Modelling, Simulation and Optimisation Methods for Low-energy Buildings

Submitted by

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: …………………………………………………………..

Abstract

This thesis covers the study of modelling techniques and optimisation methods used to help low-energy building design.

This research is motivated by the need to improve and develop computational tools to: (1) reduce the computational time needed to perform building energy simulations, and (2) account for occupant behaviour and energy use.

Lumped Parameter Models (LPMs) of buildings were investigated to reduce the computational time needed to perform annual dynamic building simulations and eventually optimisation. As a result, a methodology was created that can be used to generate LPMs that are more accurate than those produced by the methods found in the literature.

Recent research has shown that occupants' behaviour can have a large impact in energy demand calculations. To tackle occupants' uncertainty in computational optimisation, an Evolutionary Algorithm (EA) was developed that deals with uncertainties intrinsically. The results obtained in this thesis show that this method produces building designs that are less likely to present a large number of non-comfortable hours during their use by different occupants.

Unlike previous works based in re-iteration to propagate uncertainties, the algorithm shown in this thesis performs uncertainty analysis and optimisation at the same time, providing robust solutions for making effective use of resources.

One of the most significant barriers to the use of computational optimisation of building designs is the long computational times needed. This thesis describes the creation of a new algorithm to reduce the time needed to perform optimisation. The method consists of an algorithm that combines models with different physical fidelity, self-adaptive optimisation and principles of dynamic optimisation problem solving to improve the efficiency of the search for optimal designs. The time needed for the new algorithm to find the optimal designs was found to be a tenth of the time needed when the same optimum is found with a traditional method.

The method and algorithms showed in this thesis contribute to the state of the art of computational methods for the design of low-energy buildings.

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1 Introduction

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1.1 Background and motivation

There is an increasing awareness of buildings being a major source of the emissions that cause climate change. Buildings account for around 40% of the carbon emission in developed countries (Pérez-Lombard *et al.*, 2008).

The interest in reducing emissions from buildings has created the need of tools to predict and optimise the energy demand of buildings. Building modelling and simulation is not a new discipline, the oil crises of the 70s triggered developments in understanding of building physics that allowed the creation of building simulators available in the 80s (see the reviews (Wiltshire and Wright, 1988) for the UK and (Winkelmann, 1988) for the USA).

Having computational tools available to simulate building designs, allow performing optimisation using computers. This technique, based on using algorithms to make decisions concerning building design, has been seen in several scientific publications (as will be described in detail in Section 2.2), but is also starting to be included in popular building simulation suites. Examples of this are the optimisation tool for Design Builder (EnergyPlus), developed in the research project ADOPT with De Montfort University with Yi Zhang as Principal Investigator (PI) (not launched at the moment of writing), and the optimisation tool for IES-Virtual Environment, developed in the research project OPTIMISE with Loughborough University among other industrial partners. (Launched 5 September 2012).

Large companies are also showing interest in optimisation methods to assist building design as shown in the comprehensive literature review performed by Ralph Evins from Buro Happold (Evins, 2013). ARUP has also used optimisation methods in their designs that include traditional optimisation methods and evolutionary computation (ARUP, 2012)

The understanding of building physics and these new tools help in designing buildings that need a fraction of the energy of those designed in the eighties (see the Passivhaus standard (Schnieders and Hermelink, 2006)). This new paradigm of low-energy buildings and the use of optimisation techniques bring new challenges to the discipline.

Building operational conditions have a large degree of variability. The work of Schnieders and Hermelink (Schnieders and Hermelink, 2006) has shown that occupants' behaviour has a great impact in energy demands of modern low-energy buildings. This variability in the operational conditions of the building may be a problem during the design cycle as the designers will need to consider this as an uncertainty.

This thesis looks, among other things, into the impact of these uncertainties (induced by occupants) in the optimisation algorithms often used to find the best characteristics of a given design. Also, it looks into new ways of performing optimisation that will be more efficient.

This thesis focuses on two main problems: (1) the uncertainties present in the building lifecycle and its impact in the energy demand prediction and therefore in the results of a possible optimisation; and (2) the large computational times of the current optimisation methods that use complex building simulators to evaluate the possible solutions.

Further, a new way of creating simple models of buildings is developed in this research after identifying that need while addressing the problem outlined in (2). This was the creation of a methodology to create Lumped Parameter Models of buildings.

This PhD has been founded by the Wates Foundation, and the aim of the research is to improve the knowledge available in building design in a way that benefits society. All building simulators used in this research are free. This has been done in purposefully to show that the methods could be used by any professional in industry. Codes and algorithms can also be found free of charge in the webpages of their authors.

1.2 Previous and related work

The relevant literature will be described in Section 2.6. Here, it is shown the publications that overlap with the work presented in this thesis, and why their studies differ with the one offered in this document:

(1) Optimisation of low-energy buildings subjected to uncertainties: Marijt's Master's thesis (Marijt, 2009) is the first work performing optimisation that takes uncertainties into account in low-energy building design. However, this thesis does not include the uncertainties due to building occupants. Hoes et al. (Hoes *et al.*, 2011) developed a methodology where an indicator is used to measure the robustness of the solutions. But, this is a post-processing technique that does not take into account the uncertainties during the optimisation. These two works do not include a realistic verified tool to generate the occupants' profiles. Detailed and more thorough studies have considered uncertainty and optimisation separately (and will be mentioned in Section 2.6) but this has been the only one work that unites the two in the literature reviewed.

(2) Using sequential optimisation to reduce computational time: No previous work using sequential optimisation for building design has been found in the literature.

(3) Analytical creation of reduced models of buildings: Fraisse et al. (Fraisse *et al.*, 2002) developed a methodology to find LPMs of buildings in an analytical way. However, the method has been seen to be poorer in accuracy than the method propose in this thesis. Also, this method requires solving rather complex algebraic equations to obtain the value of the elements forming the model, whereas the method propose in this thesis is a set of simple operations.

1.3 Main contributions

This thesis contributes to the discipline of building design through computational methods with three new methods:

1. An optimisation method that enhances the capabilities of evolutionary algorithms for dealing with uncertainties to generate low-energy building designs those are robust to uncertainties at low computational cost. The method was tested for uncertainties induced by occupants with positive results.
2. A method that uses a self-adaptive evolutionary algorithm to make possible sequential optimisation of buildings. The method uses different assessment tools at different stages of the optimisation and reduces the computational time of the optimisation substantially when compared to a traditional run by approximately 90%.
3. An analytical way of calculating reduced dynamic models of buildings. These models can be used to simulate buildings using little computational resources and therefore need short times to run. This methodology was created to make possible the development of the methodology explained in the second bullet point.

1.4 List of publications

The main contributions of this thesis have been presented in conferences and submitted to international scientific journals. The references of these publications are:

- A. P. Ramallo González, T. S. Blight, D. A. Coley, Robust low energy design that accounts for occupant behaviour. In *1st International Conference in Building Sustainability Assessment*, Porto, Portugal, 2012.
- A. P. Ramallo González, M. E. Eames, D.A. Coley, Lumped Parameter Models for Building Thermal Modelling: An Analytic Approach to Simplifying Complex Multi-Layered Constructions. In *2nd Conference on Building Energy and Environment*, Boulder, USA, 2012.
- A.P. Ramallo-González, M.E. Eames & D.A. Coley, 2013. Lumped parameter models for building thermal modelling: An analytic approach to simplifying complex multi-layered constructions. *Energy and Buildings*, 60, pp.174-184 (Ramallo-González *et al.*, 2013).
- A. P. Ramallo González, D.A. Coley, (In Press) Using self-adaptive optimisation methods and models with different physical fidelity to perform sequential optimisation of buildings, *Energy and Buildings.*

1.5 Thesis outline

This thesis is organised as follows:

CHAPTER 2: BACKGROUND

This chapter describes the necessary background to understand the research work performed in this PhD. It has six different blocks:

- **Low-energy Buildings** presents the design principles to design low-energy buildings. The components of the building and the design methodologies. The building standard *Passivhaus* is also mentioned in this section as a successful design guideline for low-energy building design.
- **Energy Demand Assessment Methods for Building Design;** the tools available to calculate the energy demand of buildings are classified in this chapter. The tools available are organised following different criteria being the

most important for this thesis the one where the tools are classified by complexity.

- **Optimisation** formulates the optimisation methods that have been used in scientific publications related to building design. The most common optimisation methods, Evolutionary Algorithms, are described in detail.
- **Robust and Dynamic Optimisation** describes the existing methodologies to perform robust optimisation.
- **Computer aided building design** presents a contextualisation about the place of computers in building design.
- **Literature review** shows the literature relevant to this thesis at the time of writing.

CHAPTER 3: RESISTOR CAPACITOR NETWORKS

Here, the methodology to generate Lumped Parameter Models of buildings created in this research is described and validated.

CHAPTER 4: BASIC ROBUST OPTIMISATION FOR BUILDING DESIGN: THE CHANGING EVIRONMENT EVOLUTIONARY STRATEGY

This chapter shows the algorithm created in this thesis with the purpose of performing optimisation subjected to uncertainties without increasing notably the computational time. This is the second main contribution of this thesis. In this chapter the optimisation method that finds robust solutions is validated with synthetic functions, and applied to low-energy building design that is affected by the uncertainties of the occupants.

CHAPTER 5: SEQUENTIAL OPTIMISATION

This chapter explains the methodology consisting of using self-adaptive optimisation algorithms with a variety of building assessment tools, that results in a more efficient way of performing optimisation. This methodology is the third main contribution of this thesis. The methodology is validated with a practical example.

CHAPTER 6: CLOSURE

This chapter closes this thesis including the sub-sections of summary, conclusions, further work, acknowledgments and references.

Table 1.1- Distribution of the thesis.

Chapter No.	Chapter Title
1	Introduction
2	Background
3	Resistor capacitor networks as thermodynamic simulators of buildings
4	Basic Robust Optimisation for Building Design: The Changing Environment Evolutionary Strategy
5	Sequential Optimisation for Building Design
6	Closure

2 Background

Contents

Nomenclature

${c_p}^{air}$ – Heat capacity of air [J/(m^{3}K)].

ρ^{air} – Density of air [kg/m^3].

ΔT – Temperature difference between inside and outside [K].

inf – Infiltration [m^3/s].

Δt – Time period [s].

$\mathbf{x}^{(\mathrm{k})}$ – Solution number *k* on a multi-objective optimisation problem.

ω_Θ – Genetic operator.

I^q– Subspace of individuals (size q) of an Evolutionary Algorithm.

$\boldsymbol{a}_k$ – Individual *k* of an Evolutionary Algorithm.

μ – Mean of a normal distribution.

σ^2 – Variance of a normal distribution (σ is the standard deviation).

$\Delta(t, y)$ – Michalewicz operator of mutation.

$\mathrm{f}_{min}(t)$ – Minimum value of the objective function for a given generation *t.*

$\mathrm{f}_{max}(t)$ – Maximun value of the objective function for a given generation *t.*

$R(t)$ – Acceptable range of objective values for a given generation *t.*

$L(y)$ – Loss function of the Taguchi method.

α – Environmental uncertainty.

δ – Tolerance and workmanship uncertainty.

$\tilde{f}$ – Miss estimation of the objective function due to uncertainties.

$F_A(\boldsymbol{x})$ **–** Regularisation function for uncertainties A.

$F_B(\boldsymbol{x}, \epsilon)$ **–** Regularisation function for uncertainties type B.

ϵ – Regularisation distance.

$F_U(\boldsymbol{x})$ **–** Regularisation function with utility function.

$F_q(\mathrm{x})$ – Regularisation function using probability of robustness.

2.1 Low-energy buildings

This section is an introduction to low-energy buildings. The legal framework, the literature available for their study and the standard *passivhaus* are described, this is finalised by a section about the salient issues of low-energy buildings and conclusions. In this section, as in the rest of the thesis, the energy systems that provide services to the building have not been covered; more about this systems can be read in the professional guides of the American Society of Heating, Refrigeration and Air Conditioning (ASHRAE) and the Chartered Institution of Building Services Engineers (CIBSE) and on (Boyle, 2004) for renewable energy technologies.

2.1.1 Legal framework

The building sector has been highly implicated in energy reduction policies as it counts for a large proportion of the overall carbon emissions (Levine *et al.*, 2007).

Within Europe, several policies have been put in place with the aim of lowering emissions of buildings. In the seventies, the Council of European Communities had already published three recommendations for reducing energy use in buildings (last one: (EEC, 1979)); however, after the Kyoto protocol, a directive was published with a wider scope and more comprehensive description of the measures that should be taken for improving the building stock (EU, 2002). This directive had a substantial impact on the new built sector, and raised awareness amongst architects and contractors of the importance of energy efficiency. Eight years later a new directive was published amending the previous one (EU, 2010), the Energy Performance of Buildings Directive recast (EPBD recast).

With the EPBD recast EU member states will adopt new challenges concerning energy performance in buildings. The directive includes elements intended to move new and refurbished buildings towards near-zero energy by 2020 and to apply cost-optimal methodologies that lead to minimum energy use.

Some of the highlights of the EPBD recast are (adapted from (ECEEE, 2013)):

- New buildings will have to consume 'nearly zero' energy and the energy will be 'to a very large extent' from renewable sources by 31 December 2020.
- Public authorities that own or occupy a new building should set an example by building, buying or renting such 'nearly zero energy building' by 31 December 2018.
- The definition of very low energy building was agreed: "nearly zero energy building" means a building that has a very high energy performance, determined in accordance with the Annex I of the directive. The residual energy required should be covered by energy that comes mainly from renewable sources.
- There is no specific target set for the renovation of existing buildings, but Member States shall follow the example of the public sector by developing policies and taking measures in order to stimulate the transformation of buildings that are refurbished into very low energy buildings, and inform the Commission thereof in their national plans referred to in paragraph 1 of the directive.
- Minimum requirements for components are introduced for all replacements and renovations, although for major renovations, the holistic calculation methodology is the preferred method with performance calculations based on component requirements allowed as a complement or alternatively.
- A harmonised calculation methodology to push-up minimum energy performance requirements towards a cost-optimal level is set out in the Directive in a definition and an annex.
- A more detailed and rigorous procedure for issuing energy performance certificates will be required in member states.
- Control systems will be required by Member States to check the correctness of performance certification.
- Member States will be required to introduce penalties for non-compliance. Member States shall lay down the rules on penalties applicable to infringements of the national provisions adopted pursuant to this Directive and shall take all measures necessary to ensure that they are implemented. The penalties provided must be

effective, proportionate and dissuasive. Member States shall communicate those provisions to the Commission.

The importance given in this directive to the achievement of cost/optimal nearly/zero energy buildings could benefit from the methods shown in this thesis where optimisation methodologies are used to uncover to designers the best options for a given design.

Concerning the UK, the British government has improved the policy framework with the aim of reducing carbon emissions from buildings. The *Energy Act 2011* is the last policy package created for the UK. The Energy Act is a comprehensive set of policies that aim to reduce energy consumption through energy efficiency measures in homes and industry.

The Energy Act of 2011 (DECC, 2012) includes policies in three different streams:

- The Green Deal
- The private rented sector
- The Energy Company Obligation

The **Green Deal** is a UK government policy to improve energy efficiency of British domestic buildings (DECC, 2010). This initiative allows householders to install energy efficiency measures without the need to provide the initial capital cost; instead, the initial cost is spread through the energy bills of future years, the payment of the improvements will be based on what a typical household is expected to save on energy bills by having the work done[1]. The intention is that the reduction on the energy bills, due to the improvements in efficiency, will be equal or higher than the money need to pay the refurbishment.

The conditions imposed by the Energy Act for the **private rented sector** give power to tenants living in privately own houses to demand the application

[1] From www.gov.uk: https://www.gov.uk/green-deal-energy-saving-measures/repayments. Accessed the 28th of January 2013.

of energy saving measures. After April 2016, landlords could not deny the adoption of energy efficiency measures (if those fall under the scope of the green deal), and after April 2018, it will be mandatory to carry on these measures before renting a house.

The **Energy Company Obligation**, through ECO, the government aims to help 230,000 low-income households or those in low-income areas by forcing energy companies to help households economically with fabrics improvement and boilers reparations (DECC, 2010).

It can be seen in this summary that an increasing number of policies and policy instruments aim to produce a more efficient building stock. The measures mentioned, have created an increasing interest in the building sector for energy efficiency measures and low-energy building design. This interest concerns householders, contractors, architects and engineers.

2.1.2 Green/Sustainable buildings

Buildings are designed with the aim of providing comfortable spaces for their occupants. But comfort has several aspects. Baker and Steemers consider that the building should provide (Baker and Steemers, 2000):

- Thermal comfort
- Indoor air quality
- Visual comfort
- Acoustic comfort
- Adaptation opportunity

The first four are self-explanatory. The last one refers to providing the occupants with systems that allow changing some of the features to adapt to the environment (e.g. being able to open windows).

The comfort in buildings comes with the some use of resources to construct the building, and to maintain the comfort despite the changeable nature of weather and building use.

The limited amount of resources and the stricter standards and regulations of the building sector, has motivated a more thorough assessment of the way those resources are used with the aim of reducing the impact that buildings and their operation have on the environment. Buildings that are designed enhancing sustainability are normally called green or sustainable buildings; sustainable buildings are therefore buildings that provide the comfort defined in the previous listing without compromising the resources for the future. ASHRAE considers the mayor factors impacting sustainability to be (from (ASHRAE, 2009)):

- Population growth
- Food supply
- Disease control and amelioration
- Energy resources availability,
- Materials resource availability and management
- Fresh water supply, both potable and non-potable
- Effective and efficient usage practices for energy resources and water
- Air and water pollution
- Solid and water pollution
- Land use.

Several guides have been created for the design of *green buildings* as shown in (ASHRAE, 2006). Evaluating the sustainability of a building design is now common place in several countries and an obligation in the member states of the EU for some buildings. Some of the most popular schemes are Leadership in Energy & Environmental Design (LEED) in the USA and Building Research Establishment Environmental Assessment Method (BREEAM) in the UK.

For this thesis, only the problem of energy use has been considered, and computational design methods to achieve low-energy buildings are presented. In the following the reason why reducing the energy use is needed for sustainability is explained further.

Most of the energy use in buildings comes from non-renewable sources at the moment, mostly from fossil fuels. Fossil fuels are used to provide heating in cold climates, and burnt in power plants to produce electricity that is used in buildings and other services. The combustion of fossil fuels turns chemical energy into heat and combustion gases. Among these gasses, the one produced in the largest volume is CO_2, and the scientific consensus is that it is the biggest contributor to climate change. Other gasses that result from the combustion of fossil fuels are, for example, SO_x and NO_x, both contributing to acid rain that damage soils and crops and historic heritage. Additionally large volumes of particulate matter from the combustion process contribute to health impacts.

These environmental issues are important drivers to reduce energy use from fossil fuels. However, other drivers exist to create an economy less dependent on this energy source (partly extracted from (ASHRAE, 2009):

- Influence of commodities trading markets on spot and future prices
- Constrained natural gas reserves and growth in demand continuing to increase volatility in the natural gas market
- Climate change, through environmental pressure to reduce carbon emissions in the face of increased demand for electricity, and infrastructure damage from more frequent storms
- Fuel poverty. More than 4.5 million households in the UK are in fuel poverty, and Hills suggest it causes more than 25,000 winter excess deaths in the UK annually (Hills, 2012). Reduce use of energy in buildings will lead to more affordable prices of comfort.

It has been proven in some buildings, that providing comfortable spaces, does not imply the use of large amounts of energy. Reducing the energy use from non-renewable sources can be done by reducing the total energy demand of the building. For that, the building has to be designed in a way that makes the best use of the energy that is available on-site and present characteristics that maintain the comfort with little energy; this is in many cases something that relates several aspects of the design. An illustrative simplified example has been shown in Figure 2.1.

