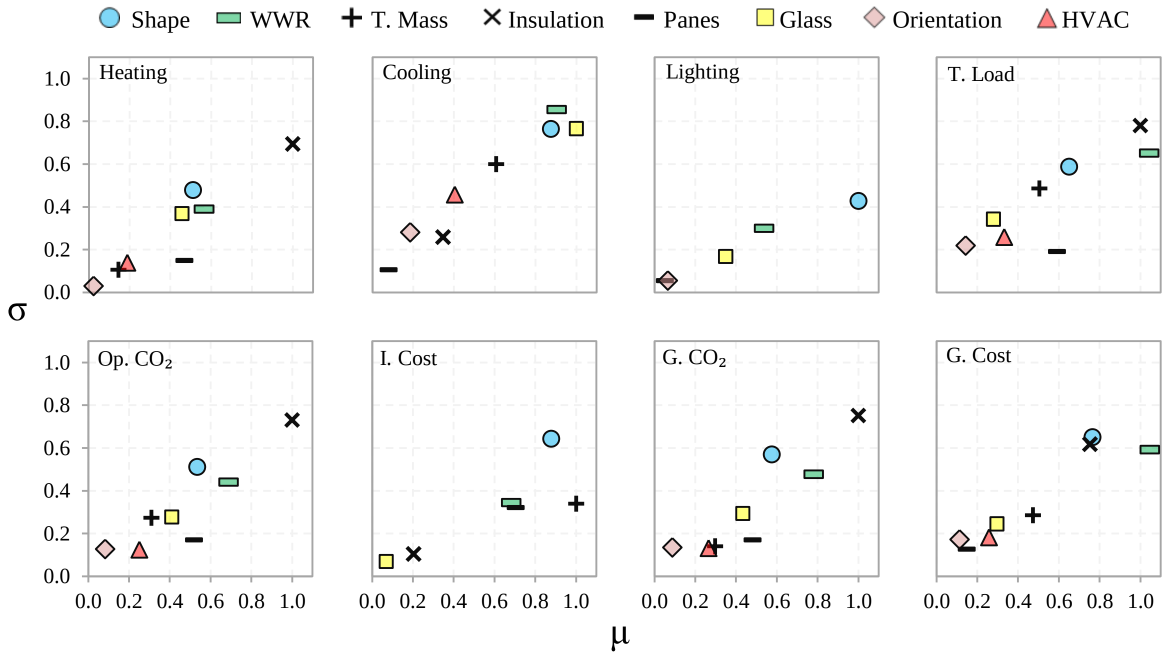

Figure 4.7. Results of Morris method for climate zone E1-Burgos.

A large amount of information can be derived from these graphs. However, the most significant findings are the following:

a) Shape has consistently medium to very high influence in all output variables and in all climate zones. Especially lighting, cooling and initial cost seem to be affected by this input. In the climate zone A3-Tenerife, where cooling loads are clearly dominant, shape has also high influence on total load and global cost. In fact, it is the climate zone where effects of shape appear to be the strongest. In the climate zone C2-Barcelona shape has also important effects on operational CO_2 and global CO_2. From 32 cases (8 output variables multiplied by 4 climate zones) shape is 6 times the most influential input factor.

b) WWR is clearly the input factor with greatest influence in the whole Morris sensitivity analysis. Excepting output variables heating, lighting and initial cost, which are affected in a relatively moderate way, all the other output variables are highly influenced by this input factor. Thus, WWR is the most influential input factor in 14 from 32 cases. Note that the influence of WWR on the lighting output variable is not as high as could be expected, in part because shape has the strongest influence in that case.

c) Thermal mass has a low to medium influence on the output variables, according to the results. The only exception is initial cost, output variable for which thermal mass seems to be the most influential input factor in all climate zones (thus being the most influential input factor in 4 from 32 cases). This is not surprising, considering that the cost of constructions increases markedly with the level of thermal mass.

d) Insulation is the input factor with greater influence on the heating output variable, with exception of the climate zone A3-Tenerife. This exception may be because heating loads are very low in that climate zone, and therefore are more likely to be altered by other factors. By contrast, in all climate zones insulation has low influence on the cooling output variable. Thus, it is expected that impact of insulation on total loads depends on the relative weight of heating and cooling loads. The results confirm that hypothesis: influence of insulation on total loads increases gradually from climate zone A3-Tenerife where heating loads have low weight, to climate E1-Burgos, where they have the greater weight. That trend is similar in results for operational CO_2, global CO_2 and in less extent for global cost, because these output variables are strongly associated to the energy loads. On the other hand, it is remarkable how insulation has been identified as not very important for the initial cost output variable. Finally, note that insulation appears as the most influential input factor in 7 from 32 cases.

e) Glass type input factor appears to have clear influence on cooling output variable in all climate zones, as well as on total load in climate zone A3-Tenerife, where cooling loads are dominant. Despite that, glass type is the most influential input factor only in one case of 32.

f) Glass panes, orientation, and HVAC input factors appear to have moderate influence on output variables. In fact, none of these factors is the most influential one in the 32 studied cases. However, the glass panes input factor has significant influence on initial cost in all climate zones. It also influences to some extent heating, total load, operational CO_2 and global CO_2, especially in climate zone E1-Burgos, which has the highest heating demands.

Beyond these observations, it is important to note that results for the lighting output variable are very similar in all climate zones. The most important factor is always shape, followed by WWR and the glass type. Also, results for initial cost are identical in all climate zones, which is logical because this variable is not affected by climate conditions in this study. In this case the input factor with greater influence is thermal mass, closely followed by shape, WWR and glass panes.

Regarding the index σ (Y-axis), which accounts for the non-linear and/or interactive effects of the input factors, the results show that it tends to increase together with the index μ (X-axis), that is, the greater the index μ, the greater the index σ. The trend is somewhat linear, although important variations can be observed in the graphs.

Results for Sobol sensitivity analysis method

Graphs in Figure 4.8 show the results of the Sobol method corresponding to the first order index, including the four selected Spanish climate zones. As previously explained, the first order index accounts for the outputs variations associated to the corresponding inputs. They can be intuitively understood, because represent the fraction of the total output variance produced by a particular input factor [121]. First order indexes are a good reference if the objective is to identify and rank energy saving measures [116].

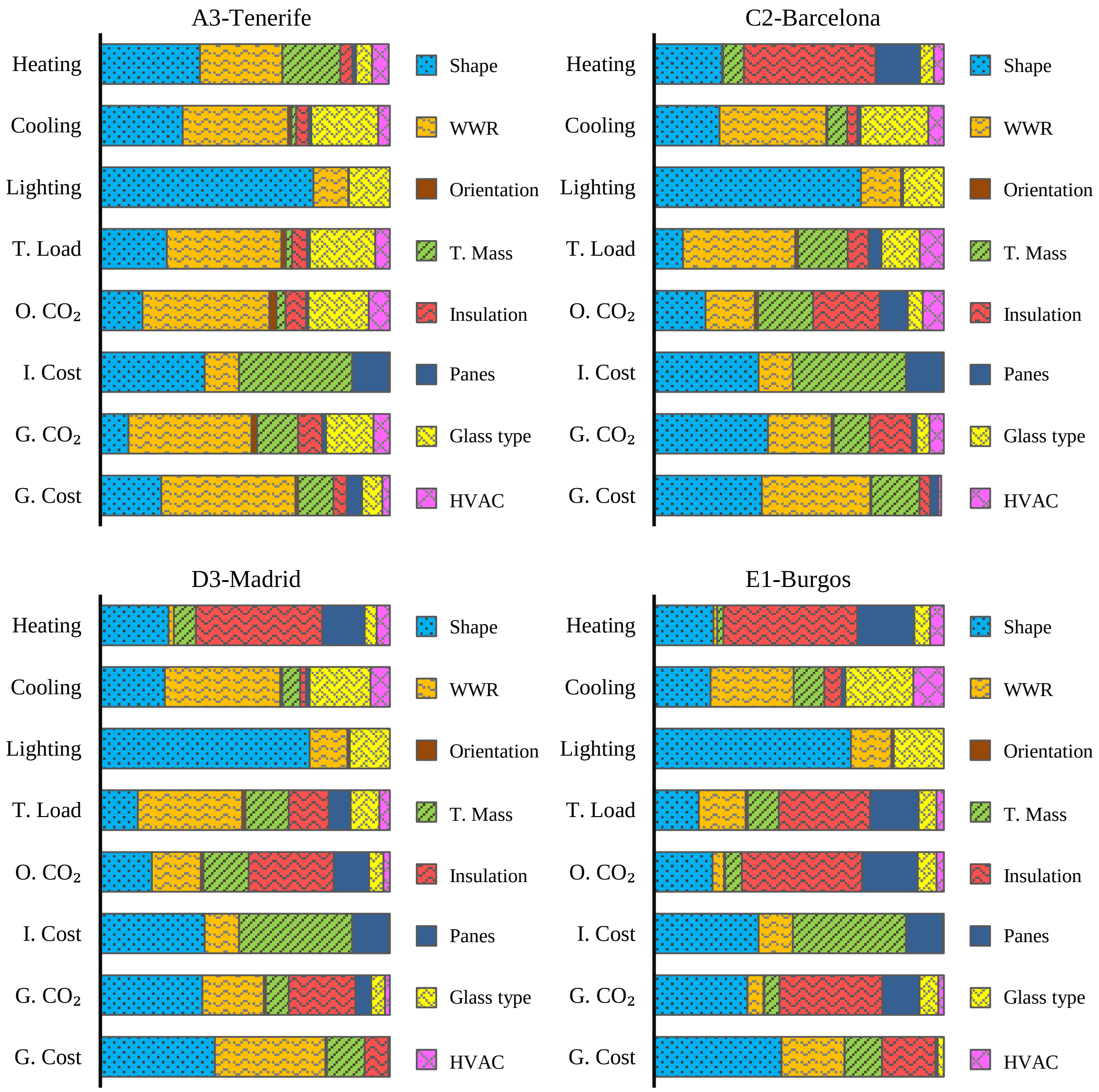

Figure 4.8. Sobol's first order sensitivity indexes for the four climate zones.

If the problem to be analyzed is fully linear, the Sobol's first order indexes should sum 1. Instead, if the model is nonlinear the sum can be less than 1, because some of the effects on the outputs are derived from interactions among input factors and cannot be captured by first order sensitivity indexes [121]. This is the case of the current sensitivity analysis: as seen in the results with Morris method explained above, there is a strong component of nonlinearity and/or interaction in the addressed problem. However, in order to keep data easily understandable, graphs in Figure 4.8 show the first order indexes values scaled in such a way that the sums are always 1, assuming that the fraction corresponding to the non-captured effects can be equally distributed among all the input factors.

Even though they are two different methods, which assess sensitivity analysis in a different way, it is expected that results of Morris and Sobol methods are reasonably similar. Thus, the results of Sobol first order indexes are analyzed taking the results of Morris indexes μ as a reference:

a) In the Sobol analysis, shape and WWR are also the most significant input factors. Coincidently, these two inputs sum 20 times being the most important factor (from 32), in both Morris and Sobol methods. However, the importance levels in this case are more balanced: shape is 9 times the most important factor (6 times with Morris method), while WWR is 11 times the most important factor (14 times with Morris method).

b) The distribution of shape importance is quite similar in climate zones C2-Barcelona, D3-Madrid and E1-Burgos, being very dominant in the lighting output variable and having noticeable weight in initial cost, global CO_2 and global cost. Shape importance has almost no change for lighting load and initial cost in climate zone A3-Tenerife, but increases for energy loads-related output variables while decreases for global CO_2 and global cost.

c) The importance of WWR is quite similar in climate zones C2-Barcelona and D3-Madrid, being more noticeable for cooling load, total load and global cost. In climate zone A3-Tenerife, where cooling loads are dominant, the importance of this input factor increases significantly, while in climate zone E1-Burgos, where heating loads are dominant, its importance decreases also significantly.

d) Sobol results allow identify thermal mass as an input factor with significant importance, although quite far from shape and WWR. As in Morris analysis, thermal mass especially affects initial cost output, being the most important input factor for this variable, independently of the climate zone (4 cases of 32).

e) According to Sobol results, insulation has also significant importance on the output variance, although it changes widely depending on the climate zone. It increases gradually from the climate zone A3-Tenerife, where cooling loads are dominant, to climate zone E1-Burgos, where heating loads are dominant. As in Morris analysis, Heating load is the output variable more clearly affected by insulation. In 8 cases of 32, insulation is the most important input factor, which brings it closer to the shape input factor.

f) One significant difference with respect to Morris analysis is that the importance of the panes input factor becomes more evident. Like insulation, as could be expected, the importance of this input increases gradually from climate zone A3-Tenerife, where cooling demands are dominant, to climate zone E1-Burgos, where heating demands are dominant. Also, its importance is more noticeable for the heating output variable, and affects consistently the initial cost.

g) Although in this analysis glass type does not appear as the most important input factor for any of the output variables, its importance seems to be even greater than the importance of the panes input factor. Similar to the Morris analysis, the climate zone where its effects are more remarkable is the A3-Tenerife. In the other three climate zones the importance of glass type input is very similar, especially influencing cooling and lighting output variables.

h) As with the Morris analysis, the importance of the HVAC input factor is moderate and quite similar in the four climate zones. In a similar way, orientation has been identified as the less important input factor.

The graphs in Figure 4.9 and Figure 4.10 offer another reading of the first order indexes obtained with the Sobol method, in this case not scaling the values to generate a sum of 1. The most important feature of these graphs, however, is that also show the weight of the total effect indexes. Similar to the first order indexes, they measure the influence of the input factors on the output variance, but including the interactions, of any order, with all the other input factors. Thus, the sum of total effect index values, for a certain input factor may be greater than 1. The red portion of the bars in the graphs represents the values of the first order indexes, while the light grey portion represents the difference between the total effect indexes and the first order indexes.

It is evident from the graphs that there is a significant component of interaction in some of the input factors. The two input factors with the greatest interaction component, by far, are shape and WWR, which also are the input factors identified as the most important in this analysis. They are followed by the input factors insulation and glass type, quite close to each other. The input factors panes and HVAC appears in the next place, with lower interaction. Finally, the two input factors with the lowest interaction component are thermal mass and orientation. Due the nature of the total effect indexes, according to the results in this analysis, it can be stated that decisions on the design variables associated especially to the input factors shape, WWR, insulation and glass type, should be taken carefully. They may not just affect the performance of the building by itself, but also modify the effect of other design variables.