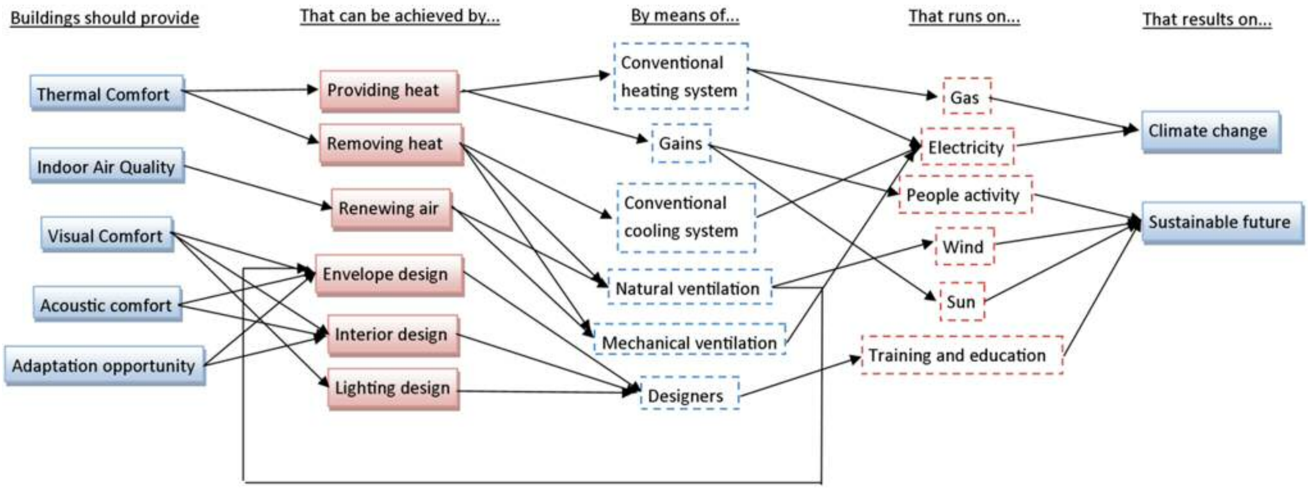

Figure 2.1 - Simplified example diagram showing how the provision of comfortable spaces relates several aspects of the design.

It can be seen from Figure 2.1, that several aspects of the building are related, and the effect of a decision in one space will have consequences in others. For example, big windows to facilitate ventilation have an effect on lighting and solar gains. This has been also described in (CIBSE, 2012) the several interactions happening between physical phenomena in buildings make interesting the possibility of evaluating several design decisions automatically to explore possible symbiosis.

Achieving low-energy buildings is therefore the result of a comprehensive design with a clear target in mind where building professionals with knowledge about building physics can contribute to the design on the early stage of the design, or by using a decision making tool that provides low-energy solutions to start with. This thesis will contribute with optimisation methods that take into account several factors of the building design and select the combinations that lead to more efficient and resilient buildings.

2.1.3 How to design low-energy buildings

Several institutions have published professional guides that help calculating the energy use of buildings and therefore allow identification of low-energy designs. Two of these institutions are the American Society of Heating, Refrigeration and Air Conditioning (ASHRAE) in the USA and the Chartered Institution of Building Services Engineers (CIBSE) in the UK. These institutions have published several books that gather scientific knowledge about building physics. With these text books, building scientists are able to understand and model the phenomena that will occur in the building and therefore estimate energy consumptions of potential designs, aiding this way the design process.

More deeply into low-energy building design, CIBSE guide F: *Energy efficiency in buildings* (CIBSE, 2012) has a more specific approach about efficient building designs. The Handbooks of ASHRAE do not include a specific volume for low-energy design.

In academia, two books represent the basics of building energy thermal calculations. Duffie and Beckman (Duffie and Beckman, 2013), focus on the thermal processes that occur in buildings due to solar radiation, and explain in detail the physics of the building elements. Clarke has also been influential in building energy simulation (Clarke, 2001). This book describes a large number of phenomena that occur in buildings and how they can be implemented in computers to be simulated. It should be also mentioned that in terms of detailed academic information about building physics, the Engineering Guide of Energy Plus offers a large compilation of algorithms and modelling techniques found in scientific publications that are used in this software (USDoE, 2013a).

These documents present common points that need to be fulfilled to achieve high efficiencies in buildings. Those points are described in the following subsections (partially extracted from (Levine *et al.*, 2007) and the previous references).

2.1.3.1 Design of the building envelope

The building envelope is the material barrier between the habitable zones and the outside of the building. It is the enclosure formed by walls and roof surfaces and their fenestration surfaces. The building envelope is the most important factor on the future lighting, heating and cooling demand of a building design. High levels of insulation, low levels of infiltration and an adequate design of the fenestration areas form the common *recipe* for low-energy buildings.

Walls, floor and roof are the largest components of the building envelope. Most walls and roofs in modern buildings include a thermal insulation layer to increase the resistance to heat flows due to regulation specifications; this insulation is key to achieve low-energy buildings. Floors also include insulation in most constructions to avoid the dissipation of heat through the ground.

The set and arrangement of different materials used in a wall is normally called its construction. The main characteristics of a wall construction concerning energy are its U-Value (units $W/(m^2K)$) and thermal mass (units $J/(m^2K)$). Although the structural layers of the walls (such as concrete, brick or wood) contribute to its resistance, a low U-Value will in most cases be the consequence of having an insulation layer in the construction[2]. A construction with an intermediate layer of insulation can be seen in Figure 2.2.

U-Values of walls and roofs have a large impact on the energy consumption what motivated the first regulations to lower heating demands in cold climates by U-Value limits for these elements (EEC, 1979)).

The second important characteristic of walls when studying the energy demand and energy related outputs, is their thermal mass. This property of walls plays an important role in how the energy flows occur in the building. The conditions of operation of buildings are highly cyclical because of the cycles of day and night in the outside, patterns of occupants inside the building. Heavy materials store part of the heat that goes through them, and release it when the temperatures are low. This is an effect that has been studied since the early years of building physics (Balcomb *et al.*, 1977). For a description on uses of the thermal mass of the building to reduce energy demands see Section 3.3.4 of (CIBSE, 2012).

[2] Some new construction materials, such as low density concrete or adapted straw-bale, claim to do both functions, and therefore eliminate the need of an insulation layer.

Figure 2.2 - Detail of a cavity wall construction with a concrete block inner face and a stone outer face with intermediate insulation.

The envelope of the building also includes **thermal bridges.** Thermal bridges are areas of the envelope that due to geometrical or material properties present higher thermal conductivity than the rest of the walls and roof. Examples of thermal bridges are the corners of the building where the area in contact with the exterior is larger, or balconies and exposed beams. The effect of thermal bridges can be reduced to achieve low-energy buildings through avoidance of complex geometries, minimising the number of corners by generating convex geometries, and avoiding elements that increase the surface area of the envelope such as balconies.

Windows are another important part of the building envelope and have a large impact in the total energy demand of the building. The aim of windows is to maintain contact with the outside and facilitate ventilation; also, windows allow solar radiation into the living spaces providing illumination and heat gains.

Glazing areas were already used by Romans in the first centuries to provide visual contact with the exterior and heat to living spaces in certain buildings. It is attributed to them the invention of the process of making glass plates, this was cited by Butti and Perlin in (Butti and Perlin, 1980):

“Certain inventions have come about within our own memory – the use of window panes which admit light through a transparent material”

Seneca, AD 65

Vitruvius suggested in his books of architecture to locate large windows areas in the south facades of roman baths, what can be seen as an attempt to use the solar radiation to produce a more pleasant sensation of warmth (Vitruvius, 2008). He wrote the following advice in the design of baths in his Book five, Chapter: 10 *Baths,* section 1, extracted from (Schofield and Tavernor, 2009):

“[…] the rooms for the hot and tepid baths should be lighted from the southwest, or, if the nature of the situation prevents this, at all events from the south, because the set time for bathing is principally from midday to evening.”

Vitruvius, circa 20 BC

Windows have a characteristic U-Value proportional to their heat conductivity. This value has been improved in the last decades with the introduction of double and triple glazed windows. Multi-layered windows were a big step forwards towards low-energy buildings.

The U-Value of windows is a measure of the conductivity of the whole window that includes the glazed area and frame. To deliver a window with low U-Value both parts have to be designed in accordance. Apart from the use of multiple layers of glass, including low emissivity coatings in the glass and thermal breaks in the frame can improve the U-Value of glazed area and frames of windows. A detailed set of U-Values of windows can be found in (CIBSE, 2006).

Single glazed windows have a U-Value of around 5.7 W/(m^2K), whereas high efficiency windows (double glazing) in the best case scenario have U-Values of the order of 1.5 W/(m^2K)(CIBSE, 2006). The heat loss through windows is independent to the heat loss through walls or infiltration, and therefore, any improvement in these elements will have an immediate impact in the energy needs of the building.

Windows also provide natural ventilation. Natural ventilation is a form of “free-cooling” of the building. However, it depends strongly on the outside conditions (mainly wind speed and outside temperature) and how the window opening is controlled. For information about “free-cooling” via ventilation see Section 3.3.6 of (CIBSE, 2012) and for control strategies of windows see Chapter 4.2.5 of the same guide.

Another important characteristic of the building envelope is the **air tightness**. Air tightness is achieved by good quality building elements, good design and quality workmanship (ASHRAE, 2009) (CIBSE, 2006).

The ASHRAE book *fundamentals* define infiltration as follows (ASHRAE, 2009):

“Infiltration is the flow of outdoor air into buildings through cracks and other unintentional openings and through the normal use of exterior doors for entrance and agrees.”

The exchange of air between the outside and the living zones has the positive effect of renovating the air of the house, pushing “used” air with pollutants and carbon dioxide out of the building and bringing in fresh air. However, the external air has a different temperature than the conditioned space. The energy needed to change the temperature of that mass of air can form a substantial part of the heating and/or cooling demand (up to 50% of the total energy demand for conditioning according to Levine and J. Rilling (Levine *et al.*, 2007). An infiltration value of 0.5 ach, what can be considered a common value for residential buildings in the US (ASHRAE, 2009), is equivalent to have a flow of air of 225 m^3/h of air infiltration[3], equivalent to 0.078 kg/s, and approximately an equivalent conductivity loss between the inside and the outside of 80 W/K (more than the conductivity losses of a 10 m^2 single glazed window).

The low-energy standard *Passivhaus* requires low levels of infiltration, and continuous air removal through mechanical ventilation equipped with heat recovery. Such systems eliminate the heat losses due to natural ventilation, as the occupants do not need to open windows to renew the air of the building. They also maximise the thermal comfort and air quality inside the building as the system works continuously unlike opening windows. As the air getting into the building is warmed by the air leaving the building (via the heat exchanger), the energy consumption need to provide conditioned fresh air is minimal.

To measure the air-tightness of a building, it is common practice to carry out a pressure test. This evaluation consists of pressurizing the interior of the building to 50 Pa over (or below) atmospheric pressure and measuring the air flow that is necessary to maintain that pressure difference. For more information about infiltration assessment and general air-tightness see (ASHRAE, 2009) and (CIBSE, 2006) respectively. An example of pressure test can be seen in Figure 2.3.

[3] In a building with 150 m^2 of total floor area and 3 m height.

Figure 2.3 - Three fans installed in one of the entrances of a recently refurbished supermarket to test its air-tightness. Bath, November 2012.

2.1.3.2 Improve the efficiency of appliances and lighting

As mentioned in the previous section, the occupants will always need to use electrical appliances and lighting. Improving the efficiency of those devices would directly reduce the energy consumption of buildings. It should be noted that incorporating high-efficiency appliances in a building might indirectly affect the cooling and heating demands.

There is also evidence for a rebound effect in improving energy efficiency of appliances, wherein domestic cost savings stemming from improved efficiency are spent on goods and services which directly or indirectly push up energy use, and thus linked emissions back up. A review of the rebound effect can be found in (Greening *et al.*, 2000).

The use of energy to run appliances and lighting is excluded in the consideration of zero-energy buildings in the UK, as this is considered as unregulated load. This can be seen in the report of the zero energy hub (ZCH, 2011).

Low-energy buildings do not eliminate the energy demand for heating or DHW and electricity; this has to be taken into account when zero-carbon housing is considered. For zero-carbon buildings, architectural design will need to include the deployment of renewable energy systems either on-site or off-site that produce carbon savings equal to the carbon emissions due to the energy used in the building (solar installations, ground heat pumps, etc.) resulting in net zero-carbon emissions.

It should be noted that the definition of zero-carbon buildings might be different depending on the assessment method and change for each country. The UK's government committed in its budget of 2013 (Treasury, 2013) to implement zero-energy-housing in 2016; however, this might happen through the so called *Allowable solutions* an option that has been considered as a set of solutions approved by the government that enhance carbon saving through external mechanisms such as social house retrofitting or renewable energy, this is regarded as a dilution of the initial definition of ZCH which was rewritten after 2010. For more information see (ZCH, 2011).

2.1.3.3 Behaviour change

The behaviour of occupants is an important factor affecting the energy use of buildings. The consideration of this is an important part of this thesis and will be addressed in Chapter 4 in more detail.

As an example of how behaviour may change energy demand, Socolow showed how different behaviours can change energy demand by a factor of two for the same building as early as 1978 (Socolow, 1978). More recent studies such as (Schnieders and Hermelink, 2006) shows an even larger variability (see Figure 2.4).

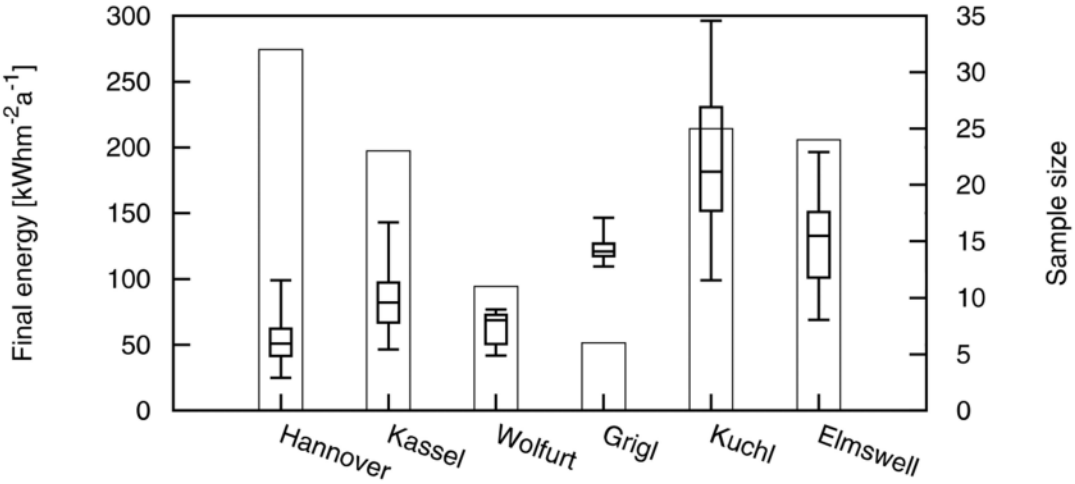

Figure 2.4 - Measured final energy consumption (candlesticks) of selected low-energy buildings (bars as sample size). The values contain all non-renewable energy supplies to the buildings, including household electricity and ancillary energy consumption. All data from the CEPHEUS data set (Schnieders and Hermelink, 2006) except the Elmswell data which is taken from Gill et. al. (Gill *et al.*, 2010).

Given the potential for behaviour to significantly impact on demand then considering how different behaviours might influence energy use in a particular building design is an essential element calculating the likely energy consumption of that design. To achieve low-energy housing it is necessary to educate the occupants, therefore creating low-energy building users.

A recent study by Coley et al. showed how the behaviour of the occupants can also substantially change the impact of climate change will have on buildings (Coley *et al.*, 2012).

Apart from the passive thermo-dynamic behaviour of the building, low-energy buildings have to be coupled with energy systems that run in renewable energy to achieve zero (or close to zero) carbon buildings. These systems have not been included in this thesis, but other text are available that describe them (see for example (Boyle, 2004))

2.1.4 A successful story: The Passivhaus standard

The *Passivhaus* standard is a low-energy building concept developed by Dr Wolfgang Feist and Prof. Bo Adamson in the late 80's. The Passivhaus concept was the result of the search for a highly efficient dwelling that could provide thermal comfort and good indoor air quality with little heating demand, and could be produced at a low cost. The first prototype, occupied in 1991, had a heating demand of less than 15 kWh/m^2 per year, the IPHA shows that that figure did not increase until 2010 (IPHA, 2010).

More than 13000 buildings have been erected using this standard (IPHA, 2010). The popularity of Passivhaus has motivated the development of a certification scheme to help contractors with the selection of the components such as insulation and windows used in these buildings, (the documents that specify the certification schemes are available in the Passivhaus Institute website[4]). A spreadsheet is also available to verify the energy consumption of designs created under this standard (Feist *et al.*, 2007).

There exist a variety of guidelines for the creation of a Passivhaus design. However, the main principles can be summarised in three rules (from (IPHA, 2010)):

- Eliminate thermal bridges and infiltration
- Use Passivhaus windows with U-Value <0.8 $W/(m^2K)$ and achieve low U-Values in the fabrics
- Use mechanical ventilation with heat recovery with efficiency > 75%

Although this may look a rather simple set of rules, the quality of workmanship that is needed to achieve the necessary levels of infiltration, insulation and thermal bridging has to be outstanding.

Following the principles of Passivhaus one can achieve great energy savings. Figure 2.5 shows that despite the variation due to building use, the average of energy use in Passivhaus is significantly smaller than the average of traditional low-energy buildings. Not only that, the worst case shown in this graph for passive house is significantly better than the best case in traditional low-energy building practice.

[4] http://www.passiv.de/en/index.php (Accessed on the 3rd of October 2012)

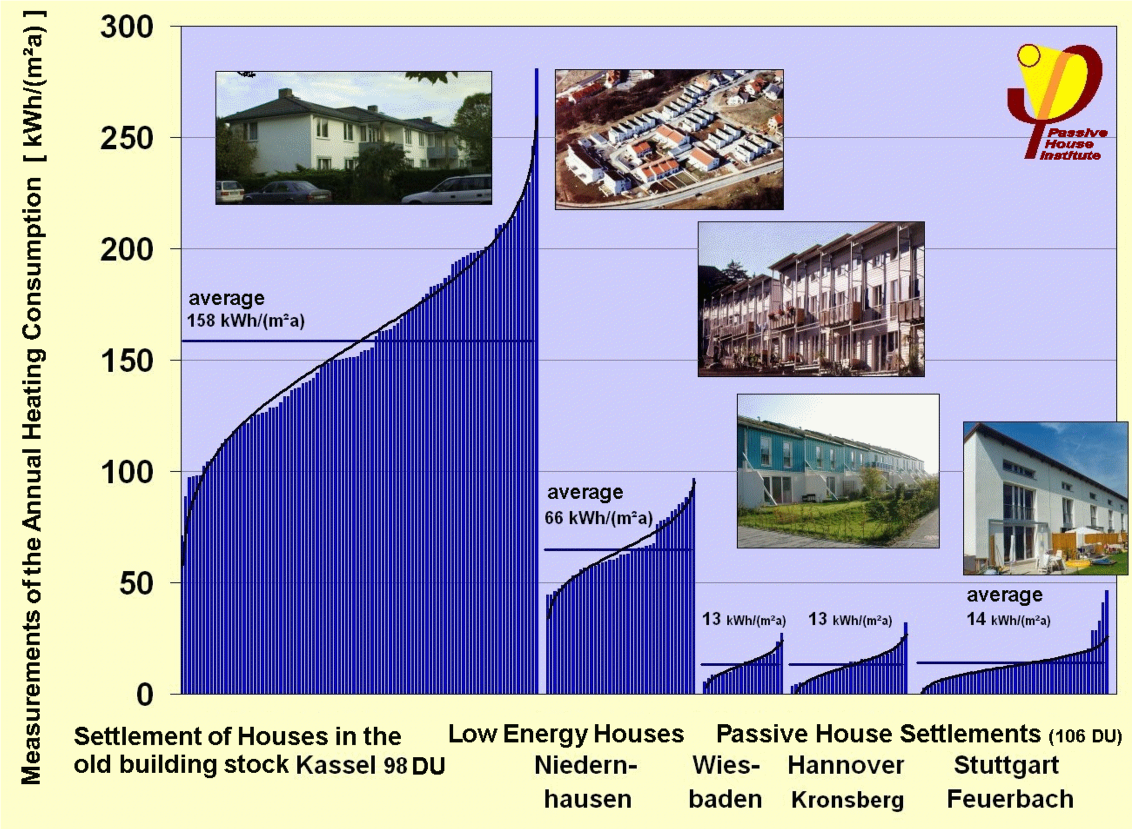

Figure 2.5 - Statistical results of measured energy demand of low-energy buildings and Passivhaus from: (Feist, 2013).

Building scientists are aware of the fact that differences could exist between the predicted energy demand of a design and the real energy demand of the occupied building. To verify the validity of the *Passivhaus* standard several buildings with this standard were evaluated under real occupation in the CEPHEUS study (Schnieders and Hermelink, 2006). The buildings analysed in this study showed an average heating demand close to 15 kWh/m^2 (within the objective of the *Passivhaus* standard). However, a substantial variability was observed on the different samples (see Figure 2.6).