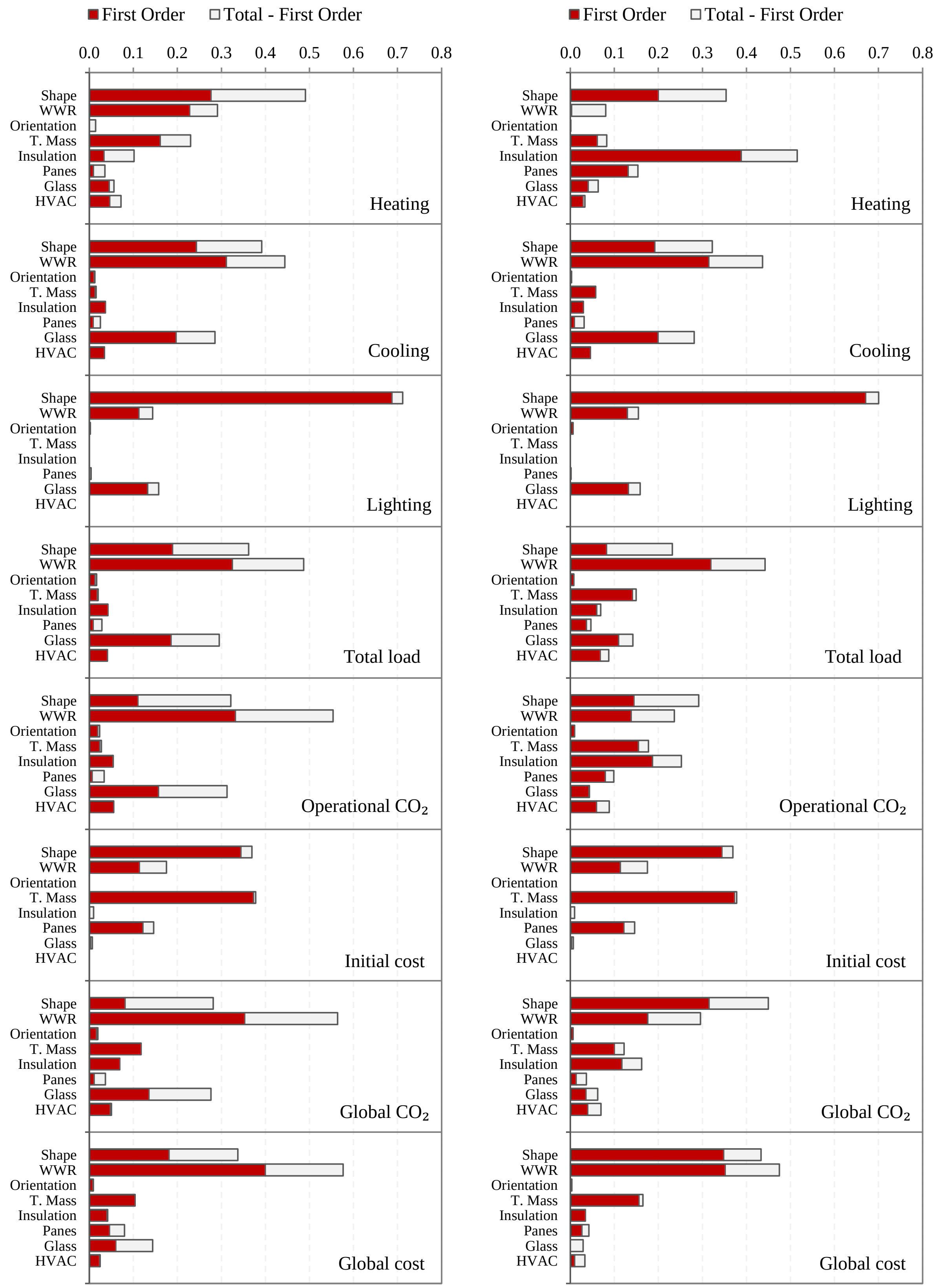

Figure 4.9. Sobol's first order indexes and difference between them and total order effects for climate zones A3-Tenerife (left) and C2-Barcelona (right).

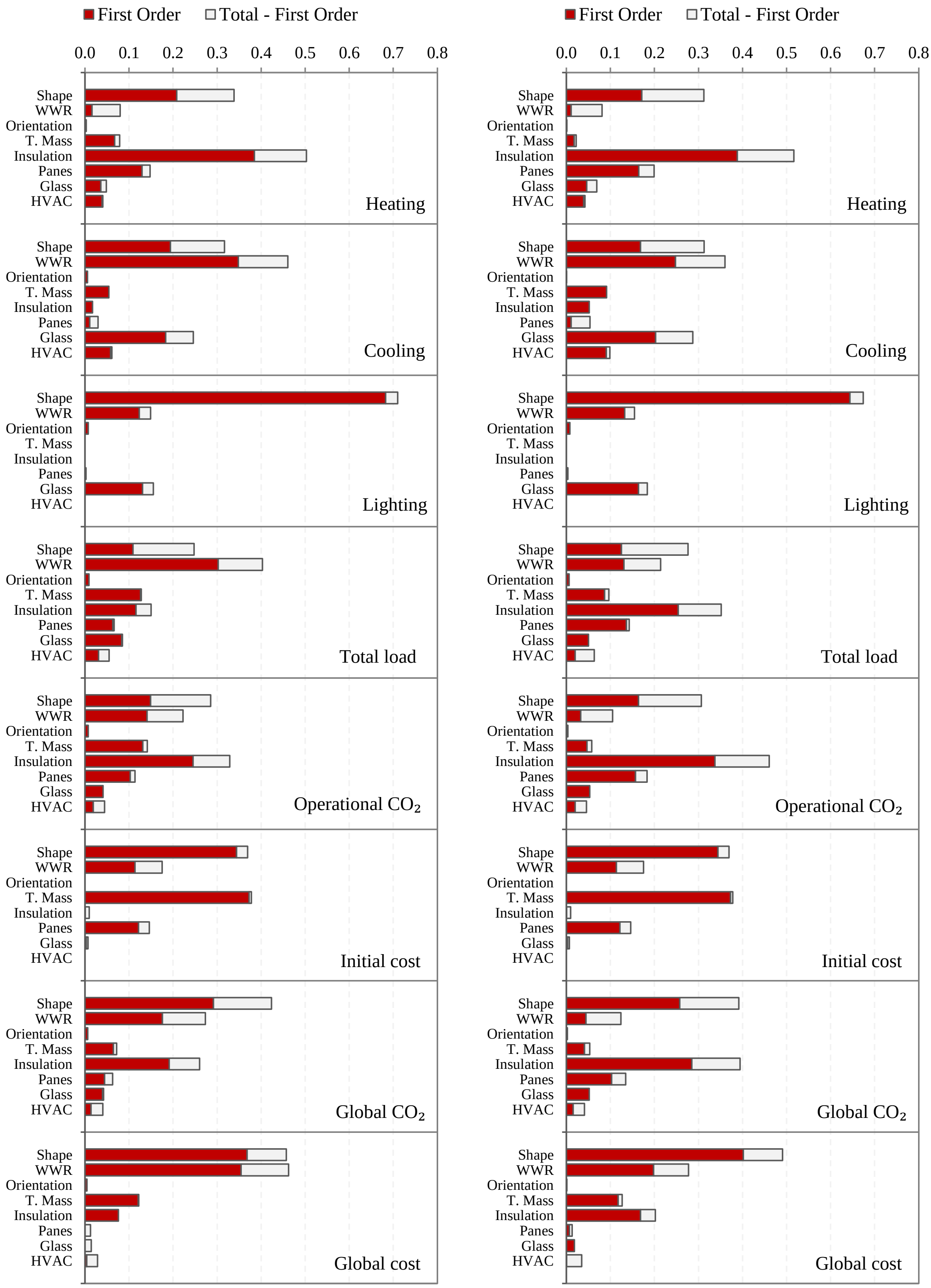

Figure 4.10. Sobol's first order indexes and difference between them and total order effects for climate zones D3-Madrid (left) and E1-Burgos (right).

Comparison of applied sensitivity analysis methods

One important question arising in this study is how the applied sensitivity analysis methods compare to each other, especially in terms of performance. By definition, and according to the findings of other researchers [103] [123] [128], the Sobol method is the most consistent and reliable, but also the most expensive in terms of computational resources. For the first statement, a general review of the results in this research reveals that results from the Sobol method seem to be more reasonable and adjusted to reality. As an example, the Morris method appears to exaggerate the effect and importance of WWR on building performance, while the Sobol method also identifies it as an important input factor, but in a more equilibrated way with respect to the other inputs. Similarly, the Panes input factor importance calculated by the Sobol method, though not high, seems to be more in line with what can be expected than the importance calculated by the Morris method.

Beyond these general interpretations, it is interesting to contrast more consistently the results and performance of both sensitivity analysis methods. Directly comparing the indexes calculated by each method is difficult, and somewhat irrelevant, as they are different measures of sensitivity in both conceptual and methodologic terms. However, considering that both methods measure the influence that input factors have on the output variables, there is at least one indicator in which they should ideally coincide: the ranking of the input factors according to their importance and impact level. In this line, the graphs in Figure 4.11 allow comparing the rankings of the input factors, estimated with basis on the results of Morris and Sobol methods, for the eight output variables in the four climate zones. The rank number indicates the position of the input factor, being 1 the most important (with higher impact). The intensity of color in each cell helps to easily identify and compare the rank position of the input factor.

A3-Tenerife

	Heat		Cool		Light		T. L.		OCO_2		I. C.		GCO_2		G. C.	
	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol
Shape	1	1	1	2	1	1	2	2	2	3	2	2	2	4	2	2
WWR	2	2	2	1	2	3	1	1	1	1	4	4	1	1	1	1
Orient.	8	8	7	7	4	4	7	7	7	7	7	7	7	7	8	8
Mass	3	3	6	6	6	6	6	6	6	6	1	1	4	3	4	3
Insul.	4	6	5	4	6	6	5	4	5	5	5	6	6	5	5	6
Panes	6	7	8	8	5	5	8	8	8	8	3	3	8	8	7	5
Glass	5	5	3	3	3	2	3	3	3	2	6	5	3	2	3	4
HVAC	7	4	4	5	6	6	4	5	4	4	7	7	5	6	6	7

C2-Barcelona

	Heat		Cool		Light		T. L.		OCO_2		I. C.		GCO_2		G. C.	
	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol
Shape	2	2	3	3	1	1	2	4	3	3	2	2	2	1	2	2
WWR	3	7	1	1	2	3	1	1	1	4	4	4	1	2	1	1
Orient.	8	8	7	8	4	4	8	8	8	8	7	7	8	8	8	7
Mass	6	4	4	4	6	6	3	2	4	2	1	1	4	4	3	3
Insul.	1	1	6	6	6	6	6	6	2	1	5	6	3	3	7	4
Panes	5	3	8	7	5	5	7	7	5	5	3	3	7	7	6	5
Glass	4	5	2	2	3	2	4	3	7	7	6	5	6	6	4	8
HVAC	7	6	5	5	6	6	5	5	6	6	7	7	5	5	5	6

D3-Madrid

	Heat		Cool		Light		T. L.		OCO_2		I. C.		GCO_2		G. C.	
	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol
Shape	2	2	2	2	1	1	2	4	3	2	2	2	3	1	2	1
WWR	3	7	1	1	2	3	1	1	2	3	4	4	1	3	1	2
Orient.	8	8	7	8	4	4	8	8	8	8	7	7	8	8	8	5
Mass	6	4	4	5	6	6	4	2	4	4	1	1	4	4	3	3
Insul.	1	1	8	6	6	6	3	3	1	1	5	6	2	2	4	4
Panes	4	3	6	7	5	5	5	6	5	5	3	3	5	5	7	7
Glass	5	6	3	3	3	2	6	5	6	6	6	5	6	6	5	8
HVAC	7	5	5	4	6	6	7	7	7	7	7	7	7	7	6	6

E1-Burgos

	Heat		Cool		Light		T. L.		OCO_2		I. C.		GCO_2		G. C.	
	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol	Morris	Sobol
Shape	3	2	2	3	1	1	3	4	3	2	2	2	3	2	2	1
WWR	2	7	3	1	2	3	2	3	2	6	4	4	2	5	1	2
Orient.	8	8	7	8	4	4	8	8	8	8	7	7	8	8	8	7
Mass	7	6	4	4	6	6	5	5	6	5	1	1	6	6	4	4
Insul.	1	1	6	6	6	6	1	1	1	1	5	6	1	1	3	3
Panes	4	3	8	7	5	5	4	2	4	3	3	3	4	3	7	6
Glass	5	4	1	2	3	2	7	6	5	4	6	5	5	4	5	5
HVAC	6	5	5	5	6	6	6	7	7	7	7	7	7	7	6	8

Figure 4.11. Comparison of input factors rankings for the 8 output variables and the 4 climate zones.

A quick glance of the graphs indicates that there are many coincidences but also some differences. More specifically, considering that there are 256 comparison cases (or pairs of values) resulting from multiplying 8 input factors by 8 output variables and by 4 climate zones, and that there are 141 cases in which the rank position is the same, it is possible to state that there is a 55% of full coincidence. However, in the great majority of the non-coincident cases the difference is only one point, for example a rank position of 1 for one method and 2 for the other. There are just 25 cases in which the difference is greater than 1, and thus it can be stated that there is only a 10% of high disagreement.

These differences are obviously a consequence of the method itself, but could be influenced by the nature and complexity of the problem. Nguyen and Reiter [103] also argue that discrete input factors (as the ones used in this research), often cause non-monotonic simulation outputs and introduce noise into the problem, perhaps increasing the disagreement among sensitivity analysis methods.

Despite the highlighted differences between the two sensitivity analysis methods, it is remarkable that if all the output variables and climate zones are considered, both of them identify shape and WWR as the most influential input factors, followed by insulation and thermal mass, in the second place, and glass type and panes in the third place. Also, they coincide in defining HVAC saving option and orientation as the least influential input factors. This information could be useful as guideline to identify which design variables should have preference when trying to improve the performance of office buildings.

Regarding the computational resources required to implement the sensitivity analyses, the difference among Morris and Sobol methods is remarkable. For each climate zone, the application of Morris method required the simulation of 90 building samples, which took about 19 minutes. On the other hand, the Sobol method required the simulation of 2304 building samples, which needed about 8 hours to be completed. It is more than 25 times the time required by the Morris method. The computer used to run the simulation had a processor Core i7 3710QM 2.30GHz (just 4 cores were used for simulations).

These results coincide with the ones obtained by other researchers, in that Sobol method offers a powerful approach to estimate in a detailed and quantitative way the impact of several input factors (or design variables). Although it has a great drawback, i.e. a high computational cost (25 times the one of the Morris method), it is advisable to use this method or a similar one whenever possible. In the field of building energy simulation, one strategy that can significantly reduce this computational cost is the use of surrogated models. On the other hand, the Morris method offered good qualitative information about the sensitivity of the different input factors, with a surprisingly low computational cost (at least compared to the Sobol method). It is a good option for models with many design variables and/or when computational cost is a concern. It is also suitable to explore sensitivity in the first stages of an analysis, perhaps to discard inputs that are not significant (not the case in this study) or to explore sensitivity under multiple scenarios.

4.4. Conclusions

In this research, it was studied the sensitivity of 8 design variables (or input factors) on 8 output variables and 4 representative Spanish climate zones. Sensitivity is understood here as the importance or level of influence that the input factors have on the variances of the outputs, thus offering guidelines to take architectural design decisions. Indeed, the sensitivity analysis tries to help answering the question: which design variables should designers focus on, in order to improve the energy and environmental performance of office buildings? Obviously, the applicability of the results has limits, derived from the scope of the predefined search space, although this approach can be extended to cover wider scopes.

Two main methods were used to calculate the sensitivity indicators, Morris and Sobol. The purpose of using these two methods, selected from the review of the sensitivity analysis-related literature, was to better validate the results, but also to compare and evaluate its usefulness for future studies. Relating the performance of the methods, the next conclusions can be pointed out:

a) The Morris method offered what seems to be the best cost-benefit relation. It provided good qualitative data about the sensitivity of the input factors with low computational cost. This method appears to be a suitable approach when there are many design variables or computational cost is a concern. Among other tasks, it can be used to explore sensitivity in early research phases and/or to discard inputs that are not significant.

b) The Sobol method showed great capability to estimate in a detailed and quantitative way the impact of the input factors. Its high computational cost represents an important disadvantage, but it is advisable to use this method whenever possible. In the field of building energy simulation, it is also advisable to explore the use of surrogate models in order to reduce the computational cost of the Sobol method.

The results of the sensitivity analyses performed in this research identified the level of influence that the addressed input factors have on each output variable, depending on the climate zone. A lot of useful information can be extracted from these results. As a summary, the next points can be highlighted:

a) Although there are some logical differences among the sensitivity analysis methods, if the whole search space of the computational experiments is taken into account, they coincide on identifying shape and WWR as the most influential input factors, followed by insulation and thermal mass, in the second place, and glass type and panes in the third place. Also, they coincide in defining HVAC and orientation as the less influential input factors in the context of this research.

b) A more detailed review of the results indicates that, as expected, the importance of the factors changes widely depending on the output variable and the climate zone. For example, the effect of the insulation and panes input factors is higher on heating load-related outputs and in cold climates, while glass type input has higher influence on cooling load-related outputs and in warm climates. Hence, it is not possible to rank the input factors in a scale of importance that is suitable for any output variable and climate zone. Instead, the effect of input factors should be evaluated specifically for the climate zone and according to the performance objectives, for example to reduce the energy loads, the initial cost and operational CO_2 or the global cost and global CO_2.

The results of sensitivity analysis can be very useful as a guide to identify which design variables may be convenient to focus on, in order to improve the performance of office buildings. Sensitivity can be interpreted as a design warning, but also as an opportunity area for improved designs. However, it is important to consider the inherent limitations of sensitivity analysis methods. One is that they are not intended, and thus are not capable, of identifying the optimal design solutions, for example the most adequate insulation level. In that sense, it is important to complement them with other type of analyses. Also, note that even if an input factor is identified as unimportant (for example orientation in this study), it does not necessary mean that it is appropriate to discard it completely. Depending on other design decisions, that particular input can still play an important role in some circumstances.

In the future, it is recommendable to extend the sensitivity analysis of architectural design variables to other building types and climate zones. In addition, a wider range of solutions, at least for some design variables such as shape, and the incorporation of other design variables, such as shading devices, would be desirable. This could help to create better guidance and tools to assist architects and designers in the task of creating more sustainable buildings.

Chapter 5. Meta-models based on ANNs

In the field of building energy analysis, the artificial neural networks (ANN's) have shown great potential to replace the simulation processes, which often represent high time and computational costs. This chapter addresses the implementation of ANN's for developing meta-models aimed to predict the energy and environmental performance of office building, depending on their architectural characteristics and considering different climate zones. Furthermore, the ANN's are assumed in this research as a resource to validate the suitability of some parameters selected to describe the architectural design variables. If the ANN's are capable of predicting energy and environmental outputs with reasonable precision, then the parameters used as inputs for their generation are a good reference. The ANN models were tested internally, as well as by implementing them in sensitivity analysis. The results indicate that, effectively, (a) the parameters chosen for describing the main architectural design variables are adequate for the creation of ANN meta-models, and (b) the developed ANN's meta-model have good accuracy and can be used with relative reliability as surrogate models for building energy and environmental analysis.

5.1. Introduction

The increasing need to reduce the energy and environmental impact of buildings [5] has led to explore different approaches to understand and predict their performance. Because experimenting with real life buildings is extremely costly and complex, energy simulation has become a widely used method to accomplish that task. Especially the so-called whole-building simulation tools, such as EnergyPlus, DOE-2, TRNSYS and IDA ICE [36], are considered a high standard to accurately evaluate the energy and environmental performance of buildings. However, the use of this type of tools usually implies a high cost in terms of knowledge, time and computational resources. In order to surpass these problems, many researchers have explored alternative methods to develop accurate models to forecast and predict the energy performance of buildings. Some of these approaches are based on Artificial Neural Networks.

ANNs are data processing systems aimed to learn the relationship among input and output variables, by interpreting previously measured or calculated data [131] Unlike other predicting techniques, they are non-algorithmic, non-digital and strongly parallel. ANNs replicate the biological neural systems. They are composed by layers of parallel elemental entities, i.e. the neurons, which in turn are connected by weighted links that drive the passing of signals or information. In general, a neuron receives inputs on its incoming connections and generates a result after combining the outputs and performing a non-linear operation. Thus, in order to be generated, the ANN has to be fed with information from the real system, through a process called training.

There have been multiple studies comparing the performance of neural networks with respect to other methods used to develop forecasting and prediction models, especially the multiple linear regressions (MLR). Most of them have found the neural networks to be more precise and capable of address very complex problems. For example, Brey et al. [132] compared the prediction of the somatic production/biomass ratio of animal populations by MLR and ANN. They concluded that the accuracy of both approaches was low at the population level, although both could be used to predict production and productivity of larger population groups. They also found that the ANN offered a performance about 6% better than the MLR. In other study, Lefèvre et al. [133] compared two methods of interpolation, in space and time, of the partial pressure of surface carbon dioxide (pCO_2) in the Atlantic sub-polar gyre. One approach was based on multiple linear regressions, while the other was based on self-organizing neural network. They concluded that the neural network was able to capture a more complex distribution. In addition, when both techniques were used with subsets of the data the neural network predicted the remains of the data to a much higher accuracy than the regressions. Also, Bakar and Tahir [134] developed a study aimed to predict bank financial performance using both multiple linear regressions and feed forward artificial neural network. The accuracy of both techniques was measured by the mean square prediction error (MSPR) at the validation stage. The MSPR value was lower for the neural network, and the authors conclude that it is the most powerful approach in predicting bank financial performance. Although none of these studies is directly related to the field of building energy analysis, they confirm the effectiveness of neural networks as a tool to develop predictive models.

In the field of building energy analysis, ANN's have been used frequently as a resource to enhance the application of other methods, such as the computational optimization. Here some examples:

- Magnier and Haghighat [99] developed a simulation-based, feed-forward, Artificial Neural Network to characterize the behavior of a residential building, in order to combine it with a multiobjective optimization algorithm (NSGA-II). The comparison among simulated outputs and the corresponding ones predicted by the ANN was pretty good, with regression coefficients very close to 1 and a maximum relative error near to 5%. The ANN model helped to reduce substantially the optimization running times.

- Wang et al. [105] implemented a back propagation neural network, which was coupled with a multi-objective genetic algorithm (also NSGA-II) for the aerodynamic optimization of turbomachinery. In order to minimize the effect of prediction error of the ANN they proposed a modified crowding distance in cooperation with a “coarse-to-fine” approaching strategy. In their testing experiments, the Pareto front was found with reasonable accuracy and acceptable computational cost.
- Zemella et al. [135] coupled an evolutionary optimization algorithm with a neural network to implement what they describe as Evolutionary Neural Network Design. The method was used to support the design of a typical façade module of an office building, developing both single and multi-objective optimizations. They state that the method allows adopting a holistic approach, which takes into account, simultaneously, all the aspects influencing the performance of the façade. The method also required reasonable computational time.
- Gossard et al. [100] implemented an artificial neural network that, coupled to the genetic algorithm NSGA-II, was used to optimize the thermophysical properties of the envelope of a dwelling. They considered two optimization objectives: the annual energy consumption and the summer comfort level. The ANN was developed from sampling datasets generated by mean of building energy simulations. According to the authors, the ANN provided fast and accurate evaluations of the objective functions used by the genetic algorithm.
- Asadi et al. [131] developed an ANN derived from energy simulations of a school building, in order to develop a faster and more efficient optimization process by mean of genetic algorithms. According to the authors, the ANN was capable of approximate the simulation results in a very accurate way. It also reduced drastically the computational time.
- Yu et al. [136] used a simulation-based back-propagation neural network model for the fast prediction of energy consumptions and indoor thermal comfort in residential buildings. Then coupled the ANN to the multi-objective genetic algorithm NSGA-II to explore optimal solutions with a wide range of trade-offs between thermal comfort and energy consumptions. It was observed that the relative errors between the ANN model and the energy simulations was small, and thus can be used with confidence in building design optimization.

Beyond their usefulness to develop predictive and surrogate models that streamline other analysis techniques, such as design of experiments, optimization and sensitivity analysis, ANN’s can also be used to evaluate the relevance of the parameters utilized to define the system itself. The hypothesis is that if the ANN model can accurately represent the energy, environmental and economic performance of buildings, then the employed input parameters are likely a good reference. In other words, if the input parameters are not enough (i.e. there are some missing parameters which are important), or they are not relevant, it is not possible to develop consistent models even with the most powerful ANN approach.

In this study the previous point is quite important, because allows assessing whether the parameters that are commonly used to guide the design process or to regulate the characteristics of buildings in energy codes are really relevant. For instance, two parameters commonly used to describe the geometric characteristics of buildings are the form factor (or its inverse, the compactness) and the aspect ratio. The important question here is whether these parameters are good enough to describe a wide range of geometric configurations. Another example is the description of the thermal properties of constructions. In that case, the parameter most employed in design guidelines and normative instruments is the insulation level, i.e. the thermal resistance (or its inverse the thermal transmittance). Again, the question is whether such parameter is enough to describe, and therefore to predict, the thermal and environmental performance of buildings, or if it is necessary to include other parameters such as the thermal mass level.

5.1.1. Objectives and scope of this study

This study addresses the development of a set of artificial neural networks, based on simulations from the parametric project explained in Chapter 2. These ANNs are aimed to provide meta-models capable of predict the energy, environmental and economic performance of office buildings, within a certain range of possible solutions. Four Spanish climate zones are considered: A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos. Consequently, four independent neural networks are implemented, one per each climate zone.

The main objective of the study is to validate a number of input parameters, in terms of their capability to represent the main architectural characteristics of office buildings. It is assumed that, if the ANNs can predict buildings performance with sufficient precision, then the input parameters are meaningful and representative. Such parameters can be useful for the development of guidelines that help designers to take decisions through the design process. Additionally, these parameters can be used as reference for establishing normative criteria in the field of energy codes and sustainability certifications.

Besides the accomplishment of the previous objective, the meta-models generated by means of the neural networks can be used to extend and enrich other type of analyses, such as design of experiments, optimization, and sensitivity analysis.

5.2. Methodology

The ANNs in this study are based on the multilayer perceptron, which is a fundamental model of the neural networks [137]. The learning task adopted for the multilayer perceptron was the function regression. It can be regarded as the problem of approximating a function from a data set of inputs and targets. The targets represent what the output, generated from the inputs by the neural network, should be. From the perspective of functional analysis and variation calculus, a multilayer perceptron is explained by four concepts: a neuron model (the perceptron), a network architecture (in this case the feed-forward), and the corresponding objective functional and training algorithm [138]. The settings assumed for the development of the ANNs are explained below.

The development of the neural networks involved the usage of three main programs: Neural Designer, EnergyPlus and jEPlus. Neural Designer is a program aimed to the implementation of deep learning techniques to discover relationships, recognize complex patterns and predict actual trends from large-scale datasets [139]. This software focuses on helping to develop artificial neural networks in an efficient and fast way. EnergyPlus is a widely recognized program used for the iterative and dynamic modeling of the most significant thermal and energy flows taking place on buildings and its mechanical systems [39]. jEPlus is an application mainly focused on parametric simulations within programs such as EnergyPlus and TRNSYS [40]. EnergyPlus and jEPlus were used together to generate the datasets required by Neural Designer to develop the neural networks.

5.2.1. Datasets for the ANN's

The datasets represent the source of information required by the ANN to solve the regression problems. They are made of inputs, i.e. the design parameters values, and their related outputs, i.e. the target values. The datasets were generated from the simulation of design solutions samples by mean of the parametric project. The samples were defined with the Latin Hypercube stratified sampling method, which offers a better coverage of the problem space and ensures that parameters have all portions of their distribution represented by input values [126].

Different sample sizes were tested, as it was observed that this factor has an important role in the quality of the ANN models. In general, more parameters require bigger samples. In their research, Magnier et al. [99] had to simulate a number of cases equal to 22.5 times the number of variables. In this study, however, it was decided to use a fairly larger number of simulation cases in order to achieve the best results. Thus, samples of 3,000 design solutions were used to develop the final ANN models (187.5 times the number of variables). These samples were randomly divided into three groups, corresponding to the training, generalization and testing instances. The portion of the sample assigned to each instance was 60%, 20% and 20%, respectively. Consequently, the 3000 instances were divided into 1800 training instances, 600 generalization instances and 600 testing instances.