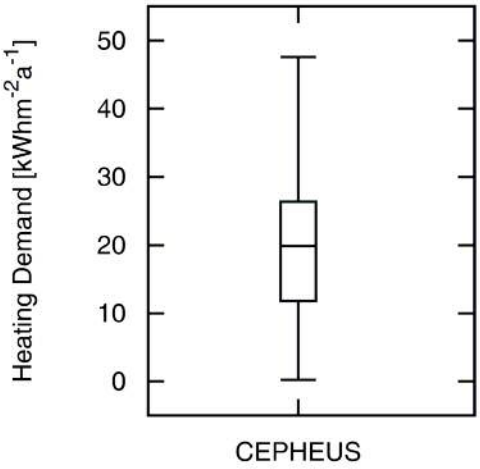

Figure 2.6 - Variability of the heating demand in the data from the CEPHEUS study. The quartiles represent the 25%-75% interval, and the intermediate line the median.

The CEPHEUS study shows that occupants' behaviour still plays an important role even in very low-energy buildings and that designers should take this into account when performing design. One of the methodologies shown in this thesis emphasises in this factor.

2.1.5 Salient issues for the new low-energy buildings

Low-energy building designs rely on high levels of insulation and low infiltration. In *Passivhaus* buildings the heating demand has the same order of magnitude as the casual gains, namely: solar, electric and metabolic gains (IPHA, 2010). The designs account for these "free" gains, as they contribute to maintaining the thermal comfort of the living areas. In the case that those gains differ in magnitude from the ones considered at the design stage, a substantial variation on heating or cooling demand might occur. For example in the case of overheating the households have to be able to increase the exchange of air with the exterior to cool down the building, the designers will have to consider this. Occupants may produce very different gains depending on the building use and their habits, and the building has to be designed in a way that comfort will not be compromised when different occupants move to the house.

The risk of overheating in low-energy buildings may also be exacerbated – in the long term – by climate change. A rise in temperatures together with the reduction of days with overcast skies may turn a good design, into a non-comfortable house in the future. De Wilde has looked into this in several publications (de Wilde and Coley, 2012; de Wilde and Tian, 2012).

Air quality is another salient problem in low-energy buildings. Poor air-tightness results in infiltration and these results in a substantial renewal of the air in a living space even if occupants do not open the windows. In low-energy buildings, infiltration has to be reduced to a minimum. When such low levels of infiltration are achieved, the designer has to account for the fact that the air will not be renewed naturally, controls might be placed in windows for automatic opening, or mechanical ventilation systems with heat recovery could be installed (as suggested in the *Passivhaus* standard).

Some authors have found out that saving on heating can also lead to a *rebound effect*. Greening et al. (Greening *et al.*, 2000), showed that technological improvement of the 100% in fuel efficiency for space heating would lead to a take-back value between 10% and 30 % what means that the improvement in the system efficiency will actually show within an interval from the 70% to the 90%. Haas and Biermayr showed that the rebound effect has been seen in space heating with a value of 25% in Austria (Haas and Biermayr, 2000). The rebound effect has not been considered in this thesis. However, its importance in low-energy building design is acknowledged.

2.1.6 Conclusions

Approaches such as the Passivhaus standard have demonstrated that it is possible to design successful low-energy buildings.

This new paradigm of housing will bring new problems to the sector that will need to be solved to achieve the goal of comfortable low-energy housing. However, it is a fact that it is possible to create low-energy buildings, and with this, reduce the energy demand of the domestic sector. These designs will need to follow the principles mentioned in previous sections.

Occupants' behaviour will remain a fundamental aspect of the energy use of a building even in low energy buildings. Fortunately, the tools to model those behaviours are available and will allow building scientists to predict realistic figures (this will be described in Chapter 4).

Buildings are becoming much more precise products than they were 30 or 40 years ago. The quality of the components and workmanship will need to be selected to a high standard to achieve the standards and regulations that have been put in place to achieve low-energy buildings. Also, the large amount of cutting-edge technologies available (such as phase-change materials, glazing with electronically controlled shading, or renewable energy micro-generation systems), require a deeper knowledge about the physics of the building. Overall, the accuracy at which building designs are conceived at the present, suggest that the uncertainties that influence these designs should be, at least, quantified and their impacts assessed. De Wilde and Hopfe (de Wilde and Tian, 2009), (Hopfe and Hensen, 2011) agreed that occupants' behaviour is an important uncertainty in the operation of buildings. The selection of this uncertainty as the main one to develop the methodologies in this thesis will be justified in Chapter 4, where the literature about uncertainties in building design and building operation is discussed.

Buildings that are designed taking into account possible uncertainties will result in more reliable solutions. Such reliability is critical if low energy philosophies are to be adopted with minimum resistance. Put simply, there is a need for such designs to be low energy on practice, not just in the drawing board.

2.2 Energy demand assessment methods for building design

The oil crisis of the 70's started a period of interest in the reduction of energy use. The building sector was noted for spending a substantial amount of money for heating in countries with temperate and cold climates, which in turn motivated the scientific community to enhance the understanding of how to reduce buildings' energy demand (such as (Ayres, 1977; Balcomb *et al.*, 1977; Jurovics, 1978; Kronvall, 1978)). The recent awareness of climate change has revived this interest.

This growth of knowledge about building energy use (and building physics in general) has come together with the development of computational tools that allow for the modelling and simulation of buildings. Currently building simulators are detailed and potentially accurate tools, that (when used properly) are able to model buildings and their systems, taking into account most of the aspects that influence their thermodynamic response (see for example (Crawley *et al.*, 2001).

This chapter briefly describes the types of energy assessment tools available at the time of writing.

2.2.1 Historical background

Before building simulators and building models were available, architects and engineers had to use hand calculations and empirical correlations to estimate the energy demands during the life cycle of the building. Unfortunately, those methods usually led to oversizing of the heating and cooling plants due to the need to apply safety factors to ensure that the systems would cover the real loads in the case that the calculation was in error. Oversized heating and/or cooling plants could work at lower efficiencies with a consequent poor use of the primary energy source. This was therefore a poor design technique.

The deployment of digital computers in universities and research institutions created a broad range of new possibilities in the estimation of energy use of buildings. Building scientists developed more complex assessment tools with the aim of achieving more accurate estimations of the energy use. As an example of the impact of digital computers in the discipline the reader is referred to Kusuda (Kusuda, 2001), which describes the impact of digital computers in his personal career.

The deployment of computers allowed the development of building energy simulators: first as simple tools, and eventually, as complex suites able to model all relevant physical phenomena of buildings. Clarke summarized the developments on energy building simulators in his book (Clarke, 2001), and separated the evolution of them into four different generations, Table 2.1 shows this classification:

Table 2.1 - Evolution of energy building simulators. Adapted from (Clarke, 2001). Italics are my contribution.

Generation	Characteristics	Consequences	Period
1	• Handbook orientated • Simplified and piecemeal • Familiar to practitioners	• Easy to use • Difficult to translate to real world • Non-integrative • Application limited • Deficiencies hidden	before 70's
2	• Building dynamics stressed • Less simplified • Still piecemeal based on standard theories	• *Larger applicability* • *Grey-box tools for practitioners*	70's
3	• Field problem approach • Shift to numerical methods • Integrated modelling stressed • Graphical interface • Partial interoperability enable	• Increase integrity vis-á-vis the real world • *The user starts losing perception of the algorithms of the simulator (black box)*	80's
4 and beyond	• Good match with reality • Intelligent knowledge based • Fully integrated network compatible/interoperable	• Deficiencies overt, • Easy to use and interpret • Predictive and multi-variate • Ubiquitous and accessible • *Blind faith to results: the simulator is now a total black box for the less-educated user* • *The complexity of the simulator might make users not to question the results*	90's and beyond

An example of a second generation simulator is the one by Balcomb et al. where the thermal behaviour of a building heated with solar gains is modelled with simple equations (Balcomb *et al.*, 1977). This paper has only six references, with only four of them related to building physics, which shows that there was a rather limited amount of literature available on this topic at the time. Just one year after Balcomb's paper, Johnson published another paper focused on studying the thermal storage in buildings (Johnson, 1977), this shows that there was some interest in the dynamic behaviour of buildings.

Ayres (1977) published the paper '*Predicting Building Energy Requirements*' in the first issue of a journal that would became one of the most influential of the discipline, the journal was *Energy and Buildings* (Ayres, 1977). This paper shows the options that were available in 1977 for building scientists to calculate heating and cooling loads, and the energy demands of buildings. The software packages mentioned in the paper are rather limited (four) and the author points out their poor usability. It could be said from reading this paper, that building professionals did not have the appropriate tools at this point to make the assessment of building energy use.

The third generation of building simulators (from the 1980's) is described in the review "*Advances in Building Energy Simulation in North America"* by Winkelmann (Winkelmann, 1988). Comparing this review with its predecessors of the late 70's, one notices how building simulators have evolved to powerful tools that are now used by researchers and practitioners. The availability of more computer power allowed the solution of multi-zone nonlinear thermo-dynamic problems including radiation or/and convection phenomena. This blossoming of software packages was possible because of the development of personal computers.

Winkelmann showed a variety of simulators in his work; their working principles and approaches to solving the physical equations are different depending on the use intended[5]. It is important to note, that TRNSYS is already mentioned in Winkelmann's review as one accurate approach to solving some of the transient physical phenomena occurring in buildings. This software is still in use and it is well known for its flexibility and accuracy (examples of the use of TRNSYS currently are: (Asadi *et al.*, 2012; Beausoleil-Morrison *et al.*, 2012; Pagliarini *et al.*, 2012)). DOE-2 is also mentioned in this review, and is also currently in use, as part of EnergyPlus and as a standalone tool. The availability of computer power, and the need of including routines to solve complex physical problems, have made complex software packages as the two mentioned before to grow in complexity with the consequent growth in computational time, when used to simulate energy use in buildings.

[5] He mentioned the software *GEMS*, that uses state-space approach to solve the differential equations that govern the building physics (the state-space formulation is considered a modern control theory method here). This approach has lost popularity over the years, but it is of high relevance for this thesis (Chapter 6).

In the same journal issue where the review by Winkelmann can be found, Newton et al. highlighted the importance of using building simulators in an appropriate manner (Newton *et al.*, 1988). This paper, written from the perspective of building simulator users, is a word of warning about how this software has to be used to get useful outcomes. This point can be read in sentences like the one on page 241:

"The naive user is as likely to be misled as helped"

or on page 243:

"…the choices of climatological data and occupancy patterns are not easy and, in many cases, there is no single correct value."

Contrasting Newton's paper with Winkelmann's, it can be seen that the deployment of comprehensive building simulators comes with the risk of using them inappropriately, potentially leading to erroneous outputs and thus misleading predictions of the energy consumption of buildings.

Newton's paper describes the steps that professionals using energy building simulators should follow to provide accurate answers to the problems at hand. Those steps are still recommended 24 years later by software developers (DoE EnergyPlus getting started pp.33-45 (USDoE, 2013b)).

To conclude this historical overview of the evolution of building simulators, the reader is referred to the work of Crawley. In this review, Crawley undertook a comprehensive study of the capabilities of the 20 most popular simulators in 2008 (Crawley *et al.*, 2008). This review can be used to find the most adequate simulator for a given problem. Also, it is the most modern review of the capabilities of building simulators at the time of writing this thesis. To get an up-to-date list of features of the building simulators the reader is referred to the software tools directory of the website of the Department of Energy of the USA[6].

The popularity of personal computers and the improvements in energy building simulators have made their use common place. So now, architects and

[6] http://apps1.eere.energy.gov/buildings/tools_directory, accessed on the 8th of January 2013.

engineers have complex building simulators available able to simulate the complex physical phenomena of a building. However, the statements quoted before from Newton's work are still true. As examples: trusted weather data needs to be found for an accurate building simulation, this is now a real problem with the uncertainty induced by climate change (this will be treated in Section 2.6.4, but for an example see (de Wilde and Coley, 2012)); and also, the occupancy patterns are difficult to predict, yet have a great impact on heating, cooling and other energy demands (this will also be described in Section 2.6.4, as an example see (Schnieders and Hermelink, 2006)).

Building simulators can be classified in a variety of ways. The next section describes how the different building simulators available currently can be classified; this classification will be used to differentiate the steps taken by the methodology described in Chapter 5.

2.2.2 Classification by model creation method (from ASHRAE)

The first classification is done by how the model of the building is created for the simulation.

ASHRAE's (ASHRAE, 2009) handbook of fundamentals divides building simulations into two groups by the approach taken:

1. Forward approach: The forward, or traditional, approach consists of creating a mathematical model using physical equations of behaviour then obtaining the outputs of the simulation using the appropriate inputs. This is sometimes called first principles modelling.
2. Inverse approach: The inverse or *data-driven* approach consists of obtaining a mathematical model of the building that fits best the inputs and outputs observed from the operation of the building post-construction. Inverse modelling includes machine learning and greybox modelling.

The **forward approach** is the most popular form of building simulation. Building elements and building energy systems are modelled in this approach with their equations of behaviour normally derived from physical laws. The fact that this simulation approach is based in the laws of physics makes this method largely "credible" to engineers and building scientists. This can be seen in the popularity that some of the simulators, for example: IES-Virtual Environment, EnergyPlus, DOE-2, ESP-r or TRNSYS, enjoy.

With these simulators, the calculations are very detailed, and therefore computationally costly. The users need to be aware of the importance of all the inputs in this kind of simulation, because, in contrast to data-driven simulators, forward simulators build the whole model with the inputs that the operator introduces. A misleading description of the building can lead to mistaken results (providing the right answer to the wrong question).

Data-driven simulations are used mainly in research. Data driven approaches are empirical. These models are able to represent very accurately the dynamic behaviour of a building for a given set of conditions (weather, occupants, etc.). However, the principles are completely different. Inverse models do not solve the equations given by the physical phenomena that occur in the building. Instead, a basic model is produced and tuned using the inputs and outputs to get the best approximation. A good example of inverse simulation is the work done by Coley et al. in (Coley and Penman, 1992). Coley created a model topology that was eventually tuned to produce the most accurate response compared with a building. Normally, data-driven models need to be rather simple models, as the information available (data series) are rather redundant and may not include enough information to adjust a large number of parameters (see Coley's example).

Data-driven models have several limitations. The individual elements of the building (such as windows, walls and infiltration) have to be grouped together into a few elements within the model. Therefore, it is difficult to evaluate the changes in the outputs that a change in a single element will produce. Also, data-driven models need data from the building after its construction, what make these models not usable for the evaluation of future designs.

The advantages of data-driven models are their low computational times. These models, having a small number of parameters, are usually easy to solve numerically. In addition, the fact that the models have been obtained to match real data, makes their accuracy comparable to forward models. Overall, this type of simulation, when available, represents reality well at a very low computational cost. This approach has not been used in the present thesis, instead, Chapter 3 shows a methodology for creating reduced models (like the ones used in data-driven simulations) by a direct approach and with the aim of achieving accuracy at a very low computational cost.

2.2.3 Classification by the levels of dynamism of the model (from CIBSE)

The second classification has been extracted from the guide to environmental design (CIBSE, 2006), and considers the models used to represent the building physics. The classification is:

1. Steady state models
2. Cyclic models
3. Transient models

This differentiation is more related with the level of simplicity and therefore the computational time needed for each model. **Steady-state models** have the form of calculation methodologies that use averaged values to estimate heating and cooling loads roughly. This kind of calculation can be useful at an early stage of the building design, but does not have sufficient accuracy to perform more detailed analysis of the energy requirements at later stages of design.

Cyclic models take advantage of the repetitive response of buildings due to the periodicity of the inputs such as outside temperature and gains. The CIBSE cyclic method is described in Section 5.8 of the CIBSE guide of Environmental Design (CIBSE, 2006). This method, despite its simple approach, is accurate for predicting energy loads and demands and inside peak temperatures compared with real buildings according to (IEA, 1991).

Transient models are able to represent the dynamic response for realistic statements of weather and gains. To produce such a detail, the simulator has to solve the equations of the model for every time-step. These models provide a very detailed output of the energy related variables but at a substantial computational cost. This approach is the one used by direct simulators such as IES-<VE> and EnergyPlus.

2.2.4 Classification by complexity

After studying the previous classifications, a large gap was noticed between transient simulators and the combination of steady-state and cyclic models in terms of model fidelity. There is a big difference in complexity between these two groups, a difference that is reflected in the computational times that each of the two groups need. Also, it has been seen that there is no room for simple dynamic simulators (using the so called Lumped Parameter Models -LPM- as the one used in (Coley and Penman, 1992)) in this classification, when they could be understood as an intermediate option between the complex transient simulators and the more simple steady-state and simple models.

As one focus of this thesis is how to produce more efficient ways of running optimisation of energy designs and as these are highly sensitive to the computational time needed for the simulator, a different classification was developed and applied in this thesis; this is built over computational time that is proportional to complexity. Although this has not been proven, it is expected that a user of this tools with the appropriate knowledge will obtain more accurate responses using the tools with the higher complexity.

The new way of classifying building simulators includes the simple simulations based in LPMs. This classification is focused in the complexity of the physical models that are used to represent the building. It is as follows:

1. Calculation based methodologies: The calculation based methodologies are sets of algebraic equations that give the energy demand of the building over a given period, normally a month. Only the main physical parameters of the building are used (such as U-Values or internal gains summaries). The application of these methodologies is straight forward, and they should be the first step for investigating the energy use of a potential project. Examples of these are the SAP, the LT method, degree day calculations or PHPP.

2. RC-network based simulators: These simulators use an electric network equivalent that uses representations of resistors and capacitors to model the behaviour of the building elements. An RC-network is a model based in the analogy that can be established between electrical current and heat flow. This is a linear first order differential model that can be solved with linear integration methods (state-space formulation, see (Ogata, 2002)). The author is

not aware of commercially available building simulators that use these kinds of dynamic models at the time of writing. The advantages of these simulators are their short computational times and their ease of implementation as computer code.

3. Benchmark simulators: Direct simulators that model most of the physical phenomena in the building. The results of these simulators are in most cases accepted by the building community as the most accurate. Examples of these simulators are IES - <VE> or EnergyPlus.

As it could be extracted by this definition of the three groups, this classification looks mainly into the computational time required for each type. When the different kinds of calculations are compared qualitatively on computational time and model fidelity, a graph like the one in Figure 2.7 can be generated.

This classification is used in Chapter 5 of this thesis, so the three groups will be further detailed in the following subsections.

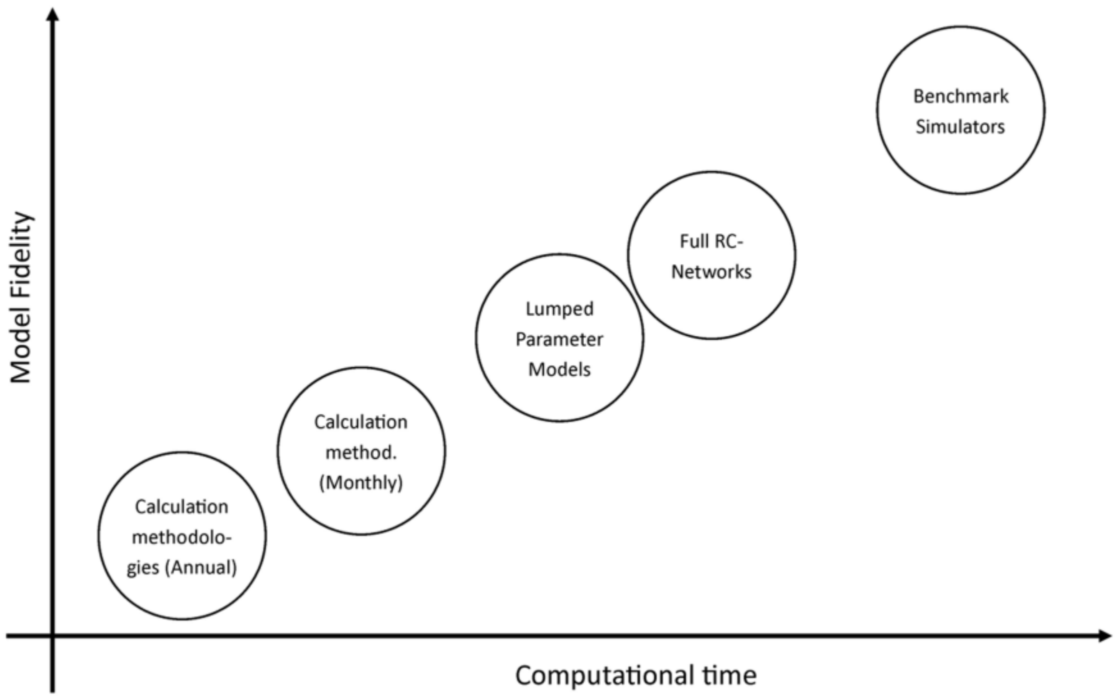

Figure 2.7 - Building simulators. Model fidelity VS computational time.