The parametric project and the input parameters

The parametric simulations project that was used for the generation of the datasets was built around the programs EnergyPlus and jEPlus. That project is described in detail in Chapter **2**, though a brief description is included here to facilitate the understanding of the current chapter. Note that some minor adjustments were made to the parametric project, in order to adjust it to the objectives of this part of the research.

The general structure of the parametric project is illustrated in the schematic tree of Figure 5.1. It consists of 10 variables, which together comprise 70 options: 16 building shapes, 8 window to wall ratios, 18 orientations, 5 thermal mass levels, 5 insulation levels, 3 glass pane numbers, 6 glass types, 3 infiltration levels, 3 usage intensity levels and 3 HVAC saving strategy options. Each unique path in the parametric tree, considering from top to bottom, represents a different design solution (or case). The total amount of possible solutions is 27,993,600, which represents the global space for the development of the ANN's. It is important to note that the parametric project consists mainly of design variables on which designers have great control. That is the case of shape, WWR, orientation, composition of constructins and glazing, and even the HVAC saving option. However the infiltration level, and especially the internal gains level have been included because they could offer important information about buildings performance. For instance, the ANN's including these variables could be used to investigate how the usage intensity can modify the impact of the design variables.

The development of the neural networks implies in the first place to translate the design variables and options, from the parametric project, to numerical parameters. This task has some difficulties, because the simulation models are described by multiple interrelated parameters. For example, each construction object is described as a set of material layers, each material being described by physical parameters that determine its thermal behavior, for instance conductivity, density and specific heat. Similarly, building shapes are described by a number of coordinates that define the size, form and location of their surfaces. It would be very impractical to use these parameters as the basis for a neural network. Instead, it is desirable to select a small number of parameters, which are relatively easy to understand and calculate and can adequately represent the characteristics of buildings. In this sense, the ANN's are not only surrogate models of the original systems, but also tools for validating the relevance of the input parameters.

In this study, 16 input parameters were selected to develop the ANN's, as in preliminary tests they shown the best overall results, that is, the most accurate neural networks. These parameters, summarized in Table 5.1, can be calculated from the design variables and options included in the parametric project. Note that some parameters have to be grouped by design option. For instance, a particular building shape is represented by four parameters: *ExtSurf/Vol*, *Wall/Vol*, *Roof/Vol* and *Wall/ExtSurf*. Similarly, a particular glazing option is represented by three parameters: *U-factor*, *SHGC* and *Visible transmittance*.

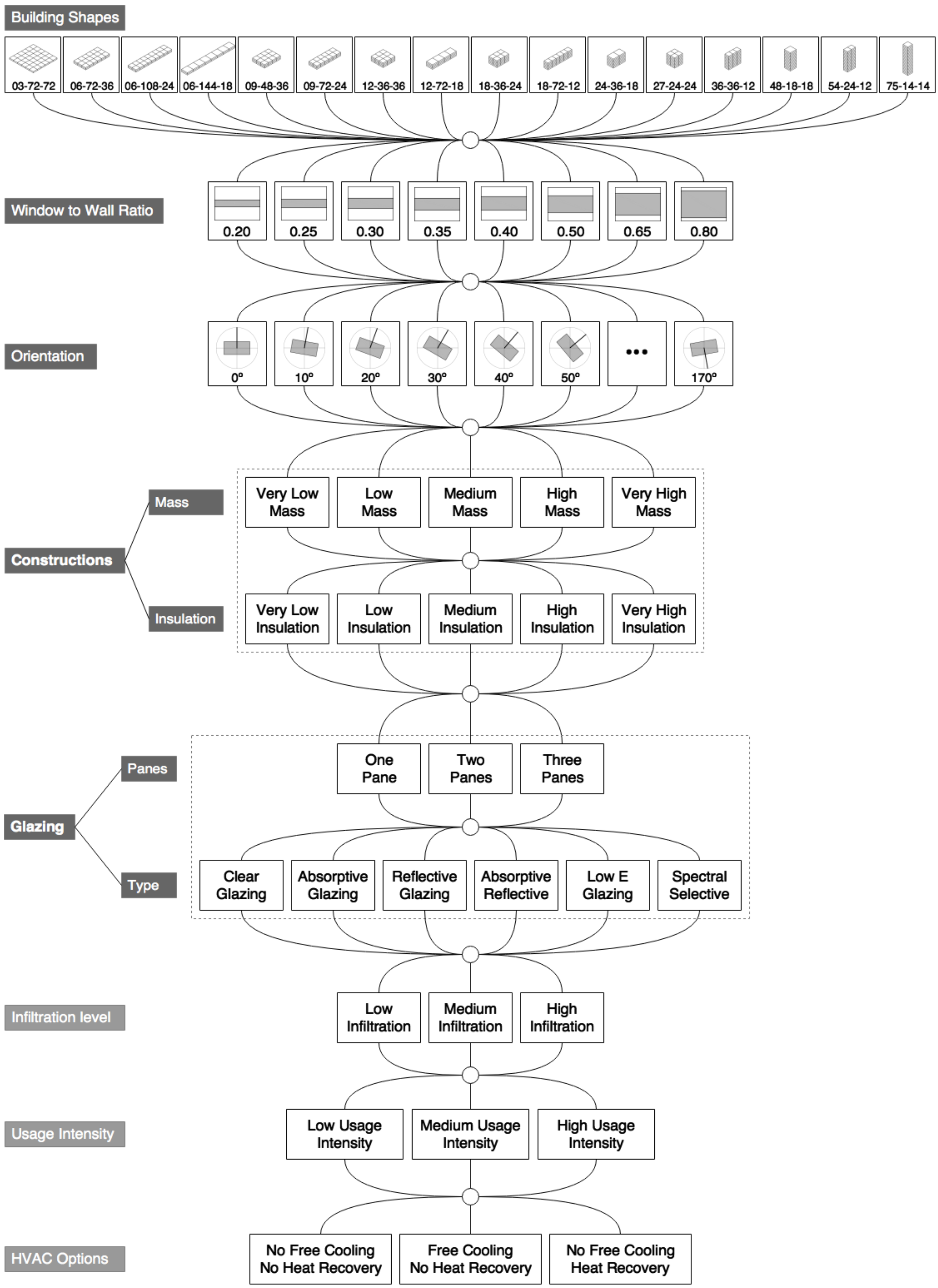

Figure 5.1. Schematic tree of the parametric project used to generate the datasets for the ANN's.

Table 5.1. Input parameters used for developing the ANN's.

Parameter		Description	Units	No. of Values
1	ExtSurf/Vol	External surface divided by Volume	Fraction	16
2	Wall/Vol	Wall surface divided by Volume	Fraction	16
3	Roof/Vol	Roof surface divided by Volume	Fraction	16
4	Wall/ExtSurf	Wall surface divided by External surface	Fraction	16
5	Glaz/ExtSurf	Glazing surface divided by External surface	Fraction	128
6	Glaz/Vol	Glazing surface divided by Volume	Fraction	128
7	WWR	Window to Wall Ratio	Fraction	8
8	Orient	Orientation angle relative to North	Degree	18
9	TMP	Constructions global heat capacity	$kJ/m^2 \cdot K$	5
10	R-Value	Constructions global thermal resistance	$m^2 \cdot K/W$	5
11	U-Factor	Glazing thermal transmittance	$W/m^2 \cdot K$	18
12	SHGC	Glazing solar heat gain coefficient	Fraction	18
13	Vis	Glazing visible light transmittance	Fraction	18
14	IntGains	Internal gains level	N/A	3
15	HVAC	HVAC saving options	N/A	3
16	Infilt	External air infiltration level	N/A	3

Building Shape

The parametric project includes 16 modular shapes, for a hypothetic office building with a useful floor area of 5,184 m^2 and an internal volume of 15,552 m^3. The name of each building shape derives from its height, length and width dimensions (in meters). These shapes can be described by a number of geometric parameters, but in this study, based on preliminary tests, four parameters were identified as the most adequate as inputs for the ANN's. The parameters and their corresponding values are shown in Table 5.2.

Table 5.2. Parameters describing the building shapes.

Shape >	03-72-72	06-72-36	06-108-24	06-144-18	09-48-36	09-72-24	12-36-36	12-72-18	18-36-24	18-72-12	24-36-18	27-24-24	36-36-12	48-18-18	54-24-12	75-14-14
ExtSurf/Vol	0.72	0.42	0.44	0.46	0.32	0.33	0.28	0.31	0.25	0.31	0.25	0.24	0.28	0.26	0.29	0.30
Wall/Vol	0.06	0.08	0.10	0.13	0.10	0.11	0.11	0.14	0.14	0.19	0.17	0.17	0.22	0.22	0.25	0.28
Roof/Vol	0.33	0.17	0.17	0.17	0.11	0.11	0.08	0.08	0.06	0.06	0.04	0.04	0.03	0.02	0.02	0.01
Wall/ExtSurf	0.08	0.20	0.23	0.27	0.30	0.33	0.40	0.45	0.56	0.64	0.67	0.69	0.80	0.84	0.87	0.91

Glazing area

The amount of glazing is defined in the parametric project by mean of the WWR, which is a constant value. However, the net area of glazing in a specific building depends not only on the WWR, but also on the surface area of external walls. In order to properly reflect this condition, three parameters have been selected to account for the amount of glazing in the ANN's:

- The WWR, that is, the same value directly specified in the parametric project.
- The glazing surface divided by the external surface. This parameter derives from both the WWR and the shape. Thus, it includes 128 possible values.
- The glazing surface divided by the volume. As in the previous parameter, depends on both the WWR and the shape and includes 128 possible values.

Orientation

The orientation of the building with respect to north can be easily changed in the parametric project, and could even be described as a continuous parameter. Here, as input parameter for the ANN's, it is defined with increments of 10º, starting from 0º up to 170º. Note that, as the glazing is uniformly distributed in all the facades of the building, this range is enough to represent 36 orientation angles covering 360º.

Constructions

The parametric project includes 25 design options to define the thermal characteristics of constructions, which are produced by combining two variables, the thermal mass level (from *Very Low* to *Very High Mass*) and the insulation level (from *Very Low* to *Very High Insulation*). As an input parameter to define the ANN's, the thermal mass level is represented by the global heat capacity (kJ/m^2•K), which is calculated with basis on standards ISO 13790-2008 and ISO 13786-2007. On the other hand, the insulation level is represented by the global thermal resistance (m^2•K/W), which is calculated according to the standard ISO 6946-2007. Table 5.3 shows the combination of values that characterize the 25 options.

Table 5.3. Parameters describing the constructions.

	VLM	LM	MM	HM	VHM	
C_G (kJ/m^2·K)	62.13	129.24	223.69	299.97	373.83	**VLI**
R_G (m^2·K/W)	0.70	0.70	0.70	0.70	0.70	
C_G (kJ/m^2·K)	62.13	129.24	223.69	299.97	373.83	**LI**
R_G (m^2·K/W)	1.40	1.40	1.40	1.40	1.40	
C_G (kJ/m^2·K)	62.13	129.24	223.69	299.97	373.83	**MI**
R_G (m^2·K/W)	2.10	2.10	2.10	2.10	2.10	
C_G (kJ/m^2·K)	62.13	129.24	223.69	299.97	373.83	**HI**
R_G (m^2·K/W)	2.80	2.80	2.80	2.80	2.80	
C_G (kJ/m^2·K)	62.13	129.24	223.69	299.97	373.83	**VHI**
R_G (m^2·K/W)	3.50	3.50	3.50	3.50	3.50	

Glazing

There are 18 different design options in the parametric project to define the composition of glazing. These options are produced by combining two variables, the number of glass panes (single, double and triple) and the glass type (clear, absorptive, reflective, absorbent-reflective, low emissivity and spectrally selective). The glazing options are defined in the context of the ANN's by mean of three input parameters: the U-factor (W/m^2•K), the SHGC and the visible transmittance. Table 5.4 shows the groups of values corresponding to all the glazing options.

Table 5.4. Input parameters describing the glazing.

	Clear	Absorptive	Reflective	Abs-Ref	Low E	Spectral	
U-Factor	5.786	5.786	5.728	4.670	3.440	3.194	
SHGC	0.821	0.608	0.513	0.270	0.645	0.476	**1 Pane**
T_v	0.881	0.431	0.338	0.142	0.850	0.779	
U-Factor	2.689	2.689	2.673	2.325	1.777	1.642	
SHGC	0.705	0.483	0.432	0.190	0.574	0.426	**2 Panes**
T_v	0.781	0.381	0.310	0.128	0.753	0.689	
U-Factor	1.755	1.755	1.748	1.591	1.309	1.232	
SHGC	0.615	0.408	0.376	0.155	0.517	0.388	**3 Panes**
T_v	0.696	0.339	0.284	0.116	0.671	0.613	

Infiltration

The simulation models of the parametric project include different infiltration rates, defined as air changes per hour (ach/h). They were pre-calculated from infiltration rates per area of external surfaces, considering three infiltration levels and assuming that (1) since infiltration occurs primarily through building envelope, the higher the relative area of external surfaces, the greater the total infiltration rate, and (2) since openings often represent weak points in terms of infiltration, and most of them are located on the external walls, then walls have greater infiltration rates than roofs and external floors. This means that the final infiltration rate depends also on the building shape. However, as an input parameter for the ANN`s, the infiltration level was greatly simplified and three simple values were used: 1 (low infiltration), 2 (medium infiltration) and 3 (high infiltration).

Usage intensity

The usage intensity is represented in the parametric project by different rates of heat gains, associated to occupancy, equipment and lighting, as shown in Table 5.5. Note that these internal heat gains rates increase almost linearly. As in the case of infiltration, three simple values were used to define the internal gains level as input parameter for the ANN's: 1 (low level), 2 (medium level) and 3 (high level).

Table 5.5. Total heat gains rates related with the usage of the building.

Usage Level	Occupancy (W/m^2)	Equipment (W/m^2)	Lighting (W/m^2)	Total (W/m^2)
Low	4.6	4.9	6.1	**15.6**
Medium	9.2	9.9	12.1	**31.3**
High	13.9	14.8	18.2	**46.9**

HVAC saving options

Finally, the parametric tree includes three options regarding the energy-saving strategy of the HVAC system: (a) *No free cooling / No heat recovery*, (b) *Free cooling / No heat recovery*, (c) *No free cooling / Heat recovery*. The economizer model operates allowing until 100% of outdoor air when there is cooling demand and external conditions are satisfactory. The heat recovery model, furthermore, involves a heat exchange between the exhaust air and the entering outdoor air. As input parameters for the ANN's these options were defined as 0, 1 and 2, respectively.