Although the computational time will depend on the project simulated, typical values might be:

- Calculation methodology (LT-method): 0.001 seconds. The computational time with these methods is normally dismissed and considered immediate.
- LPM simulator (5 resistors 4 capacitors): 0.017 seconds. The LPM calculation is constant as any building is reduced to a model with the same complexity.
- Benchmark simulator (EnergyPlus): 18 seconds. This value is characteristic for simple models (as the one described in Chapter 6). However, EnergyPlus simulations can take much longer than this perhaps in the order of several minutes. The calculation of more complex physical processes such as airflow networks is the reason why these simulators can need much larger times.

These values are included here for illustrative proposes but the reader is directed to Chapter 5, where the three types of simulators are used for a given problem.

2.2.4.1 Calculation methodologies

As mentioned before, calculation based methodologies are sets of equations that allow the estimation of heating and cooling demands. The most simple calculation methodology is the one that calculates the overall conductivity of the envelope, and multiplies this value by the temperature difference between inside and outside. However, this will only provide a basic estimation; more complex calculation methodologies are available. The LT method is described here as it will be used in further sections of this thesis.

Example of calculation methodology: The LT method

The LT method was created by Nick Baker for the European Architectural Ideas Competition “Working in the city” as part of the ARCHISOL program that was coordinated by the Energy Research Group of the University College of Dublin. This was founded by the Commission of European Communities.

Detailed information about this method, together with application examples can be found in Baker’s book: *Energy and Environment in Architecture: A Technical Design Guide* (Baker and Steemers, 2000).

The LT method is a design tool for non-domestic buildings, especially suited for office buildings. The method is able to model buildings in several locations with different fenestration levels. However, the gains from occupants and constructions of the walls are always considered the same (Table 3.2).

This method provides heating, cooling and lighting demands for the zone studied. Several graphs are provided to graphically obtain a set of factors that allow the calculation of the annual energy demands of the zone.

The graphs provided with the LT method have been obtained by solving a simple mathematical model of a given configuration of an office in different locations and with different glazing characteristics. It should be noted that the method assumes that there is no heat transfer between the zones studied as they are considered to be at the same temperature.

The architectural characteristics of the office modelled to create the curves of the LT method can be seen in Table 2.2, any office building with different characteristics as the ones in this table will present different lighting, heating and cooling demands (specially the last two).

Table 2.2 illustrates the limitations of the LT method. None of the parameters of this table can be changed; therefore its use is not recommended in the case that any of those parameters in the real building differ substantially with the ones in the table.

The LT method is similar to the slide rules that were used in the 50's and 60's: quick calculation methodology, with which the solutions are obtained by interpolation of a series of "true" points that have been evaluated with a more complex method, or have been tested in real life experimentation. In the case of the LT-method, the "true" points are calculated with a simple mathematical model that uses monthly averaged values in a steady-state case.

Table 2.2. Parameters assumed in the LT method.

Building Envelope	U – value [W/(m^{2}K)]	reflectance
exterior walls	0.6	0.4 (inside)
interior walls	0.0	0.4
ceiling	0.0	0.6
ceiling (roof)	0.6	0.6
floor	0.0	
glazing, single	5.7	(the user can select between the two)
glazing, double	3.3	(the user can select between the two)
Zone height		
room height	3m	
Gains related parameters		
external ground reflectance	0.2 (constant over year)	
ventilation rate	1 ach (constant over year)	
occupancy	10 hours/day (09:00 – 19:00)	
non-lighting gains	10 W/m^2	
datum illumination level	300 lux	
installed lighting density	15 W/m^2	
Plant related parameters		
plant efficiency for heating ratio	0.70	
plant efficiency for cooling ratio	2.25	
electricity cost (primary) ratio	3.70	
heating fuel cost (primary) ratio	1.05	

2.2.4.2 Thermal networks and Lumped Parameter Models

Thermal networks or RC-networks are models that represent buildings with equivalent analogue computers. These models have been largely used in the last few decades for research proposes. RC-networks not only provide a more intuitive representation of the building thermal elements they also allow Kirchhoff's laws to be applied and state-space formulations for their resolution.

This type of simulator will be developed further in Chapter 3. In that section, a methodology will be described, that allows the creation of the models used by simulators based in RC-networks. The way of creating simple Lumped Parameter Models analytically from complex RC-network is part of the main contributions of this thesis.

As shown in the historical background (Section 2.2.1), these kinds of simulators were substituted progressively by more complex simulators that offered larger model fidelity. This together with the availability of larger computation al resources moved researchers and professionals towards those complex simulators under the assumption that larger model fidelity could lead to larger accuracy, leaving those simulators based on RC-networks left for application in which the computational times needed to be short. The reasons why professionals moved to those simulators could be many and very diverse, one could think that the fact that complex simulators include more physical phenomena makes the tools more attractive for their users. About this movement towards more complex simulators the reader can read the references (Kusuda, 2001), (Clarke, 2001) (Ayres, 1977) (Newton *et al.*, 1988). and (Crawley *et al.*, 2008).

It should be noted that despite the fact that simulators based in RC-networks are less popular, these models are still used in research and some software applications (as in (Robinson *et al.*, 2009)).

2.2.4.3 Benchmark simulators

Crawley et al.'s review of benchmark simulators lists the building energy software that is available at the year of that review (Crawley *et al.*, 2008). From 2008 to the time of writing there have not been qualitative improvements in the capabilities of the simulators, instead, their developers are focusing on adapting them to be more accessible to architects and engineers and also in developing additional modules to aid building design (such as optimisation modules embedded in the software). Currently, building simulators offer a large possibility of options and perform a comprehensive analysis of the phenomena that occur in the real building, this allows building scientists to perform detailed analysis of the energy use of buildings.

These types of simulator have been called benchmark simulators in this thesis as these are the most complex simulators available at the time of writing and therefore the ones with the largest model fidelity. However, this does not imply a greater accuracy. These simulators have to be used by educated users with the right inputs (that are not always available) to get accurate answers. The obvious step forward in accuracy after models with high fidelity is real data; however this option is not possible when performing optimisation for building design.

The four main software packages found in the literature relevant to this thesis that fall into this category are ESP-r, TRNSYS, IES-<VE> and

EnergyPlus. Only EnergyPlus has been used in this thesis. Therefore, a brief description of this software will follow.

Example of benchmark building simulator: Energy Plus

EnergyPlus is a building simulator created to unify two packages previously available for energy building simulation: BLAST and DOE-2. This simulator will be used as the most accurate one in the sequential optimisation methodology presented in Chapter 5.

The aim of EnergyPlus' developers was to create a flexible and modular building simulator that encourages and facilitates researchers to contribute to the extension of the software. EnergyPlus uses a hierarchical system that controls several modules, which communicate using simple and clear information exchange (plain text files).

The developers of EnergyPlus include the following list of its main characteristics (transcribed from (USDoE, 2013b)):

- Simultaneous calculation of building dynamic response and energy systems.
- An adjustable time-step for dynamic simulation accuracy;
- Text-based inputs and outputs;
- Dynamic simulation based on heat balance equations, allowing the calculation of the three heat transfer mechanisms (conduction, convection and radiation) simultaneously in every component;
- Calculation of conduction through solids using heat transfer functions;
- Detail study of heat transfer through ground available.
- Algorithms for heat and mass transfer available to calculate moisture absorption in fabrics.
- Availability of several thermal comfort models.
- Improved calculations of insolation on tilted surfaces using an anisotropic sky.
- Implementation of cutting-edge technologies to control solar gains in glazing, such as shading controllable devices or electrochromic control
- Complex daylight controls available
- User defined loop-type HVAC systems that allow a great flexibility on design

- Pollutants calculation module.
- Links to other software that performs more detail analysis of specific components.

The most important conclusion after this list is that EnergyPlus offers a high degree of detail in the simulation when it is required by the user. In the case of aiming for simple simulations, EnergyPlus can be a very quick-to-run early stage tool. This simulator can carry on an annual simulation of a single-zone building in around 10 seconds on a desktop computer (Pentium 2.5GHz).

An important characteristic of EnergyPlus that should be highlighted for its relevance in this research is that it “communicates” with the user with text-based files; this makes it simple to create machine-to-machine interfaces when the simulator is integrated within a larger framework with more routines working together, for example, as part of an optimisation algorithm.

EnergyPlus is a low-level simulator, meaning that the simulator will only do what the user asks for, it does not make any evaluation or analysis of the inputs; therefore, the software should be used with care, always understanding that the inputs that have been chosen are appropriate. Otherwise the results would not have any validity (“garbage in, garbage out”). To aid the user, EnergyPlus offers a detailed documentation of the code. This documentation of more than 2000 pages allows users to understand what the simulator is doing at each stage with each element of the model. However, it shows the level of complexity that simulators can achieve, and how well trained the user must be to produce the appropriate input files and the correct interpretation of the results.

This high level of model complexity/fidelity that can be very positive for researchers might be a barrier for professionals. Other software such as IES are more black-box style, and the user is unaware of some of the decisions that are taken by default. Instead of that, in EnergyPlus, one has to understand precisely the problem, and implement all the parameters one by one, as a new EnergyPlus input is a blank page with not predefined inputs. Graphical interfaces have been developed to overcome this barrier to usability the main two are DesignBuilder (commercial proprietary software) and Open Studio which uses Google SketchUp as graphical interface, developed by NREL and released as free software.

The input of EnergyPlus is a text file (with ".idf" extension) that includes the *objects* of the simulation and is written in plain text. The objects of EnergyPlus are the building blocks that, as individual units, build the whole model and simulation. An example of an EnergyPlus object can be seen in

Figure 2.8, this object represents internal gains due to electric equipment.

```
ElectricEquipment,
    Electric,                !- Name
    ZONE ONE,                !- Zone Name
    AlwaysOn,                !- Schedule Name
    EquipmentLevel,          !- Design Level Calculation Method
    50,                      !- Design Level {W}
    ,                        !- Watts per Zone Floor Area {W/m2}
    ,                        !- Watts per Person {W/person}
    ,                        !- Fraction Latent
    ,                        !- Fraction Radiant
    ,                        !- Fraction Lost
    General;                 !- End-Use Subcategory
```

Figure 2.8 - EnergyPlus object: Electric Equipment.

Each objects contained in the input file may produce one or more outputs, these depend on the kind of objects e.g. the object of Electric equipment produces electric power output in the three components, latent, radiant and convective.

The element in Figure 2.8 would produce, among others, an output of the hourly power used by electric equipment; a window will produce, among others, the output of power gain through solar radiation every time-step, etc. The user can decide the outputs that are written to the output file and the ones that are dismissed to save computational time.

EnergyPlus has been the software selected in this thesis when a benchmark simulator was needed. EnergyPlus has been coupled in this thesis with an optimisation routine in Chapter 4 and Chapter 5.

2.2.5 New trends in building modelling

A new trend in building simulation called Building Information Modelling (BIM) should also be noted. These are computational models of buildings in which a large amount of information is stored about the design. In these models, not only the thermal characteristics of the materials will be available, but also information such as cost, supplier, weight or any other parameter that could be relevant for the project. This is similar to what is done in simulators for product design such as SolidWorks or Inventor where a single software package tends to store all the information of the product to be developed.

The fact that more information is available in BIM environments makes more feasible the use of optimisation techniques that look into optimising several parameters such as energy use cost of materials logistics or construction time using multi-objective optimisation (will be explained in Section 2.3).

2.2.6 Conclusion

Building simulators have been improved in the last forty years and are now able to model almost all the relevant energy-related physical phenomena occurring in buildings. Also, they have now included detailed user interfaces that make for more intuitive input of designs and therefore facilitate the overall analysis of the energy use in each design. Users have been pushed away from the underlying physical principles that govern the phenomena occurring in the building, and in most cases only interact with the graphical interfaces. Not only that, but the software packages are moving one step forward and implementing optimisation packages in their software developers, aiming to facilitate the whole design process.

The current building simulators have improved greatly in complexity as they are able to represent reality in a very complete way. Phenomena such as long-wave radiation reflection, phase changing materials or radiation are examples of processes that are modelled by some of these simulators. However, it should be taken into account, that there exist uncertainties in the inputs that are used in each simulation, and those uncertainties have to be introduced with the same level of accuracy that the simulator uses to calculate the outputs. The improvement in the accuracy of the simulators will reduce the errors due to modelling and simulation but will not reduce the errors due to mistaken or imprecise inputs. One could think that the point in time at which the errors due to uncertainty in the inputs (this will be explained in Chapter 4) and the errors due to poor physical modelling (when the epistemic and aleatory uncertainties are reduced to zero) modelling and simulation crossed have already happened. This is illustrated in Figure 2.9.

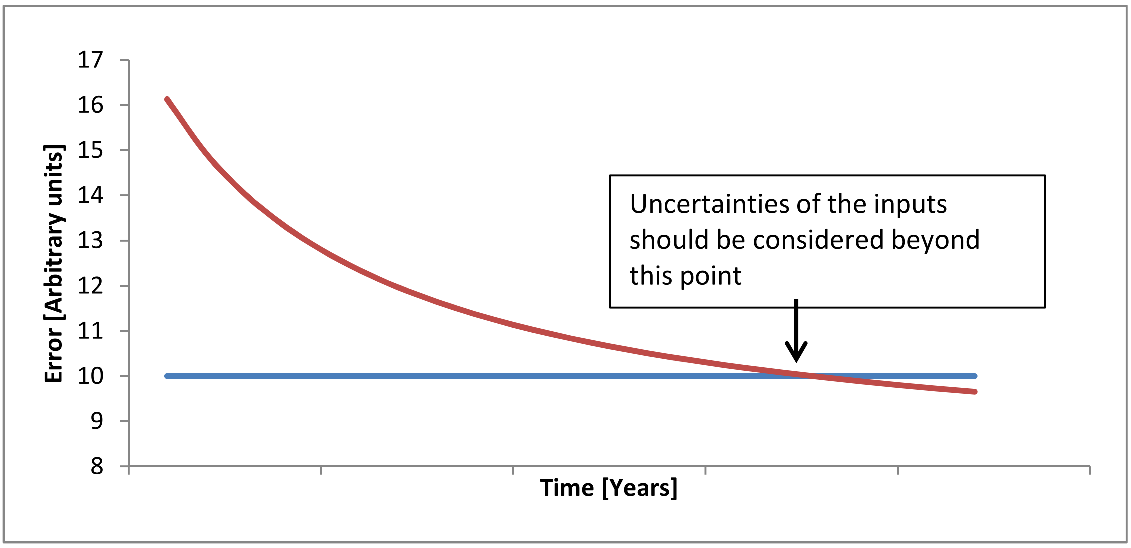

Figure 2.9 - Illustration of the evolution of errors in energy building simulation due to uncertainties of inputs (blue) and precision error due to low physical fidelity (red). The graph is only illustrative and the units in both axis only indicative.

Currently there is a large variety of detailed building simulators capable of representing reality in a very complete way when the inputs are appropriately chosen. However, simpler building simulators that were developed in the past, and were largely tested with real buildings, in real conditions, should not be totally displaced by benchmark simulators. These simpler simulators shouldn't be treated as obsolete when compared to current, more comprehensive, alternatives and should be used in the applications in which the computational time is more important than the representation of non-linear complex phenomena.

EnergyPlus has the flexibility of performing a whole energy simulation at a variety of computational times depending on the degree of complexity of the simulation and gives the possibility of running in batch mode. However it still requires longer computational times than other alternatives such as RC-networks.

2.3 Optimisation

The theory of optimisation is formed of a set of analytical and numerical methods aimed at finding the best candidate among a group of alternatives without the need of examining all those options (Paredes, 2000). Optimisation problems are presented in most cases as the optimum seeking of functions i.e. looking for the values of the variables that make a function take its minimum or maximum value. The function to be optimised is called the *objective* or *cost function*, and the variables are *decision variables*. Those optimisation problems can be represented as:

$$\begin{aligned} &Optimise && f(\boldsymbol{x}), \\ &subjected\ to && \boldsymbol{x} \in \Omega. \end{aligned} \qquad \text{Eq. 2.1}$$

where $f(\boldsymbol{x})$ represents the objective function, $\boldsymbol{x}$ represents the set of decision variables, and Ω represents the sub-space of possible solutions (also called the decision space).

Different optimisation problems require different optimisation techniques. Several works can be found in the literature where optimisation algorithms have been applied for building design. This chapter describes the most commonly used optimisation methods in this discipline. At the end, the reader can find a review of publications on building design using the optimisation technique that was chosen for this thesis i.e. Evolutionary Algorithms (they will be described later in the chapter).

The following section describes classifications used to distinguish between optimisation methods.

2.3.1 Classification of optimisation methods

2.3.1.1 Analytic and direct methods

The objective function of an optimisation problem will depend on the problem at hand. For example, Eq. 2.2 shows the energy demand for heating of a building when considering heat transfer as a steady-state process, this could be used as the objective function to minimise heating use.

$$Energy(U - Value, inf, area) = \left(U - Value * area + c_p{}^{air} * \rho^{air} * inf\right) * \Delta T * \Delta t\,, \quad \text{Eq. 2.2}$$

where $U - Value$ is the total U-Value of the building envelope [W/(Km^2)], *area* is the area of the envelope [m^2], $c_p{}^{air}$ is the thermal capacity of air [J/(kgK)], ρ^{air} is the density of air [kg/m^3], inf is the infiltration value [m^3/s], ΔT is the temperature difference between outside and inside [degree C], and Δt is the time period [s].

Knowing the mathematical form of the objective function allows the use of optimisation methods that study the properties of the objective function. These methods were largely used before the deployment of digital computers as the most efficient way to find the optimum of a function. Several authors describe these methods (Ravindran *et al.*, 2006) which are called calculus-based methods or **analytical methods**, as they are based on the analytical study of the objective function. These methods use the gradient of the objective function as an indicator of the improvement of the solution within the decision variables, when the gradient is zero the objective will not improve with small changes in the decision variables (subject also to other conditions such as convexity, see gradient based methods in the previous reference). In the case of linear functions (as in Eq. 2.2) the optima are always found at the boundaries of the problem (for the example: the minimum possible value of *U-Value*, *inf* and *area*, will deliver the building with the smallest heating demand).

For some optimisation problems, the objective value may be a set of parameters obtained from a simulator or a physical test; meaning that there is no mathematical equation that represents the objective as a function of the decision variables; these are called *black-box* problems because the user does not see what operations are done to the inputs to generate the outputs, or these operations are numerical and therefore are not based in a single algebraic expression. The lack of an expression for the objective function eliminates the possibility of studying the gradient and therefore it is not possible to apply the methods described before. In this case, one can rely only on optimisation methods that only require the value of the objective function. These methods are called **direct methods**, and work by evaluating the “quality” of the solutions across the decision space through a number of iterations. An example of this is the analysis of energy demand using a thermo-dynamic simulator such as EnergyPlus, where the operations performed to obtain the building energy demands are numerical e.g. solving the differential equations for each time step as a function of the inputs and the previous states.

Direct methods are normally based on finding patterns in the decision space that will allow the algorithm to move towards regions in which the global optimum is likely to be found. These patterns can be very different depending on the algorithms used, from directions in the actual decision space (as in the Hookes and Jeves method, explained below) to patterns in a binary string after encoding the decision space (in genetic algorithms, also explained below).

The deployment of building dynamic simulators made the use of direct optimisation methods common in research, as the user has no access within these tools to the mathematical expressions of the functions to be optimised.

2.3.1.2 Single and multi-variant optimisation methods

The number of decision variables in an optimisation problem is used to define the *size* of the problem. Most optimisation problems have to consider more than one decision variable, these problems are called **multi-variant**, in opposition with the ones in which the objective function only depends on one variable: **single-variant**. Figure 2.10 shows an objective function that depends on a single variable, seeking the optimal of this function is considered a single-variant optimisation problem. Figure 2.11 shows an objective function of a multi-variant optimisation problem.

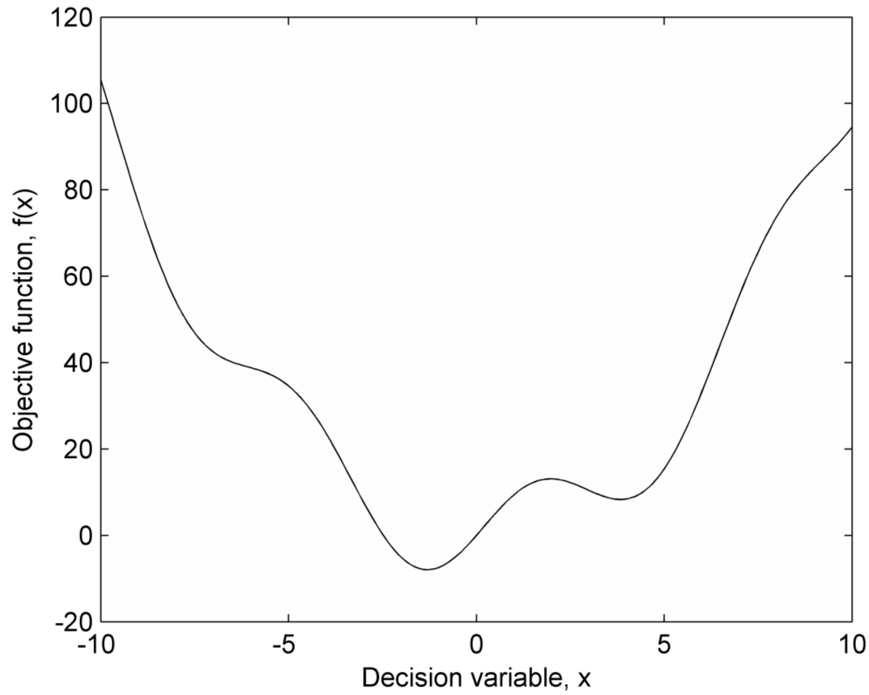

Figure 2.10 - Objective function that depends on a single decision variable: Single variant.

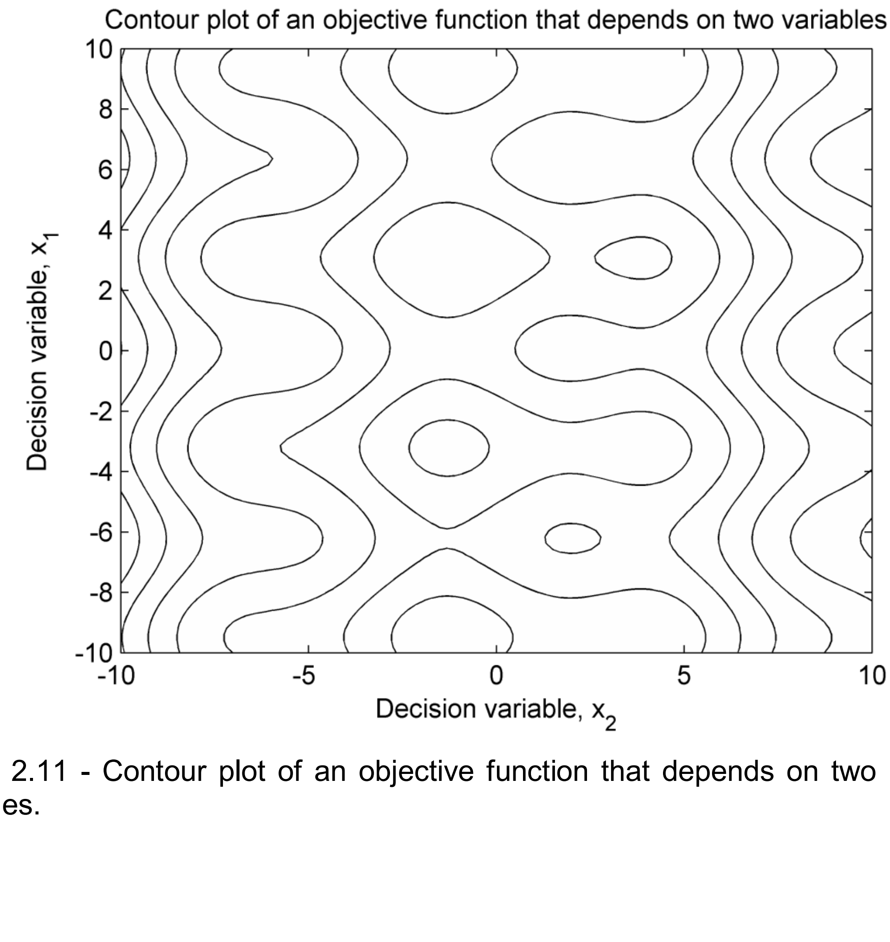

Figure 2.11 - Contour plot of an objective function that depends on two independent variables.

The most substantial impact of having a rather large number of decision variables is the size of the decision space. The number of possible solutions grows exponentially with the number of decision variables.

Both direct and analytical methods can be used to solve multi-variant optimisation problems.

Most problems in building design will be considered as multi-variant problems. The reason for this is that the designer will normally have several degrees of freedom for a building, and also, because multi-variant optimisation is able to capture potential synergies between variables. For example, the interaction between fenestration percentage and aspect ratio might have a substantial impact on the energy demand for lighting.

2.3.1.3 Constrained and non-constrained optimisation

As mentioned before, the space formed by all possible solutions is called the decision space. The decision space can be different depending on the optimisation problem. For example, when carrying out an optimisation to find the equation of the curve that fits best a cloud of points, the decision variables may take any value, so the search should be in $\mathbb{R}^n$ with n the number of decision variables. This is called **non-constrained** optimisation or unconstrained optimisation.

Optimisation problems like these are not found often in practical applications, as physical limitations normally narrow the range of values that the decision variables can take (e.g. in low-energy building design: size of a window, thickness of insulation, etc.).

Apart from the individual ranges of each variable, limitations often apply to the decision variables in the form of equations that relate decision variables. As an example, for a given building, the designer might want to limit the total area of windows for financial reasons. This can be included in the optimisation as a restriction of the kind: Summation (windows areas) < max limit.

These limitations and the ones that define the range of the decision variables are called the constraints of the problem. An optimisation problem with constraints is called a **constrained** optimisation problem.

2.3.1.4 Single and multi-objective optimisation

Single objective optimisation allows finding the point in which one single objective function presents a maximum or a minimum. Multi-objective optimisation is a more complex technique that provides a set of solutions that can be considered optimal when optimising several functions (which cannot be easily combined) at the same time.

To understand multi-objective optimisation it is necessary to understand that multi-objective optimisation is closely related with the concept of *trade-off* solutions: i.e. every solution will be a compromise between optimising one of the objectives over the rest. When two or more functions are optimised, two different scenarios may occur:

1. The objective functions are conflicting,
2. The objective functions are non-conflicting.

An optimisation problem has conflicting objectives when the optima of the objective functions appears in different locations of the decision space i.e. optimising one of the functions implies making the value of the others worse. This contradiction makes it impossible to find a point in the decision space that will provide optimal values of all the objective functions, and leads to the need for a compromise or trade-off solution. In comparison, non-conflicting objective functions have their optimum at the same location of the decision space i.e. a single solution produce the optimal value for the objective functions. These two cases have been illustrated with Figure 2.12.

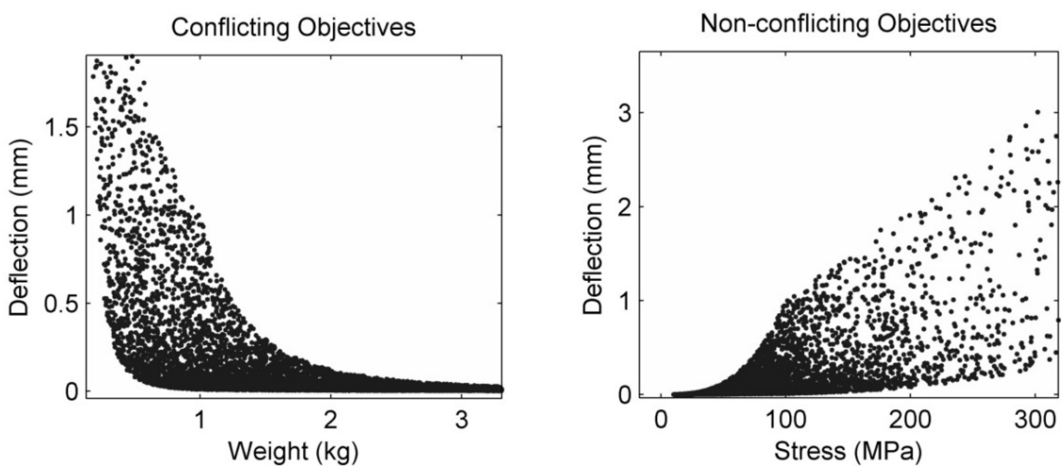

Figure 2.12 - Conflicting and non-conflicting objectives. Deflection, Weight and Stress are to be minimised. A single design will minimise Defection and Stress (right). However, there is no single solution that produces the minimum Deflection and the minimum Weight (left): These two objectives are conflicting. Adapted from (Deb, 2001).

There exists a way of evaluating the optimality of the solutions when the problem presents conflicting objectives; this is the *Pareto optimality*.

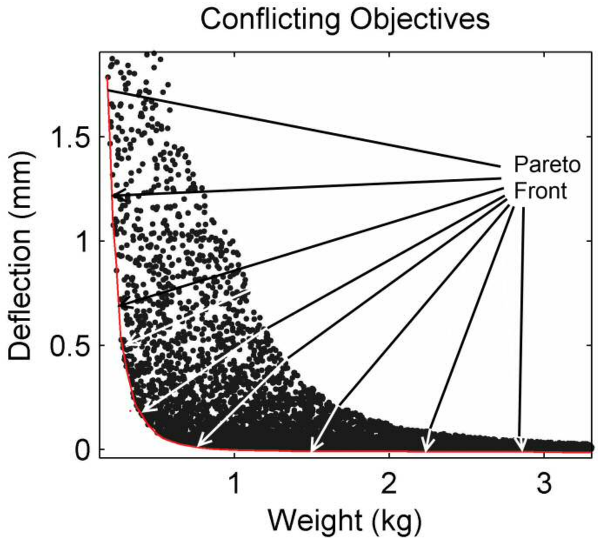

Figure 2.13 - Pareto Front (red line) over a plot of solutions with conflicting objectives.

To understand the concept of Pareto optimality, it is necessary to define the concept of dominance. Given an optimisation problem with *M* objectives, then the domination criteria of a solution over others can be defined as follows (from (Deb, 2001)):

A solution $\boldsymbol{x}^{(1)}$ *is said to dominate the other solution* $\boldsymbol{x}^{(2)}$*, if both of the following conditions 1 and 2 are true:*

1. *The solution* $\boldsymbol{x}^{(1)}$ *is not worse than* $\boldsymbol{x}^{(2)}$ *in all objectives, […].*
2. *The solution* $\boldsymbol{x}^{(1)}$ *is strictly better than* $\boldsymbol{x}^{(2)}$ *in at least one objective, […].*

Using this definition the global Pareto optimal set or *Pareto front* (see Figure 2.13) can be defined with the following statement (Deb, 2001) :

The non-dominated set of the entire feasible search space S (here called the decision space) *is the globally Pareto optimal set.*

The Pareto optimal set or Pareto front represents the solutions that are optimal when the optimisation has conflicting objectives. After obtaining the

Pareto front, the influence of one objective over the others can be studied, it is at this stage when higher levels information or other criteria difficult to evaluate quantitatively (such as appeal) might be applied to select the optimal single solution for the optimisation problem.

An alternative to obtaining the Pareto front in multi-objective optimisation is to calculate the summation of the result of this objective function multiplied a weighting factor. That transforms a multi-objective optimisation problem into a single objective one (see the algorithm VEGA in (Deb, 2001)). For example, deflection and weight are summed after being multiplied by a factor that determines which one is more important for the designer, the result is minimised as a single objective optimisation problem.

In general, using multi-objective optimisation methods is more desirable than pre-processing the objective functions to transform the problem in a single-objective one. In this thesis, only single-objective optimisation methods have been used. However, this section has been included in this chapter for two reasons: One, multi-objective optimisation is used in part of the literature surveyed below, and two, this section shows how any single-objective optimisation algorithm can be transformed into a multi-objective optimisation method by using Pareto optimality to assess the *quality* of the solutions, what is relevant because it shows that the scope of the optimisation methods shown in this thesis in further chapters, can get a much larger scope by simply being used to solve multi-optimisation problems through the use of the concept of Pareto optimality.

The next section describes a family of optimisation methods that enjoy a substantial popularity in building design. Also, these are the algorithm on which the optimisation methods presented in this thesis have been based. This is the family called Evolutionary Algorithms.

2.3.2 Evolutionary Algorithms

A section is dedicated to these algorithms as they are the central topic of Chapter 4 and 5 of this thesis, but other popular algorithms are described in Section 2.3.3.

2.3.2.1 Introduction

Evolutionary Algorithms (EAs) are a group of optimisation algorithms inspired by natural evolution. EAs are direct methods able to solve multi-objective, multi-variant, black-box optimisation problems.

The first successful Evolutionary Algorithm was presented by Fogel in 1964 (Fogel, 1964), the method was called *Genetic Programming* (GP) (Sometimes referred to as the method of Fogel, Owens and Walsh after their book: "Artificial intelligence through Simulated Evolution" (Fogel *et al.*, 1966)). This method included the main characteristics of Evolutionary Algorithms. Although this type of EA was proven to be successful, it did not gain much popularity in the following years. Instead, two new kinds of EAs were developed independently in Germany and USA namely: *Evolutionary Strategies* and *Genetic Algorithms* respectively which started being used in many disciplines, especially *Genetic Algorithms* (GA).

GAs were introduced by John Holland in 1975, as the result of his work on design and implementation of robust adaptive systems (Holland). Genetic Algorithms mimic the operations of natural evolution to improve the fitness of a group of artificial individuals over generations; the development of these algorithms was the result of the study of the evolution of species, therefore they were not conceived as function optimisers, this has been seen as a weak point of GAs later (Dejong, 1993) .

Goldberg published a book in 1989 with a comprehensive study about the potential of GAs in optimisation problems (Goldberg, 1989). The book explains several aspects of the GAs; from their implementation on computers, to their application to real world problems. Goldberg's book also made popular his *schema theory,* considered now the theoretical foundation of GAs.

Goldberg's book resulted in an increased popularity of GAs; the optimisation algorithm suggested by Goldberg was the starting point of a variety of optimisation methodologies with similar characteristics that follow the principles of Holland's ideas.

Before GAs started being used, another kind of EA inspired by natural evolution was created by Schwefel at the Technical University of Berlin. This algorithm was given the name of *Evolutionary Strategy* (ES) (Schwefel, 1965). As opposed to GAs, ESs were conceived as function optimisers.

ESs had been less popular than GAs during the eighties and nineties. However, ESs have become more popular in the last ten years. This popularity will be shown in Section 2.6.2 when reviewing the publications related to building design using EAs.

GAs, ESs and GP are considered the canonical forms of EAs (de Jong, 2006). Most EAs found in the literature can be classified as a type of one of the three canonical forms. It is therefore worth explaining these three EAs in detail; the following sections give a detailed explanation of the characteristics of EAs to describe the canonical forms in Section 2.3.2.7.

2.3.2.2 Generic EA

EAs present some properties that distinguish them from other optimisation algorithms: (1) EAs are population based algorithms; this means that a set of solutions is considered during the optimisation. (2) EAs mimic the basic operators of natural evolution:

1. *Recombination*
2. *Mutation*
3. *Evaluation*
4. *and Selection*

Depending on the EA chosen, these operators may differ or even not be present at all.

The steps followed in these algorithms are:

1. Create a random population of individuals
2. Get into the main loop until termination criterion reached:

   Main loop:

   a. Evaluate the individuals
   b. Recombine (the best)[7] individuals
   c. Select the best individuals
   d. Mutate the offspring

The detailed descriptions of the canonical forms of EAs are more complex, and a few concepts need to be explained before introducing their properties (described in Table 2.4 on page 85). These concepts are explained in the following sections.

[7] Some algorithm recombine all individuals

2.3.2.3 Encoding

The “characteristics” of living creatures are stored in their DNA: a large string of molecules able to store data in a base four (A-T-G-C) encoding system. This encoding of information on a material string allows for the creation of new individuals by copying the segments or the whole of the DNA, either from one or more previous individuals. This form of reproduction makes it possible to transfer the genetic information from one generation to another and therefore the heredity of characteristics of individuals.

This way of storing information of individuals, is also mimicked by EAs. For the application of these algorithms an **encoding** is needed. The encoding facilitates replicating the mating and mutating that occur in natural evolution. One of the most popular encoding methods in EAs, is the one introduced by Holland (Holland, 1975). This method uses binary strings (i.e. strings containing only ones and zeros) to store the characteristics of individuals (solutions). A description of this encoding can be found in (Goldberg, 1989), (Coley, 1999) or (Bäck *et al.*, 1997).

To carry out this encoding, each individual is stored in a binary string. Each binary string contains binary representations of the decision variables. To encode n variables into an l bits long binary string, a number of bits m_n is assigned to each variable. When each decision variable is assigned a number m_n of bits, the decision variable needs to be discretized, and the algorithm will only evaluate the objective function in the 2^l points of the discrete encoded decision variable. For that reason, binary encoding creates an intrinsic limitation to the accuracy of the algorithm as not the whole decision space is being explored.

Other EAs such as Evolutionary Strategies (ESs) use real encodings i.e. the string is a set of real numbers. To use this encoding, the evolutionary operators have to be able to operate on a vector of real-valued variables.

In ESs (but no GAs or GP), a string that represents an individual has not only the value of the decision variables, but also a set of parameters used in the algorithm. For that reason, an individual is represented as a set of parameters $\boldsymbol{a}$ (instead of just the set of decision variables $\boldsymbol{x}$, the additional parameters will be explained in further sections).

After carrying out the encoding of the decision variables in an optimisation problem, there exist two ways of referring to the solutions:

- Genotype/Genotypic: Value of the decision variables after the encoding (e.g. encoding a decision variable that can only take integers between 0 and 15, can be represented as the string XXX being X 1 or 0; changes in the genotype represent changes in that binary string).
- Phenotype/Phenotypic: This is the meaning of the encoded string in the “real world” (e.g. in the previous example a change in the phenotype means a change in the real variable).

10101000	11101011	10011110
11100011	00001110	11111011
00010010	11010111	10010110
11101110	00001111	00000111
11101111	10100111	00001001
00111000	11110011	00111111
00001110	11000001	11100011
10000000	01010100	10010100
00010110	10101011	00110011
11111010	01011001	10000101

(a)

1010	1000
↓	↓
10	8

(b)

Figure 2.14 - Different representations of binary encoding. (a) 30 individuals encoded in binary, (b) representation of the codons of the genome and their equivalents in integers for the first one. Adapted from (Mitchell, 1998).

2.3.2.4 Objective function

Optimisation methods are designed to find the optimum value of an objective function. The objective function is an operator that assigns a real number to each individual; it can be represented as $f : I \rightarrow \mathbb{R}$. f being the objective function, I the space of individuals and $\mathbb{R}$ the space defined by the real numbers. When using EAs, the mathematical form of the objective function does not need to be known, as EAs belong to the family of direct methods.

There exist special objective functions that have been created for investigating the efficiency and efficacy of EAs. These functions are called benchmark functions or test functions. Bäck describes some of those functions (called artificial landscapes in his book) in (Bäck, 1996).

2.3.2.5 Operators

The operators used in an EA were introduced in Section 2.3.2.2. Here, a more detailed explanation of the operators is given. The evolutionary operators change substantially depending on the algorithm, making difficult to give a general description. However, the main operators will be described in this section.

Before defining the operators, a characteristic called sexuality has to be described. An evolutionary operator can be defined as:

$$\omega_{\Theta}: I^{p} \rightarrow I^{q} \tag{Eq. 2.3}$$

where ω_{Θ} is the operator, I the space of the individuals, p the number of parents and q the number of individuals in the offspring. It can be said that the operator is (from (Bäck, 1996)):

- asexual if an individual is generated from another individual solely:

  $$\exists \omega'_{\Theta} : I \rightarrow I : \ \omega_{\Theta}(\boldsymbol{a}_1, \dots, \boldsymbol{a}_p) = (\omega'_{\Theta}(\boldsymbol{a}_1), \dots, \omega'_{\Theta}(\boldsymbol{a}_p)) \wedge p = q,$$

- sexual if it uses two individuals to create a new individual:

  $$\exists \omega'_{\Theta} : I^2 \rightarrow I : \ \omega_{\Theta}(\boldsymbol{a}_1, \dots, \boldsymbol{a}_p) =$$
  $$(\omega'_{\Theta}(\boldsymbol{a}_{i1}, \boldsymbol{a}_{j1}), \dots, \omega'_{\Theta}(\boldsymbol{a}_{iq}, \boldsymbol{a}_{jp})) \ where \ \forall \mathrm{k} \in \{1, \dots, \mathrm{q}\} \ i_k, \ j_k \in \{1, \dots, \mathrm{p}\}$$
  are chosen randomly.