2.1.2. Buildings performance and targets definition

Seven outputs were included as targets for the ANN's. They cover a wide range of building performance indicators, from simple energy loads to life cycle assessment metrics. These output variables are defined in detail in Chapter 3. A short description of each output variable is included here in order to facilitate the understanding of this research.

Heating load (kWh/m^2-y). It is the thermal load covered by the ideal heating system to maintain the required internal environmental condition during occupied periods, per floor area and per year.

Cooling load (kWh/m^2-y). It is the thermal load covered by the ideal cooling system to maintain the required internal environmental condition during occupied periods, per floor area and per year.

Lighting load (kWh/m^2-y). It is the energy load associated to the artificial lighting system used to maintain required iluminance during occupied periods, per floor area and per year. It takes into account the potential for light energy savings of the building, since the energy models include daylighting sensors.

Operational CO_2 ($KgCO_2/m^2$-y). Represents the CO_2 emissions associated to primary energy consumed by the heating, cooling and lighting systems over the life span of the building, in this case 30 years.

Initial cost (€/m^2). Represents the simple cost of main building constructive elements. It depends mostly on both opaque constructions and glazing options, but is also affected by the building shape and the proportion of glazing, since these geometric variables modify the area of the different surface types.

Global CO_2 ($KgCO_2/m^2$). It is the sum of the operational CO_2 (described above) and the embodied CO_2, which represents the carbon emissions associated to the production of materials and components of opaque constructions and glazing. Similar to the initial construction cost, the embodied emissions mainly depend on the type of opaque constructions and glazing but are also affected by geometric variables such as shape and glazing proportion.

Global cost (€/m^2). It is the sum of the initial cost (described above) and the operational cost, which is the present value of the energy consumed by the heating, cooling and lighting systems during the considered life span of 30 years. The values used in the calculations correspond to a relatively conservative approach, particularly with regard to the increasing of energy prices.

5.2.2. Configuration of the neural networks

The neural networks, in this study, are based on the feed-forward model, one of the most used in diverse research fields. It is basically composed of neurons arranged in several layers. The first layer receives, connects and scales the inputs, while the last one supplies and rescales the outputs generated by the network. Between these layers, there is one or more intermediate layers (also called hidden layers). The specific structure of the ANNs used in this research is illustrated in Figure 5.2. It is formed by a scaling layer with 16 neurons (yellow circles) corresponding to the input parameters; a two-layer perceptron with one hidden layer containing 17 neurons and one output layer containing 7 neurons (green circles); and finally an unscaling layer with 7 neurons (blue circles) corresponding to the target outputs. Both the scaling and unscaling layers use the Minimum-Maximum method. The activation of the hidden and output layers is based on the hyperbolic tangent function and the linear function, respectively.

The training strategy represents the execution of the learning process of the neural network, looking always for the best possible performance. In this case the ANN's were trained using the Quasi-Newton method as the training algorithm. It follows the Newton's method, although computes an approximation of the inverse Hessian, at each iteration, using gradient information instead of calculating second derivatives. The inverse Hessian approximation method used was the BFGS, while the training rate approach was the Brent method, with a training rate tolerance of 1.0e-6.

The performance functional has great importance in this process, as it defines the task that the neural network has to achieve and offers a quality measure of the representation that has to be learnt. Here the normalized squared error is used as objective term. That means that the squared error between the targets in the dataset and the corresponding outputs calculated by the neural network are divided by a normalization coefficient.

Finally, the neural parameters norm is utilized as regularization term, in order to control the complexity of the neural network by reducing the value of the parameters. The weight assigned to the neural parameters norm was 0.001.

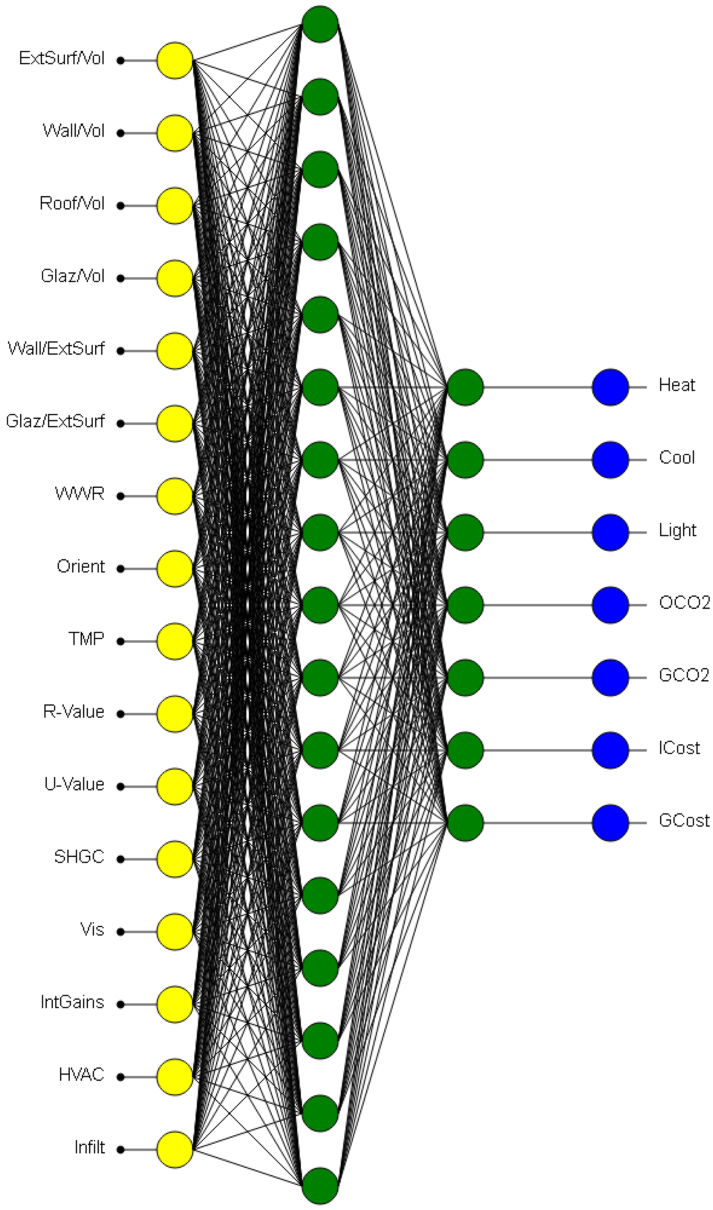

Figure 5.2. Architecture of the Artificial Neural Networks.

5.2.3. Selected climate zones

Independent neural networks have been developed for four of the twelve climate zones defined by the Building Technical Code in Spain [54] represented by the following cities: Tenerife (A3), Barcelona (C2), Madrid (D3) and Burgos (E1). The selection is aimed to cover adequately the different climates of Spain. Figure 5.3 shows monthly profiles of cooling degree days (base 20°C) and heating degree days (base 18°C) for these cities. Also shows the mean maximum and mean minimum relative humidity (circles and short lines, respectively) with the scale on the right. These data offer a good idea about the air conditioning requirements that could be present in each climate.

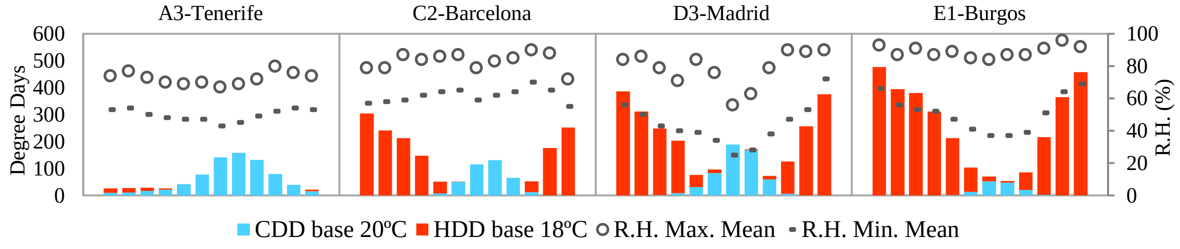

Figure 5.3. Cooling and heating degree days, as well as mean RH in the four climate zones.

5.3. Producing and testing the ANN's

After the ANNs were configured and trained, the next step was to test their performance. That was accomplished by comparing the simulation results from independent samples with values predicted by the neural networks. The samples were composed of 600 randomly selected design solutions for each climate zone.

Table 5.6 shows general statistics of the errors between the neural networks outputs and the testing samples, including the minimum, maximum and mean relative errors, as well as their standard deviations. Although some maximum relative errors are relatively high, it is remarkable that the mean relative errors are very low in all the cases. This means, in general, that the models generated by the ANNs have good quality.

Table 5.6. Statistics of relative errors between the ANN's and the testing samples.

A3-Tenerife	Min.	Max.	Mean	Std. Dev.
Heating	2.51E-06	0.2200	0.0248	0.0285
Cooling	6.93E-05	0.1170	0.0162	0.0149
Lighting	3.30E-05	0.0755	0.0152	0.0131
Op. CO_2	3.24E-05	0.1030	0.0175	0.0153
Global CO_2	7.56E-06	0.0940	0.0170	0.0150
Initial cost	4.25E-05	0.0907	0.0138	0.0124
Global cost	9.00E-06	0.0766	0.0157	0.0138

C2-Barcelona	Min.	Max.	Mean	Std. Dev.
Heating	3.06E-05	0.1210	0.0183	0.0166
Cooling	2.18E-05	0.0938	0.0189	0.0155
Lighting	1.46E-05	0.0834	0.0129	0.0115
Op. CO_2	1.18E-06	0.0775	0.0156	0.0129
Global CO_2	5.61E-06	0.0782	0.0167	0.0132
Initial cost	1.05E-04	0.1280	0.0141	0.0133
Global cost	2.45E-06	0.1170	0.0170	0.0136

D3-Madrid	Min.	Max.	Mean	Std. Dev.
Heating	2.22E-05	0.0844	0.0154	0.0130
Cooling	1.01E-05	0.1430	0.0184	0.0172
Lighting	1.82E-05	0.1030	0.0161	0.0151
Op. CO_2	2.97E-05	0.0708	0.0155	0.0125
Global CO_2	3.89E-05	0.0682	0.0176	0.0129
Initial cost	1.84E-05	0.0853	0.0164	0.0134
Global cost	4.92E-06	0.0767	0.0165	0.0133

E1-Burgos	Min.	Max.	Mean	Std. Dev.
Heating	2.25E-05	0.0624	0.0115	0.0098
Cooling	4.52E-06	0.1970	0.0243	0.0222
Lighting	1.73E-04	0.1190	0.0163	0.0171
Op. CO_2	7.56E-05	0.0741	0.0129	0.0109
Global CO_2	2.70E-05	0.0629	0.0128	0.0104
Initial cost	1.09E-05	0.0972	0.0145	0.0133
Global cost	7.22E-05	0.0862	0.0133	0.0117

Other method for testing the quality of the ANNs is to perform a linear regression analysis between the predicted values and those obtained by mean of simulations. The results of such analysis are shown in the graphs of Figure 5.4, Figure 5.5, Figure 5.6 and Figure 5.7. These graphs plot the predicted values versus the simulated ones, including the results for the seven output variables in the four climate zones. The R^2 values are close to one in all the cases, offering other indicator of the good quality of the models. The only value relatively low is the one for the heating output in the climate zone A3- Tenerife, but it is important to note that in this case the heating loads are very low and thus does not affect significantly the prediction of total loads.

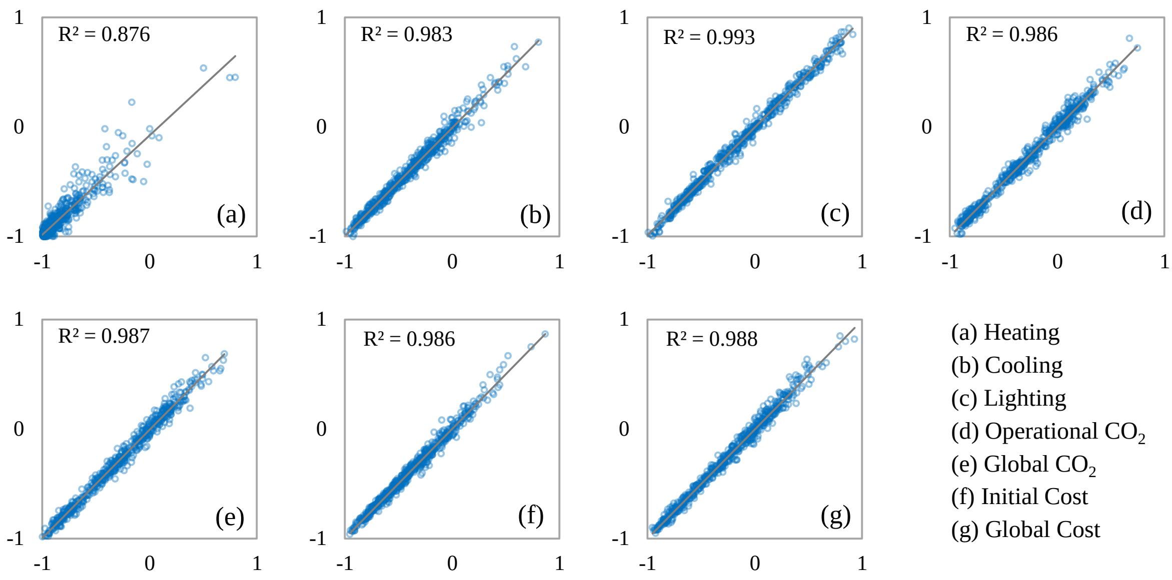

Figure 5.4. Linear regression charts for actual (X-axis) and predicted (Y-axis) values, A3-Tenerife.

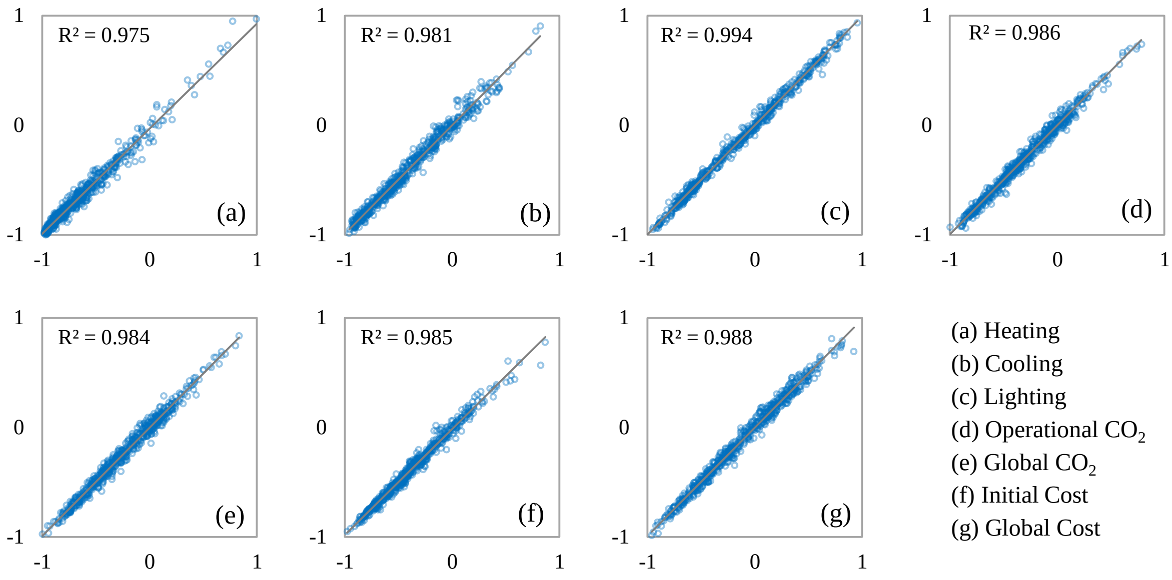

Figure 5.5. Linear regression charts for actual (X-axis) and predicted (Y-axis) values, C2-Barcelona.

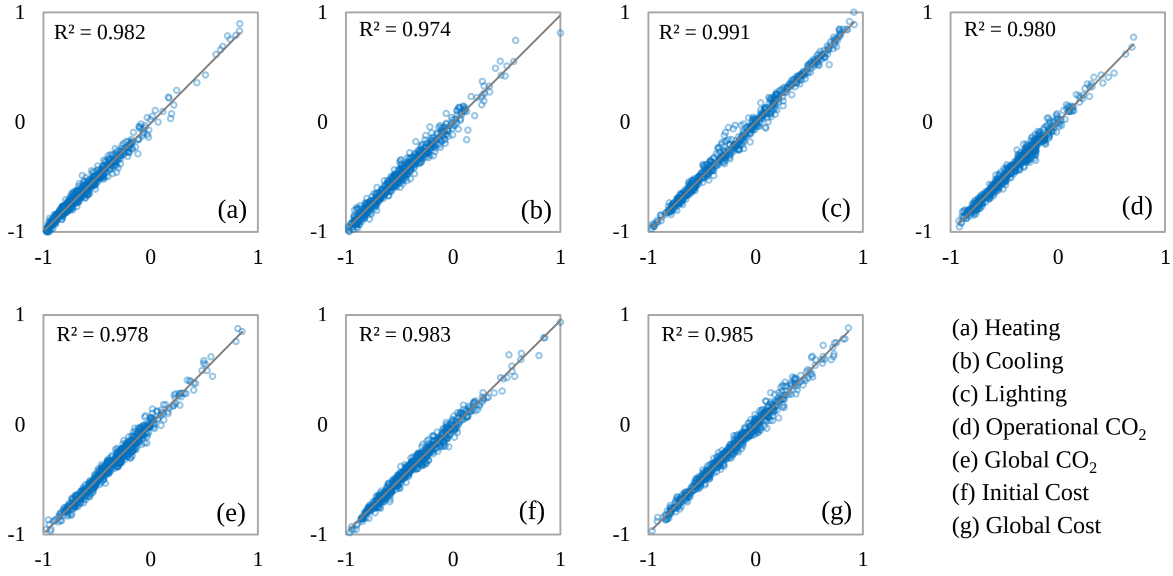

Figure 5.6. Linear regression charts for actual (X-axis) and predicted (Y-axis) values, D3-Madrid.

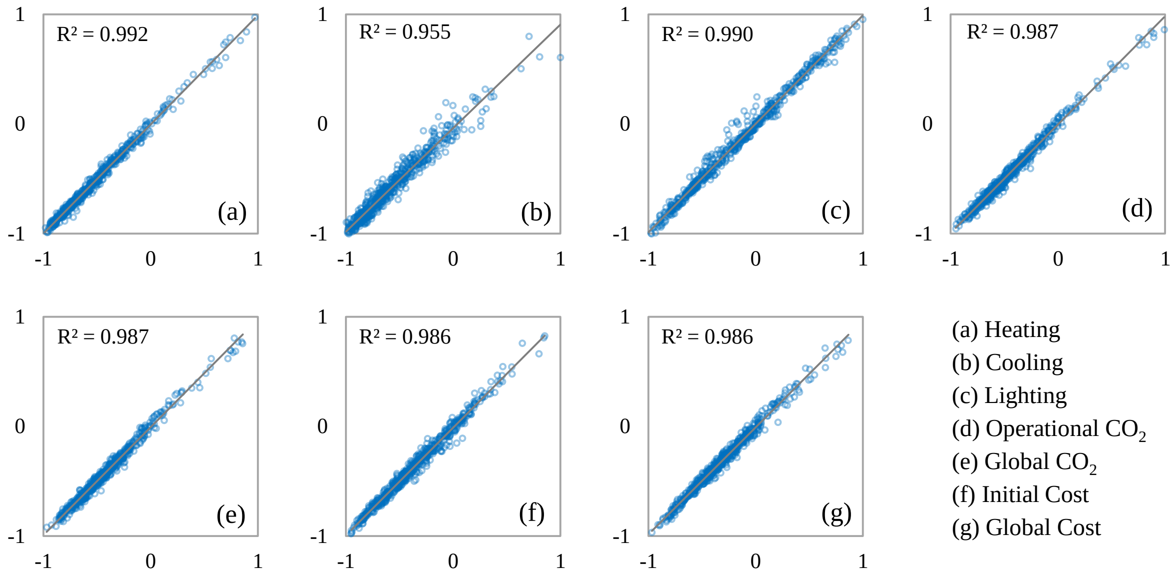

Figure 5.7. Linear regression charts for actual (X-axis) and predicted (Y-axis) values, E1-Burgos.

According to the results of the testing analysis, the developed meta-model are capable of predicting with sufficient accuracy the energy, environmental and economic performance of office buildings, at least within the limits implicitly defined by the parametric project. Therefore, these meta-models can be used to support, extend and speed other type of analyses.

5.3.1. Application examples

The Chapter 4 of this thesis describes a study in which the Sobol method was applied to investigate the relative importance of 8 design variables (shape, WWR, orientation, thermal mass, insulation, glass panes, glass type and HVAC) with respect to 8 performance indicators (heating, cooling, lighting, total loads, operational CO_2, initial cost, global CO_2 and global cost), considering the

Spanish climate zones A3-Tenerife, C2-Barcelona, D3-Madrid and E1-Burgos. The input factors and outputs required by the method were obtained from simulations generated with the parametric project described in Chapter 2, fixing the usage intensity of buildings at the medium level. The current study consisted on replicating and extending that sensitivity analysis, now calculating the inputs factors and the outputs by mean of the meta-models derived from the developed ANNs.

Replicating the Sobol sensitivity analysis

As previously stated, the first part of this study consisted on replicating the Sobol sensitivity analysis described in Chapter 4, with exactly the same conditions and settings, but now calculating the input factors and outputs by mean of the meta-models derived from the ANNs.

The results are shown in the graphs of Figure 5.8. They include the Sobol first order indexes calculated from simulation results (i.e. the parametric project) and from outputs generated by the ANN meta-models, although only the heating, cooling and lighting loads have been considered as output variables. In this way, it is possible to compare the sensitivity results obtained in each case, and therefore verify the reliability of the meta-models for this type of analysis.

If only the design variables with high impact are considered, for instance those having a Sobol first order index greater than 0.1, the mean error percentages (among both series of data) are 6.6%, 3.1%, 5.6% and 8.0% for climate zones A3-Tenerife, C2-Barcelona, D3-Madrid y E1-Burgos, respectively. Therefore, the global mean error percentage, i.e. considering the four climate zones, is 5.8%. It means that the sensitivity results generated from the ANNs meta-models are relatively precise, at least for the most important design variables. In the case of the design variables with low impact, i.e. those having a Sobol first order index smaller than 0.1, the sensitivity results generated from the ANNs meta-models can have significant error percentages, compared with the results from simulations. However, this does not affect much the overall results, especially if it is considered that the mean error percentages for the sum of all the Sobol index values, in each climate, are 1.35%, 3.03%, 3.22% and 3.21% for the climate zones A3-Tenerife, C2-Barcelona D3-Madrid and E1-Burgos, respectively.

Extending the Sobol sensitivity analysis

The second part of this study consisted of calculating the Sobol sensitivity indexes, with basis on the ANN's meta-models, considering also the low and high usage intensities (in addition to the medium usage intensity previously calculated). The main goal was to test the application of the meta-models to investigate to what extent the usage intensity, and therefore the level of internal gains, can affect the relative impact of the design variables on the energy, environmental and economic performance of office buildings. The results are shown in Figure 5.9, Figure 5.10, Figure 5.11 and Figure 5.12, which allow comparing the Sobol first order sensitivity indexes for eight design variables, when the building usage intensity is low, medium or high.

Considering again only the design variables having a Sobol index greater than 0.1, and those cases in which the maximum difference among the three indexes is at least 15%, the design variables appearing more times in the comparative analysis are shape, WWR, thermal mass and insulation (17, 14, 13 and 8 times, respectively). It can be stated that these are the variables whose relative importance is most affected, positively or negatively, by the usage intensity of the building. Remarkably, the order of these variables in terms of affectation level is very similar to the order in terms of relative importance identified in Chapter 4.

Furthermore, it is observed that, in general, when the usage intensity increases, the relative importance of the design variables decreases. From a total of 256 cases (8 variables x 8 performance indicators x 4 climate zones), only 58 (23%) clearly show an augment of the Sobol index when the usage intensity increases, while in the other cases the Sobol index decreases or is irregular. The only two design variables that consistently show an augment of the Sobol index if the usage intensity increases are thermal mass and HVAC option. In other words, the importance of architectural design variables seems to increase when internal gains from occupancy, equipment and lighting decrease.

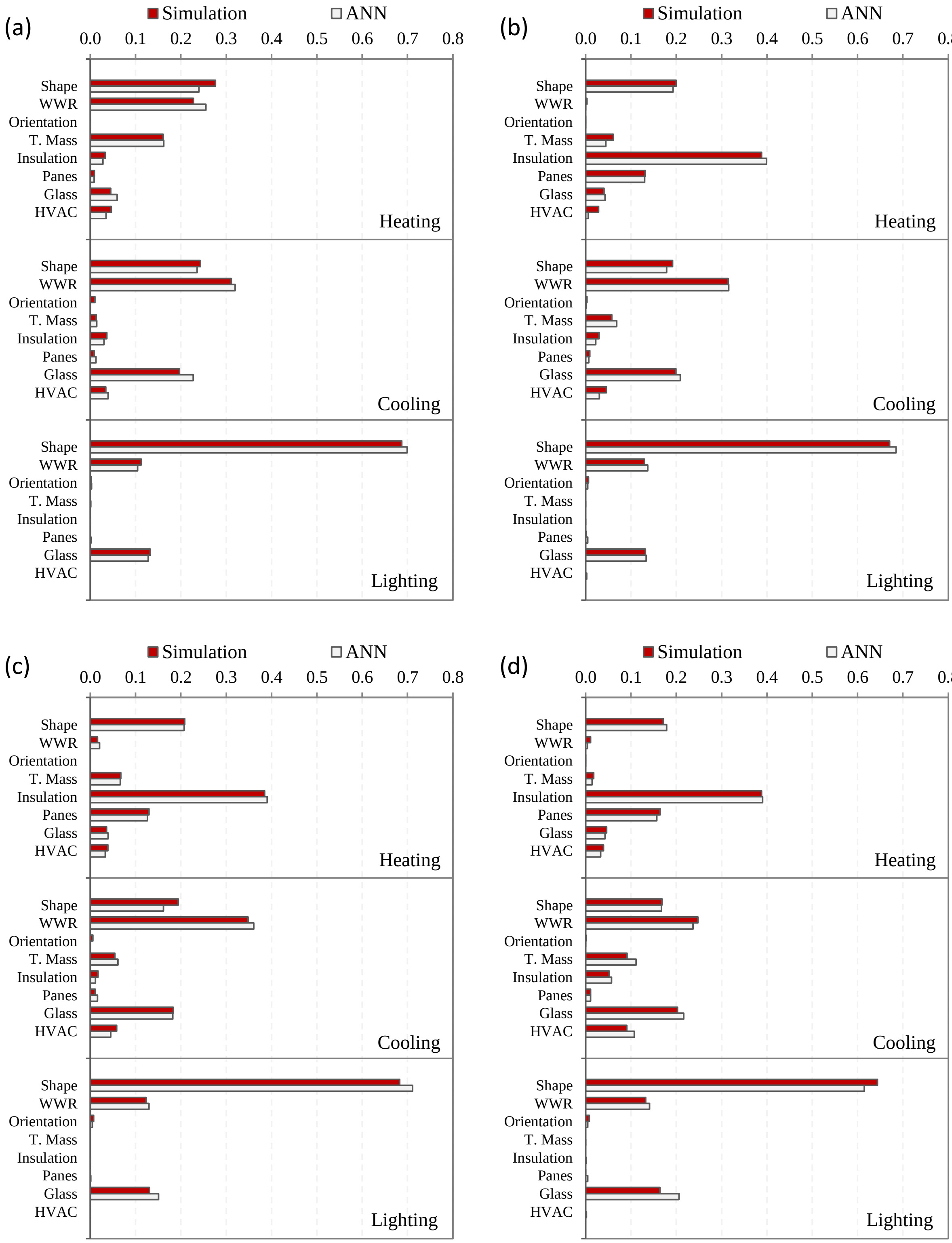

Figure 5.8. Sobol's first order indexes calculated from simulation results and from the ANN meta-models, for climate zones A3-Tenerife (a), C2-Barcelona (b), D3-Madrid (c), and E1-Burgos (d).