- panmimic if all individuals in the previous generation are used to create a new individual:

$$\exists \omega'_{\Theta} : I^p \to I : \ \omega_{\Theta}(\boldsymbol{a}_1, \dots, \boldsymbol{a}_p) = (\omega'_{\Theta}(\boldsymbol{a}_1, \dots, \boldsymbol{a}_p), \dots, \omega'_{\Theta}(\boldsymbol{a}_1, \dots, \boldsymbol{a}_p)) .$$

After this classification the main evolutionary operators are described.

2.3.2.5.1 Mutation

Mutation is, in natural evolution, a crucial mechanism for the origin of new species; in EAs, the mutation operator is an asexual operator that allows the continuous exploration of the decision space at any stage of the optimisation.

The mutation operator is implemented in EAs as an operator that randomly changes the values of the decision variables of an individual. This could be done, depending on the algorithm, at a genotypic level, or a phonotypic level (see section 2.3.2.3).

When the decision variables are encoded with a binary string (as in GAs) the mutation operator flips one or more of the bits to its opposite value (from 0 to 1 or from 1 to 0) therefore making a change at the genotype level. The scope of this change in the value of the decision variables will be different depending on the position of the bit; therefore, the scope of mutation is stochastic in binary encoding. The number of bits that are flipped in a population is determined by a parameter of the algorithm called the *mutation probability*. The mutation probability is used in each generation to calculate if a bit will be flipped or not. This is done by sampling a random number and comparing it with the mutation probability; therefore, the number of bits mutated is also stochastic.

The mutation operator under binary encoding “moves” an individual a random distance from one position to another of the decision space. The fact that a single bit flip may greatly modify the solution is called the *Hamming effect* and can be undesirable in an optimisation problem (for a description on Hamming effect and its implications in optimisation see (Bäck, 1996)). An alternative is the use of the *Gray binary code*, code that makes smaller the change of the real value of the decision variable after flipping a single bit. More about the Gray code can be read in (Coley, 1999).

Mutation operators for EAs in which the decision variables are real-encoded (rather than binary encoded) have a different working principle. To maintain the meaning of the mutation operator, they have to be implemented as an operator that moves an individual to another position of the decision space i.e. makes a change at a phenotypic level. A way of doing that is to modify the decision variables with a random number. Canonical ESs, for example, use a normal distribution to modify the value of the decision variables in mutation. That way, an individual to be mutated, will be “moved” following a normal probability distribution centred in its current location, that way the mutation is more likely to perform small modifications of the decision variables than larger ones. Hence, depending on the variance of the normal distribution, the mutation will have a different scope.

Fogel summarized the different mutation operators that can be found in the literature in Section 3.2.2 of (Bäck *et al.*, 1997). In his review, Fogel shows that the most common mutation operators are those which the scope of the mutation is calculated by sampling a normally distributed random number (Bäck and Schwefel, 1993; Fogel and Atmar, 1990; Fogel and Stayton, 1994; Rechenberg, 1973; Schwefel, 1981). These mutation operators generate individuals in the proximity of their parents.

The probability density function (pdf) of a normal random variable takes the form:

$$g(x) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp[-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}]. \qquad \text{Eq. 2.4}$$

If $\mu = 0$, then σ^2 (the variance), is the only parameter of the equation. If this pdf is used to determine the scope of the mutation, the variance will determine the magnitude of change of the mutated individuals. The value of the variance is sometimes called the *step size* of the mutation. Schwefel and Fogel implemented, in Evolutionary Strategies and Evolutionary Programming by respectively in (Schwefel, 1987) and (Fogel, 1991), a mechanism to adjust the step size internally by the algorithm. This self-adaptation consists on adjusting the step size (variance) of the mutation (for each or all the decision variables) depending on the progress of the run. As in a gradient-based optimisation method, the algorithm recognises the improvement of the objective function in each iteration and determines with that information the step size. Self-adaptation allows algorithms to be self-terminated, as the algorithm is able to recognise when the improvement of the objective function has become smaller than a given value.

The step size can also be adjusted following the iteration number (no self-adaptation); this can be done, for example, with a deterministic rule dependent on the generation number. An implementation of this control of step size can be found in Michalewicz's work (Michalewicz, 1996). The method is described by Eq. 2.5.

$$x_i^t(t) = \begin{cases} x_i(t) + \Delta\big(t, ub_i - x_i(t)\big) & if\ u < 0.5 \\ x_i(t) - \Delta\big(t, ub_i - x_i(t)\big) & if\ u \geq 0.5 \end{cases} \qquad \text{Eq. 2.5}$$

where $x_i(t)$ is the *i*-th decision variable, of the solution ***x*** at generation *t*. And $[lb_i, ub_i]$ defines the upper and lower bounds of each decision variable, u is a real uniform random number with $u \in [0,1]$, and the function $\Delta(t,y)$ is defined as:

$$\Delta(t,y) = yu(1 - \frac{t}{T})^b \qquad \text{Eq. 2.6}$$

with *T* the maximum number of generations of the run, and *b* a parameter that determines the degree of non-uniformity: the higher this value the more generations with similar steps sizes would occur at the end of the optimisation. The reason for having a deterministic step size control is the ability to stop premature convergence, and the possibility of fixing the number of generations that will be tested, feature that is not available if the optimisation is self-terminated.

For more information about mutation mechanisms see Chapter 6 of Bäck (Bäck, 1996). For other mutation operators used in EAs see Chapter C3.2 of Bäck, Fogel et al. (Bäck *et al.*, 1997).

2.3.2.5.2 Recombination

Recombination, in natural evolution, is the ability to create new individuals that share genetic information with their parents. Recombination in EAs allows exchanging characteristics between two or more solutions to create others.

In algorithms where individuals are encoded as **binary strings**, the recombination (normally called crossover) is done by exchanging segments of the genotypes of the parents to create the new individual. The crossover operator is controlled in these algorithms by the crossover probability; this value determines the probability of the parents to be recombined rather than simply copied to the next generation.

This parameter of the algorithm is similar to the *mutation probability*. The *crossover probability* or p_c is a random uniform number with $p_i \in [0, 1]$. Every time a new couple of parents are selected, a random number with flat probability distribution and range [0, 1] is sampled; if the number is smaller than p_c the parents are crossed; if the random number is larger than p_c a copy of the parents will appear copied in the next generation.

For a more detailed explanation about crossover in binary strings and formal analysis of the operator see section C3.3.1 of (Bäck *et al.*, 1997) or (Goldberg, 1989) and for a more analytic description of the effects of crossover in the overall algorithm see (Bäck, 1996).

The recombination for EAs in which the decision space is coded in **real-valued strings** offers more possibilities than in binary crossover, because the decision variables do not get masked in the encoding. Bäck shows the different kinds of recombination in ESs (that use real-valued individuals) in a graph that can be seen in Figure 2.15. A short description of them can be read in Table 2.3. This figure shows an example of real crossover in an optimisation in which the objective function depends in two variables, here called x_1 and x_2. P_1 and P_2 are the two parents. The points marked as *(1)*, *(2)*, *(3)* and *(4)* are possible offspring of the recombination of the two parents. It can be seen that *(1)* are individuals that are obtained by simply exchanging the values of the decision variables of the parents, *(2)* is the intermediate linear recombination (or median) of the two parents, *(3)* is located randomly over the line that defines all the possible linear combinations of the parents and *(4)* is located inside the bounding box generated with the values of the parents.

The recombination operator should be chosen depending on the optimisation problem that needs to be faced, but the discrete operators seem to be more appropriate if the convexity[8] of the objective function is unknown, this

[8] Convexity is the property of functions that determines its curvature. $f(x)$ is convex in $\mathbb{R}$ if $f'(x) < 0$ for all x, $f(x)$ is concave in $\mathbb{R}$ if $f'(x) > 0$ for all x. Convexity is important in optimisation because a function that is only convex in the decision space only has one maximum, and the gradient-based methods always converge to it, functions that are only concave only has one minimum and the gradient-based methods always converge to it.

is because in this case, a good value of fitness of two individuals does not imply a good value of fitness in a linear combination of them.

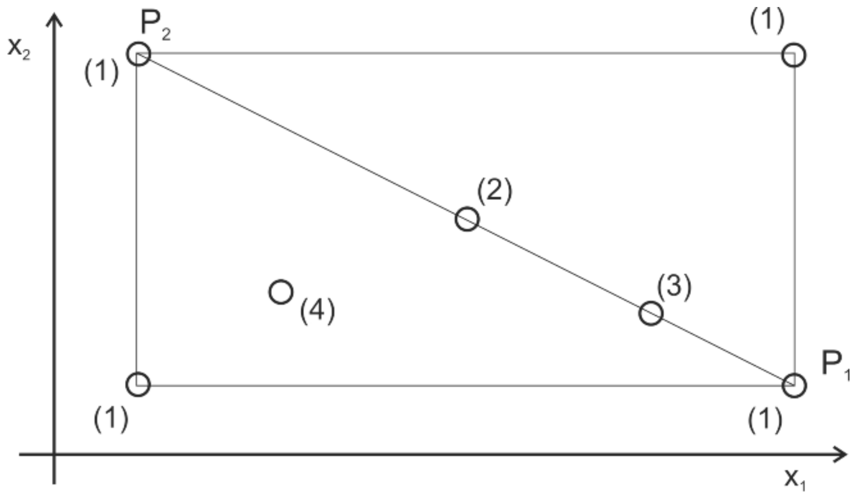

Figure 2.15 - Possible recombination (numbers in brackets equivalent to Table 1) in ESs. Two dimensional decision space. Adapted from (Bäck, 1996).

Schwefel proved the effectiveness of recombination in ESs for certain functions in his work (Schwefel, 1977) p. 171.

Table 2.3 - Recombination operators for real-valued individuals. The numbers on brackets are represented in Figure 4.3.

Name	Description
Sexual discrete (1)	Each decision variable is randomly selected from each parent
Panmimic discrete	Each decision variable is selected from a random parent of the population
Sexual intermediate (2)	The decision variables are the arithmetic average of the decision variables of the parents
Panmimic intermediate	The decision variables are the arithmetic average of the decision variables of the population
Sexual generalized Intermediate (3) (4)	The offspring is a lineal combination of the parents.
Panmimic generalized	The offspring is a lineal combination of the parents population

2.3.2.5.3 Selection

The selection operator is the main force of EAs to evolve towards optimal individuals. The selection operator can be called before recombination (used for selecting the best individuals that will be crossed as in GAs) or after recombination (to select the individuals that will survive in a population that has been enlarged due to recombination as in ESs).

The selection operator does not depend on the encoding of the decision space. In opposition, the selection operator is normally chosen by the user depending on the optimisation problem. Each canonical form of EA uses a specific form of selection; however, they can be changed or modified to produce different behaviour of the population over the evolution of the algorithm. One of the most important measures of the selection mechanism is the *takeover time* *(τ^*)*. This measure of "effectiveness" is defined as the number of generations needed by the best individual to take over the whole population with the selection operator working solely i.e. mutation and recombination switched off (Bäck, 1994; Goldberg and Deb, 1991).

The selection can be stochastic or deterministic[9]. The most popular of the **stochastic** selection operators is the proportional selection operator or *weighted roulette wheel*. This operator was the one used in the original work of Holland (Holland) in GAs. The proportional operator selects the individuals by providing a probability of being selected proportional to their fitness (see (Goldberg, 1989; Coley, 1999) or (Bäck *et al.*, 1997)).

Another stochastic selection mechanism is *tournament selection*. Tournament selection selects randomly a subgroup of *q* individuals from the original population, and takes the one with the highest fitness. This method is easy to implement as it does not require any pre-processing of the original population (such as ranking). The parameter *q* in tournament selection is an indicator of the selective pressure of the mechanism: the higher its value the more individuals are tested and the more likely it is that only a few highly-fit individuals will survive to the next generation.

Among the **deterministic** selection operators, the *rank-based selection* operator is an operator where the population is sorted by fitness to select the

[9] Deterministic: the selection of individuals is determined by its fitness; stochastic: the probability of an individual of being selected is determined by its fitness.

first n individuals. ESs use this form of selection operator in their canonical form as introduced by Schwefel (Schwefel, 1977). Another deterministic selection operator is the *range-based* selection operator. This method is used in this thesis and works similarly to the operator above. The *range-based* selection operator uses a parameter k to define a minimum fitness that is acceptable, the individuals with lower fitness are discarded. The range of fitness of the population is calculated in each generation (t) by:

$$R(t) = k\left(\mathrm{f}_{max}(t) - \mathrm{f}_{min}(t)\right), \qquad 0 < k < 1; \qquad \text{Eq. 2.7}$$

with $\mathrm{f}_{max}(t)$ and $\mathrm{f}_{min}(t)$ the maximum and minimum value of the objective function in that generation, and t the generation number. Once that range ($R(t)$) is calculated, only the individuals for which

$$\mathrm{f}\left(\boldsymbol{a}^i\right) > \mathrm{f}_{max}(t) - R(t), \quad \textit{in maximisation} \qquad \text{Eq. 2.8}$$
$$\mathrm{f}\left(\boldsymbol{a}^i\right) < R(t) + \mathrm{f}_{min}(t), \quad \textit{in minimisation}$$

will be selected, with $\boldsymbol{a}^i$ individual number i of the population and k the parameter that determines the selection pressure.

This selection operator implies that a different number of individuals are selected in each generation, making it a distinctive condition from the selection mechanisms found in the canonical forms of EAs. For other selection operators and a more formal descriptions of the mechanisms that make them work see section C2.1 of (Bäck *et al.*, 1997).

2.3.2.6 Constraint handling in EAs

There are several ways of handling constraints when using EAs. The most basic option is to encode the solutions in such a way that the decision variables cannot take values that are outside the decision space. This is straightforward with range-type constraints and binary encoding. In this case, the binary strings are created in a way that each solution will represent a point in the feasible decision variable.

In the case of algorithms with real-encoded solutions, the decision variables can take an infinite number of values. To limit the algorithm to the feasible decision space, the mutation operator can be given information about the boundaries to avoid creating solutions outside the decision space.

For constraints that relate the decision variables, the common practice is to modify the fitness of the solutions that are outside the decision space with a penalty function. The penalty function penalises the solutions that are outside the feasible decision space by assigning then a lower fitness, with the size of the penalty being in relation to the scope of the violation of the feasibility condition. For more information about constraint handling in EAs see (Coley, 1999) Section 4.3.

2.3.2.7 Canonical forms of Evolutionary Algorithms

Now that the operators used in EAs have been explained, the canonical forms will be described. There exist three main groups of EAs that represent three different approaches or methodologies to solve an optimisation problem using EAs. The names of these canonical forms have been mentioned before:

- Evolutionary Strategies
- Evolutionary Programming
- Genetic Algorithms

Apart from these three canonical forms, there have been modifications to obtain specific optimisation methods suited to specific problems; or in general, improvements in the speed and efficiency of the algorithms (for example the one that will be used further in this thesis by Hansen: CMA-ES (Hansen *et al.*, 2003)). However, the canonical forms have been extensively tested and constitute the bases of Evolutionary Algorithms (Bäck *et al.*, 1997).

Bäck summarized the characteristics of the canonical forms of EAs in the table that has been transcribed as Table 2.4 (Bäck, 1996).

Table 2.4 - Characteristics of the canonical forms of EAs (from (Bäck, 1996)).

	Evolutionary Strategy	**Evolutionary Programming**	**Genetic Algorithm**
Representation	Real-valued	Real-valued	Binary-valued
Fitness is	Objective function value	Scaled objective function value	Scaled Objective function value
Self-Adaptation	Yes[10]	No	No
Mutation	Gaussian, main operator	Gaussian, only operator	Bit-inversion, background operator
Recombination	Discrete and intermediate, sexual panmimic, important for self-adaptation	None	z-point crossover, uniform crossover, only sexual, main operator
Selection	Deterministic, extinctive or based on preservation	Stochastic, extinctive	Stochastic, based on preservation
Constrains	Arbitrary inequality constraints	None	Simple bounds by encoding mechanism
Theory	Convergence rate for special cases, (1+1)-ES, (1+/,λ)-ES, global convergence for (μ+λ)-ES[11]	Convergence rate for special cases, (1+1)-EP, global convergence for (1+1)-EP	Schema processing theory, global convergence for elitist version

It should be mentioned that, although the three canonical forms of EAs has been proven to be effective, GAs and ESs are the most popular algorithms in practical application, particularly for building design.

2.3.2.8 Multi-Objective Evolutionary Algorithms (MOEAs)

The three canonical forms explained above show the main forms of evolutionary algorithms in their single-objective form. However, the algorithms can be adapted to be used in multi-objective problems.

Recalling Section 2.3.1.4 of this chapter, in multi-objective optimisation problems the algorithm is aimed at finding the Pareto Front instead of a single solution.

[10] In Bäck's reads: Standard deviations and rotation angles.

[11] (1+1)-ES, (1+/,λ)-ES and (μ+λ)-ES are specific ESs, for a full description see [12] Bäck, T., Fogel, D.B. & Michalewicz, Z., 1997. *Handbook of Evolutionary Computation*. Oxon: Taylor & Francis Group.

To perform multi-objective optimisation that will provide the Pareto front, it is necessary to assign fitness to the solutions proportional to their proximity to the real Pareto front. Goldberg solved this problem using the dominance concept. Goldberg separates the population in several non-dominated fronts and assign a fitness to the individuals that correspond with their front order (Goldberg, 1989). This idea was used by Srivinas and Deb to create their algorithm Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994).

One of the most popular multi-objective EAs is the one developed by Deb in (Deb, 2001) called the Non-dominated Sorted Genetic Algorithm II (NSGA-II), this algorithm is based in the assignment of fitness depending on the non-dominance, but also includes some features that provide a more efficient search. For more details of this algorithm see the previous reference (Deb, 2001).

The following section is a short review of the literature where the authors have used EAs to aid building design.

2.3.3 Other optimisation methods used in building design

The review by Evins shows the optimisation methods that have been used in the literature of building design previously. These methods are:

- Pattern Search (for example Hooke and Jeeves). This method moves a single point in the decision space through the coordinates one by one until it finds the optimum for that dimension, the process is repeated for all the coordinates of the decision space and then an equivalent movement is done combining the previously successful direction. This is done repeatedly while reducing the time step.
- Linear Programming. This algorithm is only valid to solve linear problems with linear constrains. This limits its application. The methods based in linear programing use the properties of the linear system to find the optimum that is always located in the extremes of the decision space.

- Non-linear Programming. This is an extension of the previous family of methods where the objective function and constrains can be non-linear.
- Harmony Search. This is a population based optimisation methods where combinations of variables are evaluated with a background noise that makes a continuous exploration the decision space.
- Particle Swarm Optimisation. This is also a population based algorithm where the population moves through the decision space with a speed that is determined by the improvement of the objective in previous steps.
- Ant Colony Optimisation. This is an optimisation method suited to solve “sales man” kind of problems. The method mimics how ants deposit pheromones in the land to create the optimal pathways that communicated resources and the nest.
- Simulated Annealing. This is a probabilistic method wherein the probability of staying in an area of the decision space depends on the results of the objective function after the application of background perturbations.

2.3.4 Conclusion

There are many optimisation algorithms that have been used in building design. It is important to understand the optimisation problem at hand, providing a good definition of the decision variables and the constraints to produce a clear understanding of the decision space, and secondly, understanding the form of the objective function.

It has been seen how EAs enjoy a large popularity when looking into optimisation methods for building design. The clear strength of these methods is the fact that they can be used to optimise objective functions when the analytical form is not known i.e. black box optimisation problems.

Even though the three canonical forms of EAs are used as function optimisers, GAs are the most popular optimisation methods in the discipline. In terms of multi-objective optimisation, this prevalence of GAs is even clearer.

There are two clear problems when performing optimisation to find low-energy building designs: (1) optimisation that takes into account uncertainties is not well covered in the literature, and (2) the computational times needed to carry out optimisation with an accurate thermo-dynamic simulator are in most of the occasions too long thereby making the process unviable.

The next chapter will describe robust optimisation methods and how these algorithms could improve optimisation for building design.

2.4 Robust and dynamic optimisation

The previous chapter described optimisation as the method to find optimal values of a given objective function. However, optimisation considered as the mathematical tool to help real decision making is substantially different. Real problems are subjected to uncertainties, in the design process, and in the life cycle of the product. Robust designs are less sensitive to uncertainties and therefore are more desired than those which performance get worse when used under conditions that differ compared to the ones assumed in the design process.

A robust solution is a solution that does not lose (or lose little) optimality when varying either the decision variables or the conditions under which it was evaluated.