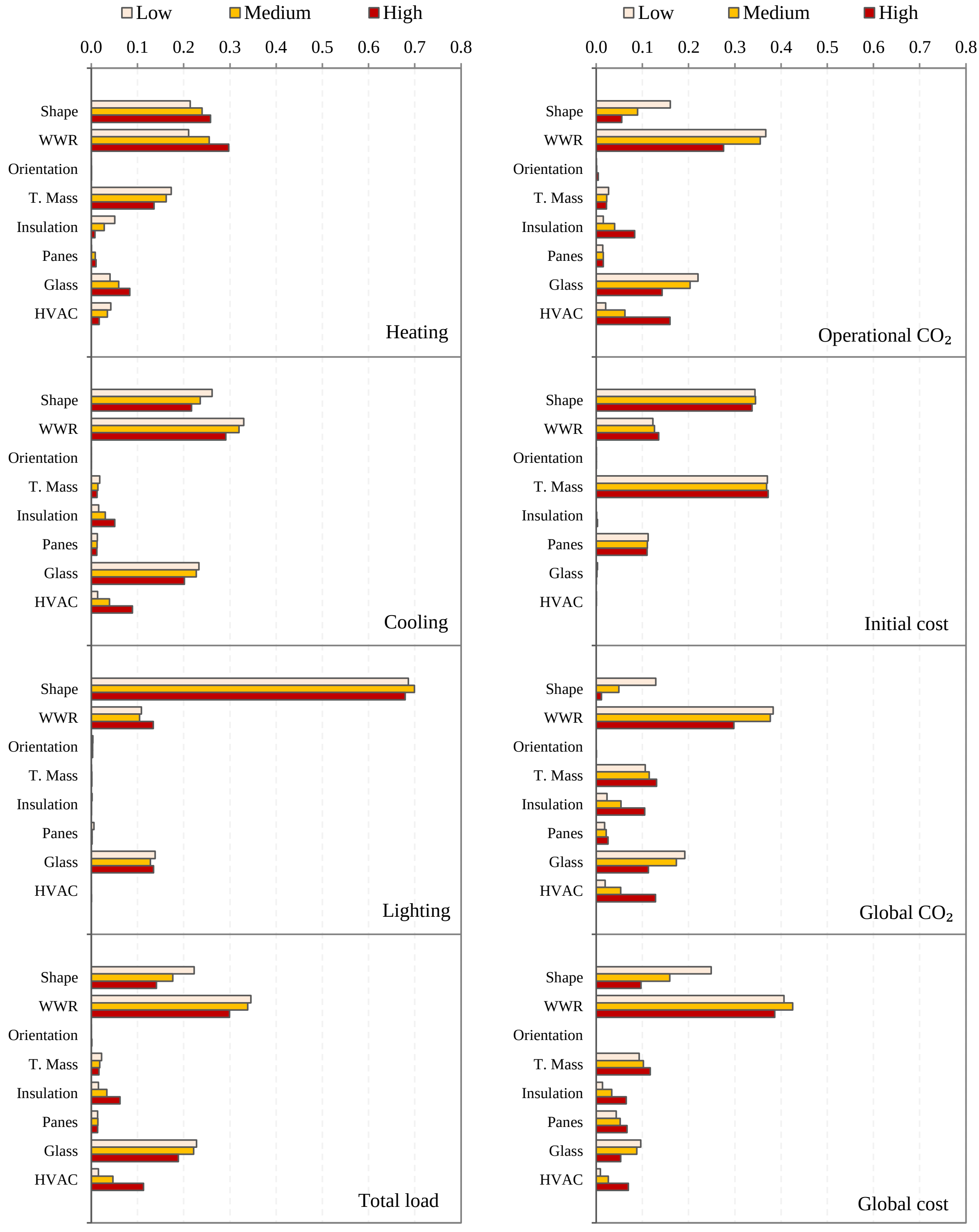

Figure 5.9. Sobol's first order indexes calculated considering low, medium and high internal gains, climate zone A3-Tenerife.

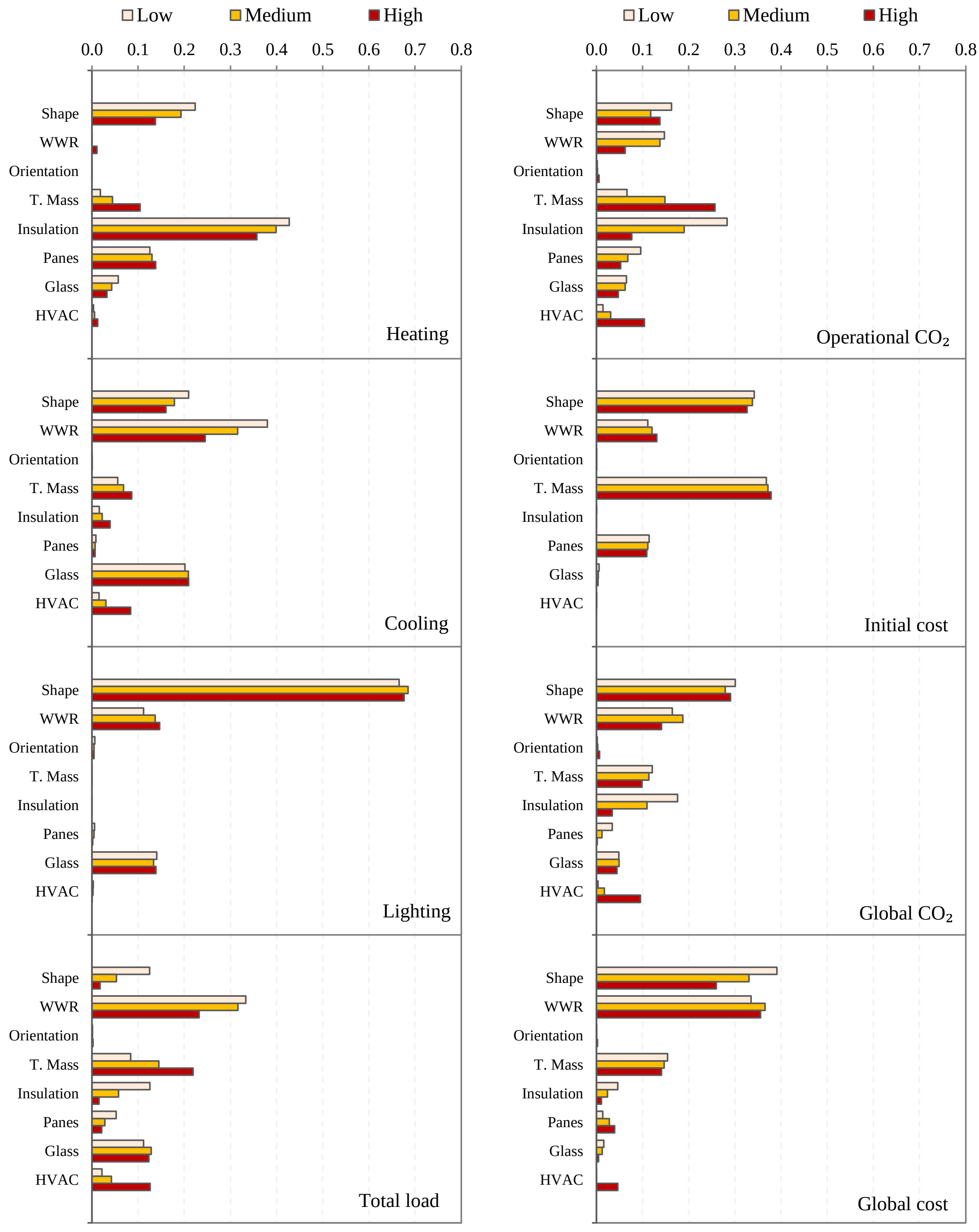

Figure 5.10. Sobol's first order indexes calculated considering low, medium and high internal gains, climate zone C2-Barcelona.

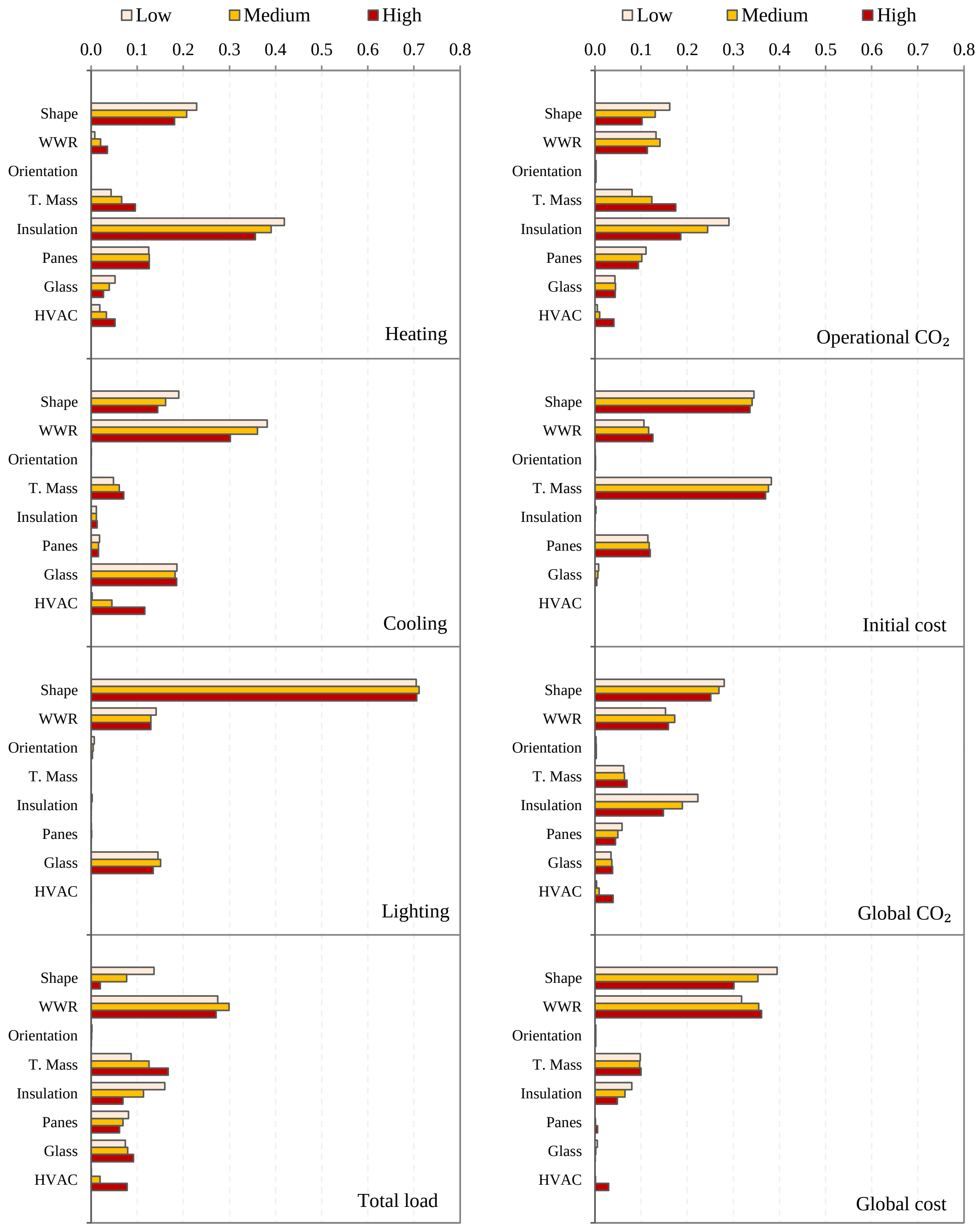

Figure 5.11. Sobol's first order indexes calculated considering low, medium and high internal gains, climate zone D3-Madrid.

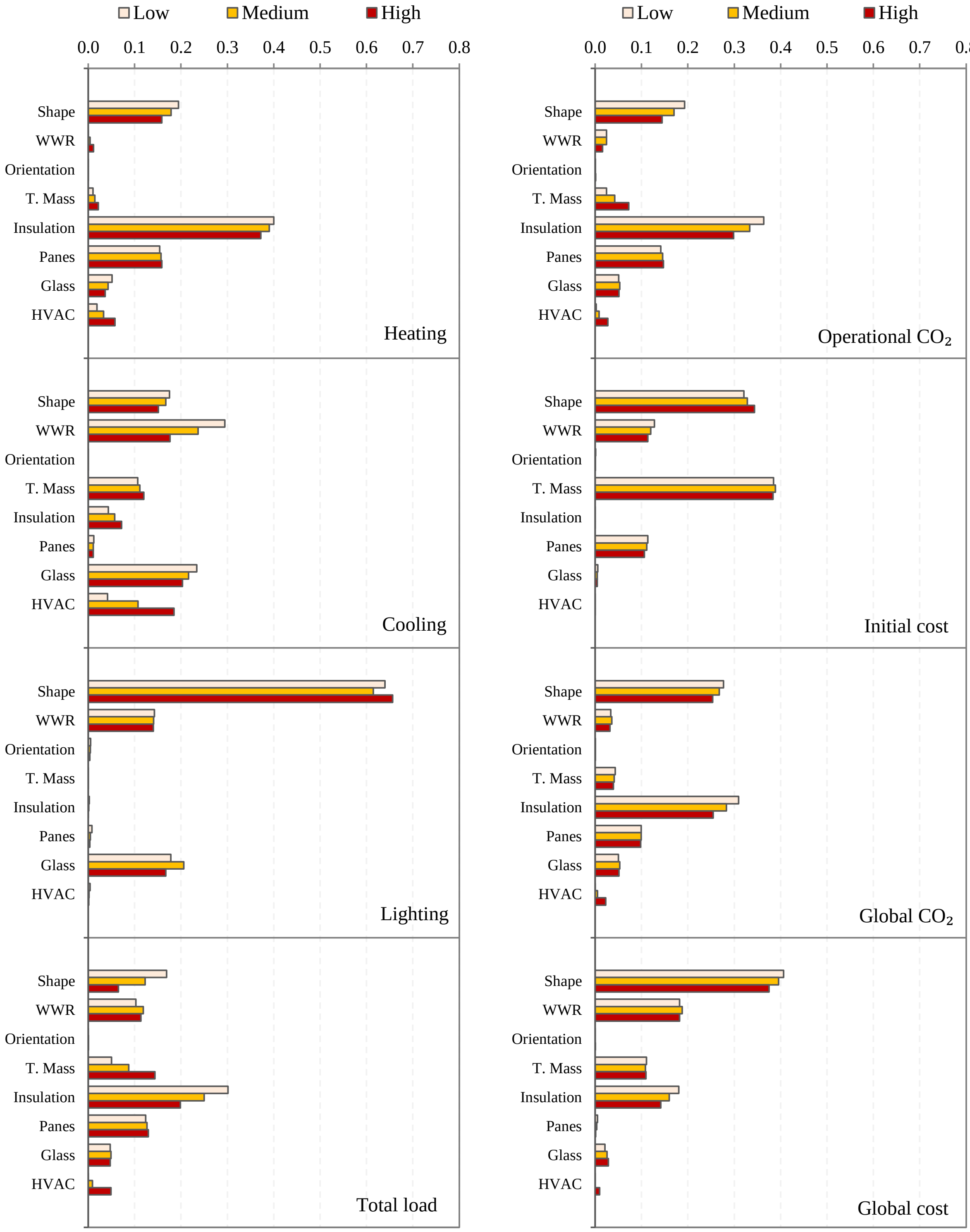

Figure 5.12. Sobol's first order indexes calculated considering low, medium and high internal gains, climate zone E1-Burgos.