When an optimisation algorithm is successful, it provides a solution that has the optimal objective value. However, if the solution has to be robust against noisy parameters (such as manufacturing tolerances or uncertain operation conditions) then the optimal design might be different. There even exist arguments about the need for optimisation in the design process, Marczyc argues that optimisation always implies making less robust designs (Marczyc, 2000); however, other authors (such as Beyer and Sendhoff (Beyer and Sendhoff, 2007)) have shown that some optimisation algorithms are capable of producing solutions that provide robustness and optimality.

Section 2.2 showed how building energy assessment tools are now able to model many of the physical phenomena that occur in buildings. Also, it was outlined that a certain accurate calculation of the energy demands is only possible when the problem is well defined and the inputs are certain. This thesis looks, among others things, into the problem of optimising low-energy building designs subjected to uncertainties. Chapter 4 presents an optimisation algorithm and its application to perform robust optimisation of buildings. But firstly, this section describes the methods available now-a-day to perform optimisation subjected to uncertainties, from the Taguchi method (pioneer of robust design) to modern algorithms based in evolutionary computation.

This chapter focuses in these algorithms, their application to real-world problems and their potential for building design.

2.4.1 Taguchi methods: Pioneer Robust Product Design

Taguchi methods were the first approach to product design that treated in quantitative way robustness as a virtue of the product (Taguchi, 1986). This methods are commonly used for robust product design (Fowlkes and Creveling, 1995; Roy, 2010).

The principles of these methods are to find design options that fulfil a given objective or requirement with very low sensitivity to noisy uncontrollable factors.

Taguchi changed the understanding of valid designs; he incorporated a series of measures that could be used to quantify the validity of a design, the first example is the *quality loss function*. This measure is a way of evaluating the robustness of a design. If a given characteristic of a product had to belong to an acceptable range defined by an Upper and a Lower Limit (UL and LL) then, in traditional product design, any design that presented a value of the objective within that range was considered to be as good as any other. Taguchi introduced the *quadratic quality loss function* (or quadratic loss function) that provides a value of the loss (in monetary units) due to the lack of quality i.e. bias to the target value of that characteristic of the product. He defined the quadratic loss function as:

$$L(y) = k(y - m)^2, \qquad \text{Eq. 2.9}$$

where *L*(*y*) represents the loss in monetary units, *k* is a scaling factor, *y* is the actual value of the objective, and *m* is the target of the objective. With this equation, Taguchi relates the loss of quality of the products with real monetary loss for the company. Producing higher quality products (or components) might well represent a smaller loss for the company, as less quality control need to be put in place, and there are fewer rejections.

Taguchi’s concern about quality motivated a whole new approach to product design. His method consists of the three following steps:

1. Creation of a design with the features needed to cover the objectives of the product.
2. Adjust the characteristics (decision variables) of the product to make it robust against noise factors.
3. Tune the characteristics (decision variables) of the product to achieve the optimal targets of the objectives (e.g. efficiency, speed, weight).

Although Taguchi’s method opened the door to robust design, it is not an optimisation method itself but a way of achieving a given objective without exploring the options available. This method was included in this chapter for its relevance in the development of robust design. However, new techniques are available that rely on automatic optimisation algorithms that are able to cope with uncertainties and explore the decision space to find the best design in an automatic manner.

Before describing the optimisation algorithms that are able to cope with uncertainties, the next section will show where the uncertainties can be found in an optimisation problem following the classification used by (Beyer and Sendhoff, 2007).

2.4.2 Uncertainties within optimisation problems

Robust optimisation is an attempt to find the optimum (or optima) of a given function subjected to uncertainties. The objective or cost function represents the quality of the different solutions. This function (or functions for multi-objective optimisation) is a representation of reality and will be always subjected to uncertainties and inaccuracies. The model, even when most accurate, will be an approximation of the real world.

The uncertainties that are presented within an optimisation problem were classified by Beyer and Sendhoff in four types (Beyer and Sendhoff, 2007):

A. Changing environmental and operating conditions. The objective value is not dependent on the decision variables solely; it depends on a set of parameters that cannot be controlled by the designer but have a substantial influence on the result. The objective function needs to be considered as:

$$f = f(x, \alpha), \qquad \text{Eq. 2.10}$$

with α a set of real parameters representing the uncertainties.

B. Production tolerances and actuator imprecisions. The decision variables that are considered cannot always be achieved with enough accuracy within the production process. When uncertainties of type A are also present the objective function has the form:

$$f = f(x + \delta, \alpha), \qquad \text{Eq. 2.11}$$

where δ can be a function of x for the most general case.

C. Uncertainties in the system output. The system can have mistaken outputs due to inaccuracy of the mathematical models or the measuring devices of the outputs. The function then will take the form:

$$\tilde{f} = \widetilde{f}[f(x + \delta, \alpha)]. \qquad \text{Eq. 2.12}$$

D. Feasibility uncertainties. These uncertainties are applied to constrains and not to the objective function, changing the shape and/or size of the decision space.

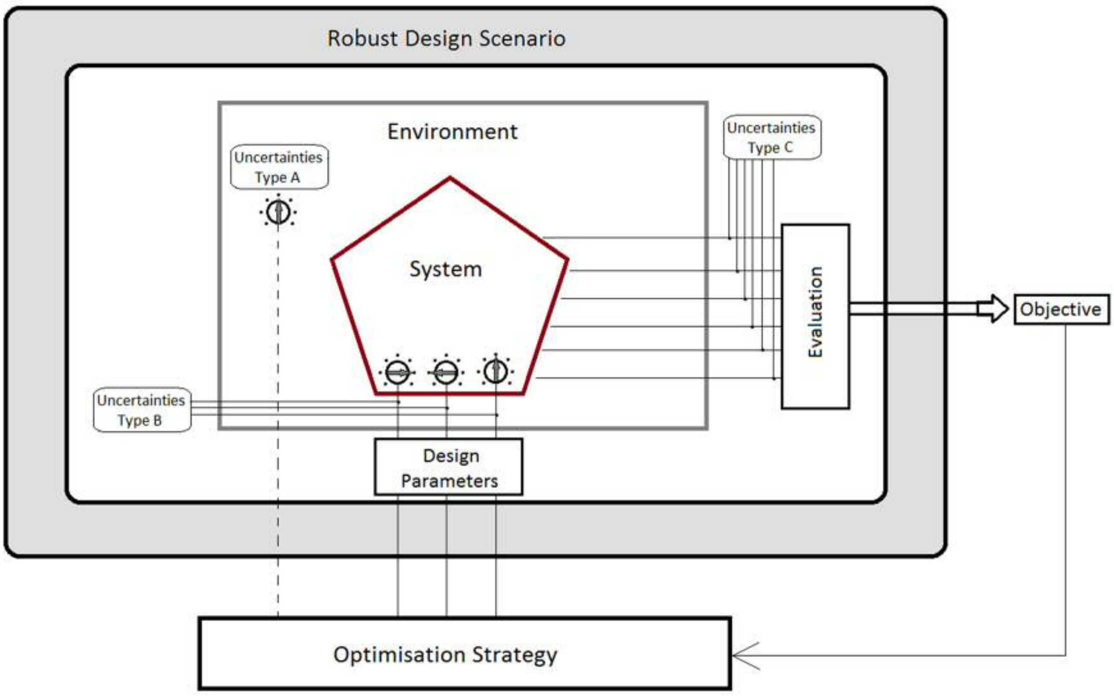

Figure 2.16 - Uncertainties on an optimization problem. Recreated from (Beyer and Sendhoff, 2007).

These uncertainties are present in every real-world optimisation. Figure 2.16 shows Beyer and Sendhoff's diagram which visualize uncertainties on an optimisation problem. The reader is referred to this review for a more detailed explanation about uncertainties in optimisation problems and to (Swiler and Giunta, 2007) for a report showing the types of uncertainties. Most of the work mentioned in Beyer and Sendhoff's paper refers to product design, especially mechanical engineering; however, the principles are valid for any optimisation problem.

Schueller and Jensen point out in their review about optimisation with uncertainties (Schueller and Jensen, 2008), how virtual prototyping (Finite Elements models) introduce uncertainties to the design. This problem is extendable to building energy modelling and simulation, technique that is now a common place in building design. Table 2.5 shows equivalences between the uncertainties in product design due to the use of virtual prototyping and the uncertainties introduced by the use of thermo-dynamic building simulators.

Table 2.5 together with the graph of Figure 2.16 suggest the need of robust optimisation methods when designing low-energy buildings. Taguchi's methods could be a way of approaching this challenge. However, the limitations of Taguchi's method have motivated the development of other techniques to obtain robust solutions of optimisation problems with uncertainties (Beyer and Sendhoff, 2007). The next section will introduce these methods.

Table 2.5 - Similarities between uncertainties introduced by virtual prototyping in product design and uncertainties introduced by building thermo-dynamic models in building design. Left column from (Schueller and Jensen, 2008).

FE models (product design)	**Building models (building design)**
Inaccuracies in estimating material properties (e.g. Young's modulus, density, toughness, yield strength, etc.) and/or geometrical properties (e.g. cross section, nodal location, etc.).	Inaccuracies in estimating material properties (e.g. insulation conductivity) and/or geometrical properties (e.g. thickness of insulation, size of cracks)
Insufficient modelling detail, e.g. the model is not able to capture the behaviour of a singularity such as a crack.	Insufficient model detail, e.g. the model is not able to calculate properly the solar gains, as cast shadows from outside objects may occur, or the air flows.
Inexact modelling of boundary conditions or material behaviour.	Inexact modelling of boundary conditions, such as weather data files, ground temperatures or outside temperatures affected by the heat island effect.
The model is a discrete representation of a continuous (real) system.	This is a particular characteristic of FE models. However, thermo-dynamic building simulators take several simplifications too (see Chapter 3).

2.4.3 Robust Optimisation Methods

In this section, the different ways of dealing with optimisation subject to uncertainties will be explained. When an optimisation problem presents uncertainties, the values of the objective function for the possible solutions could be misleading, and therefore the algorithm could provide a solution that, when sampled enough number of times, appears to be sub-optimal.

Two basic ways of dealing with these uncertainties can be found in the literature, these are:

- Pre-processing the optimisation problem (the objective function) to produce an optimisation problem without uncertainties, and then apply a *traditional* optimisation method.
- Adapting the optimisation algorithm to internally tackle the problem of uncertainty.

These two approaches are shown in the following sub-sections.

2.4.3.1 Eliminating the uncertainties by pre-processing the optimisation problem

The methods that pre-process the optimisation problem to eliminate the uncertainties are based on multiple evaluation of the objective function. That allows having a set of values of the objective function in each decision space that can be used to calculate the minimum or maximum of that point or a statistical estimator.

When the uncertainties are deterministic i.e. the uncertainties are defined by a set of parameters that belongs to a sub-space that can be defined, a way of tackling the uncertainties is the use of the robust counterpart. This is also called *robust regularisation* (Lewis, 2002), and consist on evaluating the value of the objective function in the proximity of each of the solutions evaluated (for uncertainties type B), or for a set of environmental parameters (for uncertainties type A). The value of the objective function over that area of the decision space is then used to evaluate the sensitivity of the objective function to the uncertainties. This method has been applied in the literature to problems with uncertainties of type A (ElGhaoui and Lebret, 1997), and uncertainties of type B (McIlhagga *et al.*, 1996).

On a problem with uncertainties of type A, the robust counterpart can be produced as:

$$F_A(\boldsymbol{x}) = opt\, f(\boldsymbol{x}, \boldsymbol{\alpha}), \qquad \boldsymbol{\alpha} \in \mathbf{A}, \qquad \text{Eq. 2.13}$$

where $F_A(\boldsymbol{x})$ is the robust counterpart, $\boldsymbol{\alpha}$ is the set of environmental parameters (uncertainty type A) in a $\mathbf{A}$ the subspace defined by the operating conditions of the system that is being optimised and $\boldsymbol{x}$ is the vector of the decision variables. The counterpart F_A at each point of the decision space will be the optimum of the set of values produced by sampling $f(\boldsymbol{x}, \boldsymbol{\alpha})$ for all possible values of $\boldsymbol{\alpha}$. If the optimisation problem is a minimisation, the largest of the values of the objective function will be chosen for F_A , if the problem is a maximisation, the minimum value of the set is used.

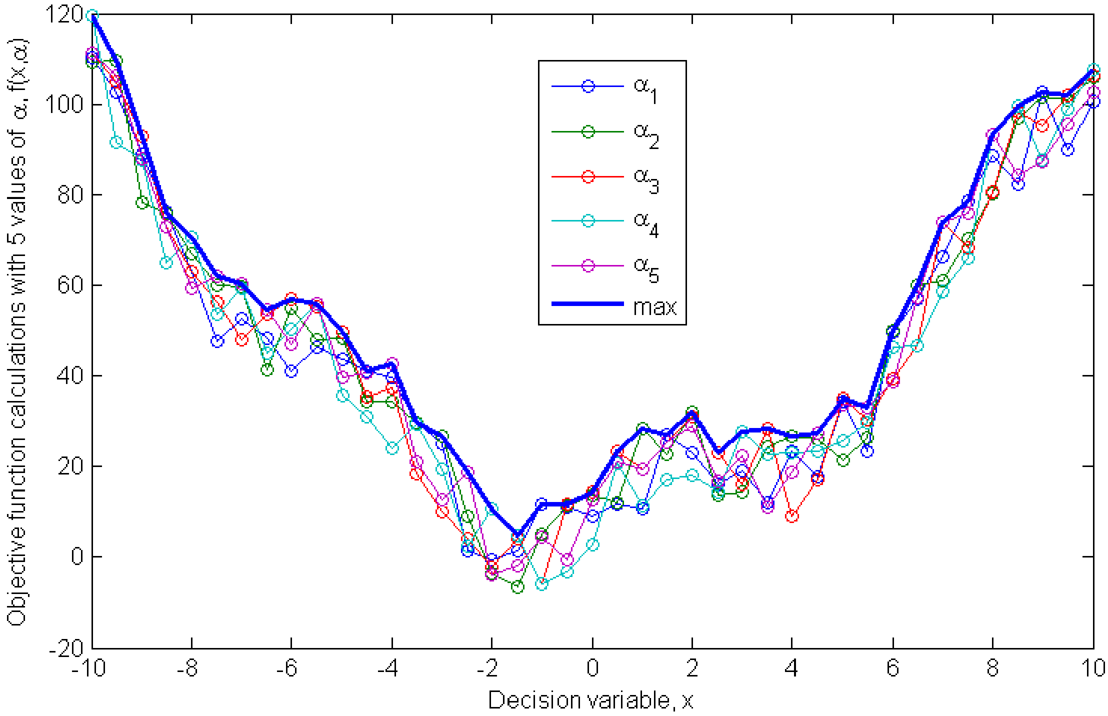

Figure 2.17 - In objective function where the objective depends on an environmental variable that cannot be controlled, the minimisation of the maximum of several evaluations is a way of finding a robust minimum.

For the case of uncertainties of the type B, the robust counterpart can be obtained doing a regularization of the function. That can be done by applying a similar formula to Eq. 2.13. In this case, the robust counterpart depends on a *regularization* parameter ϵ:

$$F_B(\boldsymbol{x},\epsilon) = \underset{\xi \in X(\boldsymbol{x},\epsilon)}{\text{opt}} \; f(\boldsymbol{\xi}), for\ all\ \boldsymbol{\xi} \qquad \text{Eq. 2.14}$$

with $X(\boldsymbol{x},\epsilon)$ represents a neighbourhood of the solution $\boldsymbol{x}$ and $\lim_{\epsilon \to 0} f(\boldsymbol{\xi}) = f(\boldsymbol{x})$. This form of creation of the counterpart of the objective function will require the selection of the regularization parameter according to the degree of robustness needed.

The robust counterpart approach can be considered as a *worst case scenario* philosophy. Another way of tackling uncertainty in optimisation is to consider that the uncertainties are defined by statistical estimators such as probability distributions. In this case, uncertainties can be treated by *expectancy measures of robustness*.

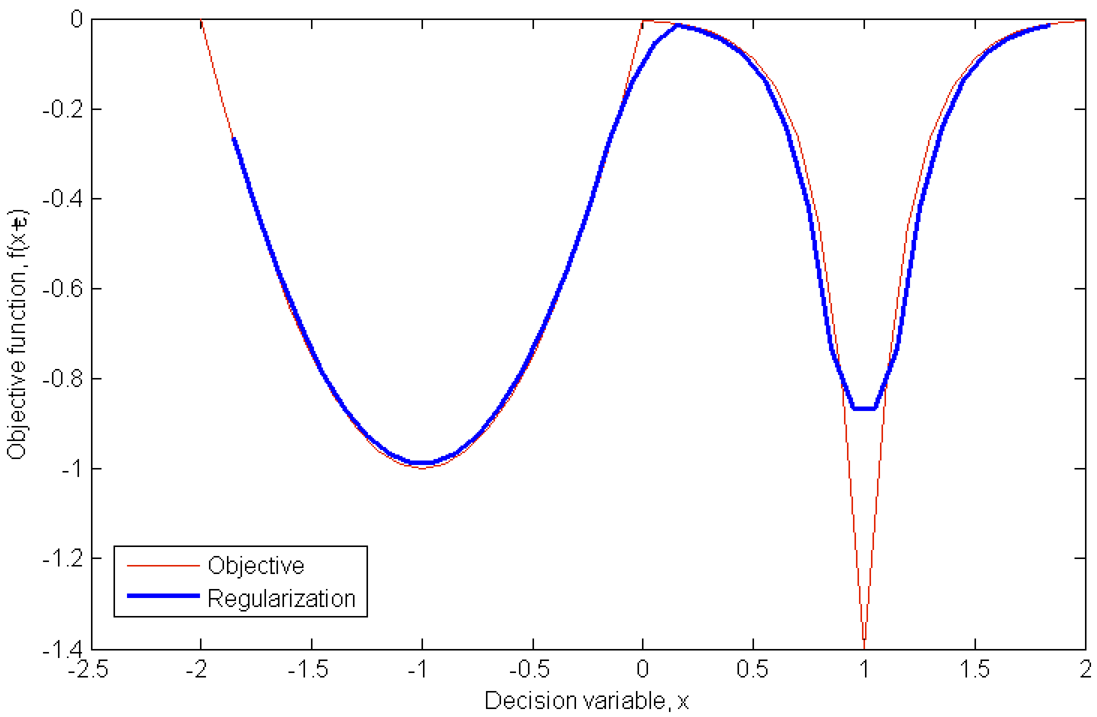

Figure 2.18 - Using the robust counterpart to dismiss solutions that are not robust to changes in the decision variable.

This approach can be applied when there is information available about the nature of the uncertainties and the form of the objective function. The *aggregation approach* makes use of a *utility function* *U*(*f*) to define the robust counterpart as the *conditional expectation* of *U*(*f*):

$$F_U(\boldsymbol{x}) := E[U(f)|\boldsymbol{x}]. \quad \text{Eq. 2.15}$$

where *U*(*f*) is a utility function defined by the operator. An example of utility functions are the *momentum measures* introduced for evolutionary robust optimisation in (Beyer, 2003):

$$U(f) = sign(f)|f|^k. \quad \text{Eq. 2.16}$$

This method allows one to account for uncertainties when the probability distribution of the uncertainties is known. This method is particularly useful for uncertainties of type B. For an example of the application of this technique see (Wiesmann *et al.*, 1998; Branke, 1998; Jürgen, 2001).

Finally, uncertainties can be treated by calculating the number of solutions that belong to a desired region of the decision space. If the optimisation is a minimization, it is desirable that the solutions of the optimisation present the smallest value of the objective, thereafter a desirable threshold q can be defined, and then one can consider optimal the solutions that make true:

$$f(\boldsymbol{x}) \leq q. \qquad \text{Eq. 2.17}$$

When the function *f* is affected by uncertainties, the objective value for a given solution might vary, and therefore some of the evaluations may appear out of the threshold q. It is then desirable to select the solutions $\boldsymbol{x}$ that are more likely to make true Eq. 2.18 i.e. the points with the higher probability of belonging to the region defined by *q*. This can be found by:

$$\Pr[f \leq q|\boldsymbol{x}] \rightarrow max. \qquad \text{Eq. 2.18}$$

So for minimisation the counterpart can be written as:

$$F_q(\mathrm{x}) = \Pr[f(\boldsymbol{x}) \leq q|\boldsymbol{x}]. \qquad \text{Eq. 2.19}$$

The equivalent for maximization can be done changing the inequality "≤" by "≥". In both cases, $F_q(\mathrm{x})$ is maximised as that represents obtaining the solutions with higher change of falling into the valid threshold.