5.4. Conclusions

This chapter addresses the development of a set of meta-models from artificial neural networks. A feed-forward neural model has been implemented to generate the meta-models, using datasets of inputs and outputs calculated by whole-building simulations. 16 input parameters were used to describe 10 design variables, while 7 outputs were used to define the energy, environmental and economic performance of office buildings.

The meta-models where tested by comparing simulations results versus values predicted by the ANNs, using independent samples of 600 randomly selected design solutions for each climate zone. The statistics of the errors between the predicted values and the simulated ones showed very low mean relative errors. Similarly, the linear regression analysis showed good adjustment between both set of data, with R^2 values near to 1.

These data allow concluding that the ANNs have generated meta-models that approximate well the results obtained from whole-building simulations. It means, in the first place, that the input parameters selected for feeding the ANNs are a good representation of the main architectural characteristics of the buildings, as defined in the parametric project. Therefore, these parameters are good candidates to be used as part of guidelines for the decision-making during the early phases of architectural design processes. Also, can help to extend the scope and improve the criteria used in current building energy codes.

On the other hand, the ANN meta-models can be used to implement or extend other type of analysis, such as design of experiments, sensitivity analysis and optimization. Here, as an example, the meta-models were used to extend the sensitivity analysis developed in Chapter 4. The results allow confirming the good potential of the meta-models.

Chapter 6. General conclusions

This thesis focused on understanding how the main architectural design variables affect the energy, environmental and economic performance of buildings. It is a complex problem, because (a) the possible solutions to these variables are numerous; (b) the design variables interact and affect each other in complex ways; and (c) evaluating and improving the performance of buildings involves multiple performance objectives, quite often contradictory.

Different methods of analysis were implemented to achieve the purpose of the thesis. The basis was a parametric simulations project developed around the programs EnergyPlus and jEPlus. The parametric project had an important role, since it provided the data required for the implementation of the other analysis methods. However, it can be stated that the most important role of the parametric project was to establish the framework for the whole research, including its limits and scope. It was not an easy task, since it was important to establish a framework broad enough to understand the complex problem under study, but at the same time manageable in terms of the resources and time required to complete the investigation. The parametric project answered, at least in part, some of the initial questions: Which are the most significant architectural design variables and options? How to integrate these variables in a model aimed to study their effect on buildings performance?

Three different studies were developed with basis on the parametric project. They were independent but complementary: (a) optimization analysis; (b) sensitivity analysis; and (c) generation of a set of meta-models based on artificial neural networks. All those studies were applied to four Spanish climate zones, represented by the cities of Tenerife (zone A3), Barcelona (zone C2), Madrid (zone D3) and Burgos (zone E1).

The **optimization analysis** allowed investigating the best design solutions in terms of energy, environmental and economic performance of buildings. Three optimization scopes were included in the study. The most basic scope covered a single performance objective, which consisted on the total load (sum of heating, cooling and lighting loads). The intermediate optimization scope covered two performance objectives, the operational CO_2 and the initial cost (or capital cost). The most comprehensive optimization scope covered also two performance objectives, the global CO_2 (operational CO_2 plus embodied CO_2) and the global cost (initial cost plus operational cost). The main conclusions of the optimization study are the following:

- Building shapes with low-medium height and high aspect ratio offer the best overall performance along the different optimization scopes and climate zones. Within the limits of this study the shape 18-72-12, and secondly the shape 18-36-24, offer the best trade-off among energy, environmental and economic impacts.
- Reducing the amount of glazing as much as possible seems to be an important strategy to optimize the energy, environmental and economic performance of buildings. In this study the lowest WWR (0.20), appears practically in all the optimal solutions along the different optimization scopes and climate zones. This strategy is frankly contradictory with current architectural trends worldwide, but should be taken into account if searching for real optimal solutions.
- Coinciding with other studies, the optimal orientation along the different optimization scopes and climate zones is close to 0º, i.e. the larger facades facing north and south. However, there are small variations. For instance, in the climate zone E1-Burgos orientations of 350º and 355º are common among the optimal solutions.
- High levels of thermal mass show favorable effects in terms of energy performance, but the corresponding increasing in initial cost and embodied CO_2 leads to low values when more comprehensive optimization objectives are pursued, for example global CO_2 and global cost.

- Envelope insulation offers clear benefits when heating demand is significant. However, according to the results, it is evident that the advantages of high insulation levels have a limit and, furthermore, they could be detrimental under certain conditions. For instance, optimal solutions for the climate zone A3-Tenerife, where cooling demand clearly dominates, have always very low insulation level. On the other hand, the climate zone E1-Burgos, the coldest in this study, is the only one where the highest level of insulation appears consistently in optimal solutions.
- Results regarding the optimal number of panes are somewhat irregular, although 2 panes can be considered a good overall choice along the different optimization scopes and climate zones.
- The spectrally selective in the first place, and the low-e in the second, are the glass types that offer the best overall energy, environmental and economic performance. It is important to take into account that these options are associated, within the limits of this study, to very low WWR.

Beyond the previous points, that identify the role of the main architectural design variables on searching optimal solutions, it is important to highlight some conclusions about the effect of selecting one optimization scope or other:

- The optimization of office buildings based exclusively on its energy performance could lead to sub-optimal solutions from a more comprehensive point of view. For example, taking the total energy load as the unique performance objective generates solutions that tend to have a relatively poor performance in terms of global CO_2 and global cost. This tendency is because energy optimal solutions include design options that significantly increase the initial cost and the embodied CO_2, in this case especially the amount of thermal mass. It is also clear that this tendency becomes stronger as cooling demand increases, as it can be deduced by comparing the results for the four climate zones.
- It is also evident that choosing solutions with low initial cost leads to very bad solutions in terms of global CO_2 and global cost. This trend is the opposite of the one explained above, as the comprehensive performance deteriorates significantly with the increasing heating demand. In that case, the rising energy consumptions generate higher operational CO_2 and operational cost.
- These results seem to support the idea that, if the optimization process has been done with basis on the operational CO_2 and the initial cost, it is better to choose solutions located near the central part of the Pareto front. In this way, it is less probable to select a solution apparently optimal but which in fact offers a poor performance from a more comprehensive performance criteria. However, it is necessary to take into account the specific settings of this study.

The optimization study offered a better understanding of the effect that architectural design variables have on energy, environmental and economic performance of office buildings. These results cannot answer all the possible questions, since the study focused on exploring the optimal design options. However, they could be useful as guideline for the decision-making during the early architectural design stages. They can also help to improve or fine-tune the normative criteria in the field of building energy performance. In the future, it would be desirable to extend the scope of this study, for example covering other usage conditions, more complex building shapes and a more wide range of climate conditions. The usefulness of the optimization analysis can then be increased substantially.

The **sensitivity analysis** focused on investigating the relative importance of the main architectural design variables, that is, which of them should have priority if we want to achieve buildings with high energy, environmental and economic performance. The Morris and Sobol methods were used to calculate the sensitivity of eight design variables (or input factors) regarding eight output variables. Among the conclusions of the sensitivity analysis are the following:

- Although there are some logical differences among the sensitivity analysis methods, if the whole search space of the computational experiments is taken into account, they coincide on identifying shape and WWR as the most influential input factors, followed by insulation and thermal mass in second place, and glass type and panes in third place. Also, they coincide in defining HVAC and orientation as the less influential input factors in the context of this research.
- A more detailed review of the results indicates that, as it was expected, the importance of the factors changes widely depending on the performance indicator (energy loads, operational CO_2, initial cost, etc.) and the climate zone. For example, the effect of insulation and panes input factors is higher on heating load-related outputs and in cold climates, while glass type input has higher influence on cooling load-related outputs and in warm climates. Hence, it is not possible to rank the input factors in a scale of importance that is suitable for any performance indicator and climate zone. Instead, the effect of input factors should be evaluated for the specific climate zone and according to the performance objectives, for example to reduce the energy loads, the initial cost and operational CO_2 or the global cost and global CO_2.

On the other hand, the purpose of using two sensitivity analysis methods, which were selected from the literature, was to validate to some extent the results, as well as compare and evaluate the usefulness of the methods for future studies. Regarding their performance, the next conclusions can be pointed out:

- The Morris method offered what seems to be the best cost-benefit. It provided good qualitative data about the sensitivity of the input factors with low computational cost. This method appears to be a suitable approach for models with many design variables when computational cost is a concern. Among other tasks, it can be used to explore sensitivity in early research phases and/or to discard inputs that are not significant.
- The Sobol method showed great capability to estimate in a detailed and quantitative way the impact of the input factors. Its high computational cost represents an important disadvantage, but it is advisable to use this method whenever possible. In the field of building energy simulation, it is also recommendable to explore the use of surrogate models in order to reduce the computational cost of the Sobol method.

The results of sensitivity analysis can be very useful for identifying which design variables may be convenient to focus on, in order to improve the performance of buildings. Sensitivity can be interpreted either as a design warning or as an opportunity for efficient designs. However, it is important to consider the inherent limitations of sensitivity analysis methods. One is that they are not intended, and thus are not capable, of identifying the optimal design solutions, for example the optimal insulation level. In addition, if an input factor is identified as unimportant (for example orientation), it does not necessary mean that it is appropriate to completely discard it. Depending on other design decisions, this particular input can still play an important role in some circumstances.

The last part of the research addressed the development of a set of **meta-models** by means of **artificial neural networks**. The main objective was to evaluate how well a set of input parameters represents the architectural design variables, regarding the energy, environmental and economic performance of buildings.

In this case, a feed-forward neural model was used to generate the meta-models, using datasets of inputs and outputs calculated by whole-building simulations from the parametric project. 16 input parameters were used to describe 10 design variables, while 7 outputs were used to define the energy, environmental and economic performance of buildings. The meta-models where tested by comparing simulations results versus values predicted by the ANNs, using independent samples of 600 randomly selected design solutions for each climate zone. The statistics of the errors between predicted and simulated values produced very low mean relative errors. Similarly, the linear regression analysis showed good adjustment between both set of data, with R^2 values near to 1.0.

These results allow concluding that the ANNs generated meta-models that approximate well the results obtained from whole-building simulations. It means, in the first place, that the input parameters selected for feeding the ANNs are a good representation of the main architectural characteristics of buildings, as defined in the parametric project. Therefore, these parameters are good candidates to be used as part of guidelines for the decision-making during the early phases of the architectural design process. Also, can help to extend the scope and improve the criteria used in current building energy codes. On the other hand, the ANN meta-models can be used to implement or extend other type of analysis, such as design of experiments, sensitivity analysis and optimization. Here, as an example, the meta-models were used to extend the sensitivity analysis implemented in Chapter 4. The results allow confirming the potential of the meta-models.

In resume, the studies conducted as part of the research allowed to meet the initial goals. Within the limits established by the research itself, now we know some of the architectural design solutions that are optimal to achieve buildings with high energy, environmental and economic performance. Also, we know the relative importance of each of the design variables if optimal solutions are pursued. Finally, they were identified a number of parameters that properly define the main architectural characteristics, so they can be used to evaluate buildings performance with a good level of accuracy and detail. Hopefully, the main contribution of this thesis is to define and implement a methodological approach that can address the energy and environmental problems of buildings from a more holistic perspective. Rather than focusing on refining and expanding a specific method, the approach has been to explore diverse analysis methods around the same problem. This holistic approach can be very useful to reach comprehensive design guidelines, and it can also help to improve the criteria used on the definition of building energy codes and sustainability certification systems.

6.1. Future work

The development of this thesis, like any other, required to establish clear scopes and limits. These limits gave coherence to the research process, and allowed to achieve the research objectives within a reasonable time. The obtained results, however, opened many research lines that would be of great interest for future projects. As an example we can point out the following:

- To extend the range of design solutions for some of the design variables. For example, to include buildings with different sizes and more complex shapes.
- To include other architectural design strategies, such as natural ventilation, shading devices, ventilated constructions, green roofs, etc.
- To address other types of buildings, such as housing, schools, hotels, etc.
- To expand the scope of building performance indicators, e.g. including stricter life cycle analysis methodologies.
- To study the relationship between the architectural features of buildings and the available HVAC technologies, looking for the best possible integration.
- To implement other analysis methods, like design of experiments (DOE) and data mining.

These research lines could lead to an even broader understanding of the effects that the architectural design variables have in the energy, environmental and economic performance of buildings. In addition, they could allow consolidating a more consistent database that better help to take the adequate decisions during the design process, as well as to improve the criteria used to regulate the architectural characteristics of buildings.

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Journal papers

A. Ordoñez, I. Korolija, Y. Zhang, A. Coronas. A parametric project to study the impact of main architectural design variables on energy performance of office buildings.

(In process)

A. Ordoñez, Y. Zhang, I. Korolija, A. Coronas. Comprehensive optimization of main architectural design variables using whole-building simulation and evolutionary algorithms.

(In process)

A. Ordoñez, I. Korolija, Y. Zhang, A. Coronas. Relative importance of main architectural design variables on office buildings energy, environmental and economic performance

(In process)

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