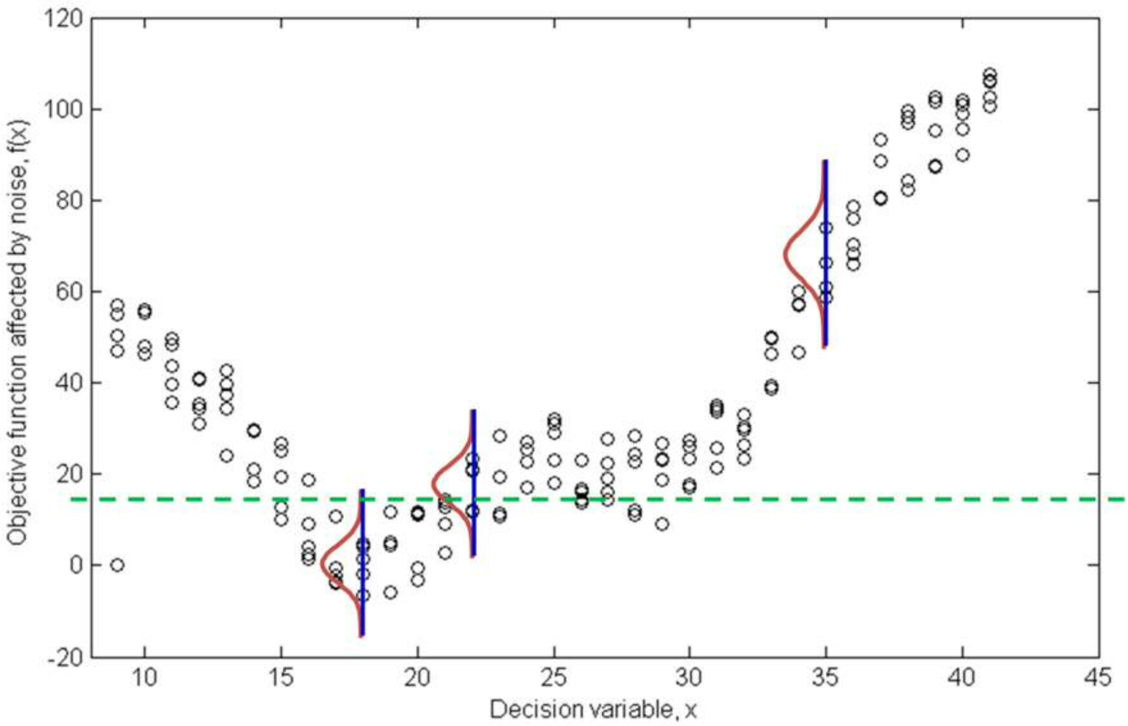

Figure 2.19 - Using the probability of being under a given threshold to calculate robust optima.

The methods described in this section, require some level of sampling Eq. 2.13 or Eq. 2.14, or some knowledge about the uncertainties (such as their probability distributions) in Eq. 2.15 and Eq. 2.19. These two requirements could be a barrier for the application of these techniques. Many problems do not allow sampling in the internal iterations of the optimisation because that would increase the computational time greatly, and other do not provide information about the probability distributions of the uncertainties. The method described by Eq. 2.19 would need one to calculate the probability measure: $\Pr[f \leq q|\boldsymbol{x}]$, obtaining this analytically would not be possible in most cases , and obtaining it by sampling would be computationally costly.

These methods allow for the modification of an optimisation problem affected by uncertainties of type A and B. These kinds of uncertainties were the main uncertainties considered in this thesis. However, for more of these techniques accounting for uncertainties of type C and D see (Beyer and Sendhoff, 2007).

2.4.3.2 Evolutionary algorithms as optimisation methods that produce robust solutions

Some optimisation algorithms are able to produce robust solutions due to the nature of the way they explore the decision space. The most popular group of optimisation methods with these capabilities are Evolutionary Algorithms (EA) (Beyer and Sendhoff, 2007; Jin and Branke, 2005).

Evolutionary Algorithms (explained in more detail in Chapter 4) are optimisation algorithms based on analogies with natural evolution. These optimisation algorithms are able to produce robust solutions. This is because, in general, more adaptable individuals in nature survive more than less adaptable ones. Holland’s publication introducing genetic algorithms (Holland, 1975) was the result of an intense study of, among others, adaptive processes of natural systems, and showed a direct correlation with robustness. Schuster and Yamaguchi also pointed out in their work the prevalence of adaptable individuals against optimal in nature (Schueller and Jensen, 2008). Marczyk (Marczyc, 2000) argued that optimisation will always be the opposite of robustness and, for that, not always desired in a design processes.

It is clear that design through natural evolution implies certain levels of robustness if one looks at the changing nature of the environment. One could think that EAs, being based the principles of natural evolution, might also produce robust solutions. Beyer and Sendhoff undertook a review of the use of EAs in uncertain environments on section 4.2.3 of (Beyer and Sendhoff, 2007), where they cite seventeen articles in which robust optimisation was performed using EAs. Jin and Branke did another survey (Jin and Branke, 2005) that focuses exclusively in evolutionary algorithms excluding any other optimisation method.

The work of Jin and Branke explains the different approaches that have been taken to deal with uncertainties when using EAs. This thesis has focused on uncertainties of type A i.e. uncontrolled environmental parameters that affect the value of the objective function. There are several options to deal with these uncertainties, and the two reviews mentioned above give a detailed understanding on how to implement uncertainties-proved algorithms.

2.4.3.3 Optimisation under dynamic environments

In some cases, optimisation algorithms are aim at finding an extreme value of a given function that depends on environmental parameters, for example minimise vibrations in a side mirror under different wind speeds or maximise efficiency in an internal combustion engine used at different rpms by injecting the right amount of fuel on-the-go. The user may want different results for the optimisation, depending on the problem. Two main approaches may be taken:

1. Carry out an optimisation that will "follow" the optimum as it moves within the decision space as the environment changes. This is the usual approach in optimal control of buildings, the conditions of the building (weather operation etc. changes all the time, and the control has to find the optimal heating for every instance). This approach has been called **optimisation <u>in</u> dynamic environments**.

2. Perform an optimisation that will provide a solution that will be near-ideal for all environments, therefore adopting a compromise solution. Examples of this are optimisations of building elements for building design; these elements should be optimal although the environmental conditions change (e.g. overhangs). This approach has been called **optimisation <u>for</u> dynamic environments**.

The first approach in this classification has been intensively studied and there has been a review of optimisation in dynamic environments recently written by Cruz et al. (Cruz *et al.*, 2011). Optimisation in Dynamic Environments (OIDE, referred to as the Dynamic Optimisation Problems in (Cruz *et al.*, 2011)), consists on carrying out an optimisation that will "stay alive" during the problem (sometimes called on-line optimisation). This means that the results of the algorithm are read "on the go"; as opposed to static problems where the algorithm is run once and the output is the final result. In the review of Cruz et al. a detailed explanation of the methodologies to perform OIDE is explained. This kind of algorithm will be used in this thesis to perform sequential optimisation of buildings in Chapter 5.

The basic mechanisms of OIDE algorithms are the maintenance of a diversity of solutions during the optimisation. This provides some continuing knowledge of the decision space at any point of the optimisation. The spread of solutions within the decision space makes easier for the algorithm to move the population to a new peak that may appear with a change of the environment.

Jin and Branke (Jin and Branke, 2005) describe the four approaches found in the literature to make an EA able to cope with dynamic environments; these measurements are:

1. Generate diversity after change. This consists of increasing the scope of the mutation operator when a change on the environment occurs. This requires the algorithm being able to recognize a change in the environment.

2. Maintaining diversity throughout the run. To this end, several control parameters are adjusted so the algorithm does not converge to a few solutions. This can be done through crowding mechanisms (to see crowding mechanisms and nesting in EAs see, for example, (Deb, 2001)).

3. Memory-based approaches. The algorithm is provided some memory to store information about the location of peaks in previous generations, making those areas of the decision space preferable for futures changes in the environment.

4. Multi-population approaches. This approach is similar to the differentiating characteristic of the MIGA (Multi-Island Genetic Algorithm). Several populations evolve independently, what will eventually make them focus in different areas of the decision space.

Although applying these modifications to the algorithms improves the efficiency when used for optimisation in dynamic environments, it should be noted that some algorithms are better than others when facing one of these problems. For example, self-adapting EAs are able to change the scope of their internal operators if a change on the landscape is noticed by the algorithm (see the CMA-ES in (Hansen *et al.*, 2003)).

In the case of **optimisation for dynamic environments (OFDI)**, the aim is to find a solution that is optimal for most of the environments. Therefore, the problem is of the type of robust optimisation with uncertainties of type B. In this case, the problem is tackled with the algorithms shown in Section 4.1.

The work of Weicker and Weicker is an example of using EA to find the optimal value of a function those changes depending on an environmental parameter. Weicker and Weicker checked the performance of different EA's operators when optimising a function whose optimum value and position do not change over generations, but the rest of the landscape does. This is an example of finding an optimum that will maintain an acceptable value for different environments.

Another interesting work within along these lines is the work done by Branke (Branke, 1998). Branke shows how EAs create robust solutions without any modification. He focused on proving an understanding about how EAs produce solutions that are robust against uncertainties of type B; however, the work introduces a couple of functions that can be used to test the ability of an EA to produce robust solutions against uncertainties of type A.

2.4.4 Conclusions

Robust optimisation is a mature powerful tool that should be used in problems where the designs are subjected to uncertainties. There is little work on robust optimisation for low-energy building design (reviewed in Section 2.6). However, this chapter shows that appropriate methodologies are available and could be applied to certain problems faced in building design. However, the long computational times needed to assess the quality of the solutions when optimising low-energy buildings might suppose a barrier when the methods shown in this chapter are implemented in this kind of problems.

Optimisation for dynamic environments is a kind of optimisation that could be applied to building design, where several environmental parameters can change during the life cycle of the building. Examples of uncertainties of type A are the weather or the occupants. Chapter 4 shows how a robust optimisation methodology was applied to produce robust solutions in a low-energy building optimisation problem. It might also work where the environmental changes during design e.g. we do not know the modelled number of occupants at the start of the design cycle, or how aggressive value engineering might be.

The method suggested in this thesis differs from the common way of propagating uncertainties based in sampling (like Monte Carlo simulation and Latin Hypercube Sampling) in the way that the optimisation propagates the uncertainties at the same time that it moves the solutions towards the optimum/a.

Optimisation in dynamic environments is a discipline that has been applied for several real-world problems. The access to these optimisation methods, has allowed the author to develop the sequential optimisation method for building design that will be explained in Chapter 5.

2.5 Computer aided building design

Building design is a complex process that involves a variety of professionals with different backgrounds and expertise. In this thesis, several algorithms are presented that could improve the computational tools that are used to perform building design. In this section, a context for computational methods used in building design optimisation is given.

2.5.1 Building design

Design is an intellectual endeavour based on creativity and judgment. Creativity contributes with coming up with new designs; judgment eliminates or modifies some of these due to the constraints and requirements of the project. This was illustrated by Schevers and Tolman (Schevers and Tolman, 2001)with the graph shown in Figure 2.20.

Figure 2.20 shows how a design process has an intrinsic iterative nature, by using creativity and judgment of options to reach an optimal design.

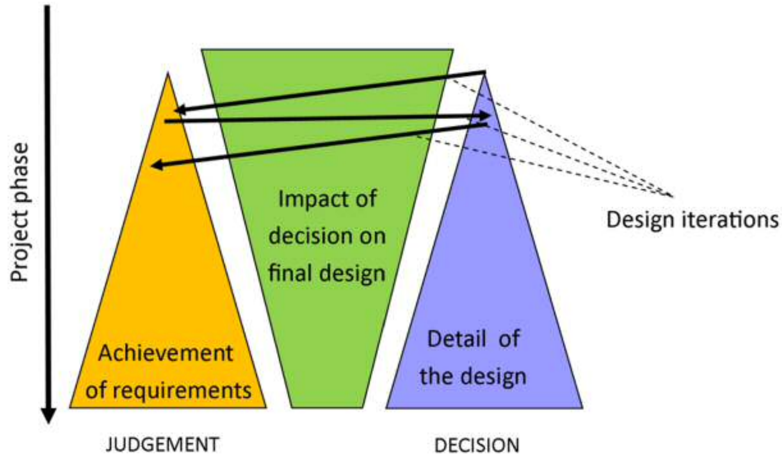

Figure 2.20 - The iterative design process as an iteration of decisions and judgment. From (Schevers and Tolman, 2001).

As mentioned before, building design requires a team of experts working together. There are many aspects that have to be determined, and this is done by going through several steps called *design stages*. Several authors have used different ways of defining design stages. The definition of Eastman was used in this thesis (Eastman, 1999), and has the following steps:

1. Feasibility study
2. Design
3. Construction planning
4. Construction
5. Operation
6. Demolition

The first three steps are the first stages of the life cycle of the building and describe the part of design. For this thesis, only the steps that involve design are considered; the stages are described in the following.

The **feasibility study** consists on a preliminary evaluation of the available resources together with the aims of the project. Eastman considers this stage to have the following subsections:

a. Building use field studies
b. Building use research
c. Construction time estimation
d. Project cost estimation

e. Building program analysis
f. Project income, productivity or cash flows

These six processes are included in the feasibility study, and they are based in preliminary studies. There will be several processes that will require information about the building (e.g. cost); therefore, the designer, even for the feasibility study will need a rough idea of what the design will be. Therefore, it can be seen that at this stage, certain exploration and judgement/selection of options will be performed.

In Eastman's book, the feasibility study is followed by the main design stage. He divided this stage into the following sub-stages:

1. Predesign
2. Site analysis
3. Schematic design
4. Design development
5. Construction documents
6. Bidding and negotiations
7. Construction contract administration

Only steps from 1 to 4 are relevant for this thesis as these are the steps where the use of optimisation algorithms has the most potential according to the literature shown in Section 2.6.2. Also, it has been seen that some authors consider the design stage as pre-design and detailed design only.

In the design stage, the options are evaluated with a greater level of detail than in the feasibility study; this is currently done by using specific software packages that analyse the performance of the designs through virtual prototyping. Examples of these tools are:

- Mechanical systems simulations tools. For example EnergyPlus, TRNSYS, and IES-<VE>.
- Lighting simulations. Also included in the software mentioned before (except TRNSYS).
- Acoustic simulation. Such as Odeon or EASE.
- People or traffic flows. For example SimTread.
- Energy simulations. Like IES-<VE> or EnergyPlus.

The last group in this list is not included in Eastman's book, as he considered the energy efficiency of the design as something performed externally by an expert system support. However, building energy simulation is now performed as much as or even more often than the first four of the list due to the strong regulatory requirements of the sector in the present (see Section 2.1.1). The regulations force designers to do building simulations so they have an estimate of the annual energy demand of the design, and there has been a growing literature concerning the adoption of such assessment tools by building professionals.

The design stage is a process with the same nature as the feasibility study, as the iterations between decisions and judgment have to also be done, with the difference that in design, there is a higher level of detail. One could therefore consider that Figure 2.20 could represent both feasibility study and design.

The fact that both stages imply a plethora of potential designs opens the door for optimisation in both cases. Optimisation is, as said before, the discipline of finding the best solutions to a given problem without the need of evaluating all the possible options. One could see that this fits well with the design process as described before.

2.5.2 Building energy simulation in building design

Computers are used in almost every intellectual endeavour, and building design is not an exception. The algorithms presented in this thesis are aimed at helping building design at a variety of stages; for that reason, an overview of these stages and potential opportunities of assistance with computational methods are described in this section.

Mahdavi et al. showed that the main professional reasons for using building performance simulation tools (BPST) is for the calculation of heating and cooling loads (100% of the professional interviewed). They also found that the most common reason why they use BPST is to meet regulatory requirements (75.8%).

When BPST are used at the design cycle, is however not that clear. Different authors showed different results: Mahdavi stated that 57.6% of the professionals (architects and engineers) that were asked, use BPSTs for construction documentation, 18.2% for design, and only a 6.1% for the preliminary design (here called pre-design) (Mahdavi *et al.*, 2003). However, de Wilde et al. showed that most of the building simulations (~55%) are performed by architects in the preliminary design (predesign), whereas for the construction drawings it is close to zero. In the case of the consultants, the methodology of measuring the answers changes slightly, but de Wilde et al. showed that the stage at which more simulations are being run (they start and end in different point of the design) is the conceptual design (pre-design) phase (de Wilde *et al.*, 2001). These differences can be due to the geographical differences of the study; one done in Austria and the other one in the Netherlands). Altavilla et al. drew from the results of their studies that engineers made the most use of building simulations at the design stage, and detail design stage. The architects, however, use the tools mostly at the stage of the definition of the design (pre-design). Altavilla et al. defined the design stage to be formed of: *Early design stage, scheme design stage and detailed design stage*.

The literature shows, therefore that building professionals tend to use BPST at the early stage of the design process when a large number of decisions have to be taken and the number of constraints are limited, or to do specific calculations more related with the calculation of energy systems, and energy demands.

2.5.3 Place of optimisation in building design

In the two stages of building design (i.e. feasibility study and design) the building professionals have to produce feasible or optimal designs (respectively). For this, they use tools to evaluate the options (as mentioned above). If the tool that evaluates the design options is computer based, the designer could create a set of rules that bound the possible designs (such as floor area limitation due to site shape or cost of the construction) and use a computer algorithm to examine and evaluate the options available.

In this thesis, three ways of denoting the way of performing the design have been used. If the designer investigates the options by generating every option for later evaluation manually, it has been called *assisted design*. The process is assisted because the designer has computational tools to evaluate the quality of the designs but each design option has to be introduced in the assessment tool manually with the consequent use of resources (designer's time). This has been illustrated in Figure 2.21.

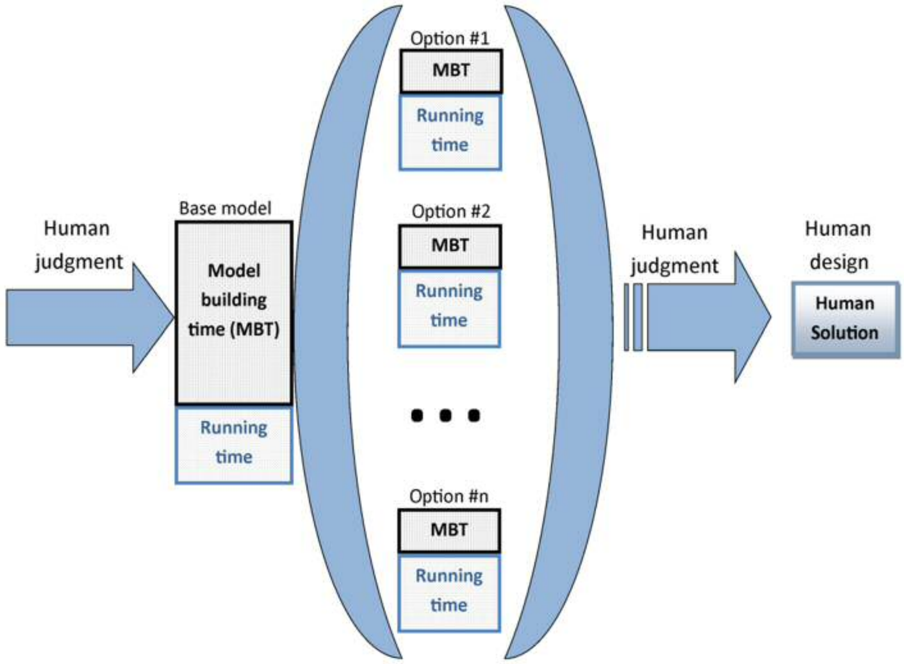

Figure 2.21 - Assisted design.

Another way of exploring and evaluating the design options is to couple the assessment tools with decision making algorithms. The most commonly used decision making algorithms are optimisation algorithms. These algorithms explore the design options, and provide the designer with the best ones for a given criterion or set of criteria. This way of performing the design process has been called semi-automatic design or automatic design.

Semi-automatic design is the use of an optimisation algorithm to generate a set of solutions that are near optimal for the later use of higher level information to select the best one. This last selection is done applying human judgment. This method facilitates the work of the designer as the options given by the algorithm are near-optimal and therefore s/he does not use her/his time for the exploration and evaluation of poor solutions. An example of this method is the work of Coley and Schukat (Coley and Schukat, 2002), and all the works where the optimisation is multi-objective (see Section 2.6.2).

In specific cases, the designer wants to get a final answer from the optimisation algorithm. This is more common at the later stage of design (design development) where the decisions taken are not going to modify largely other parameters and the solution tends to be unique (for example nominal power of the heating system). This has been called **automatic design**, examples of this are (Ooka and Komamura, 2009) or (Bloomfield and Fisk, 1981). Automatic and semi-automatic design have been shown in Figure 2.22.

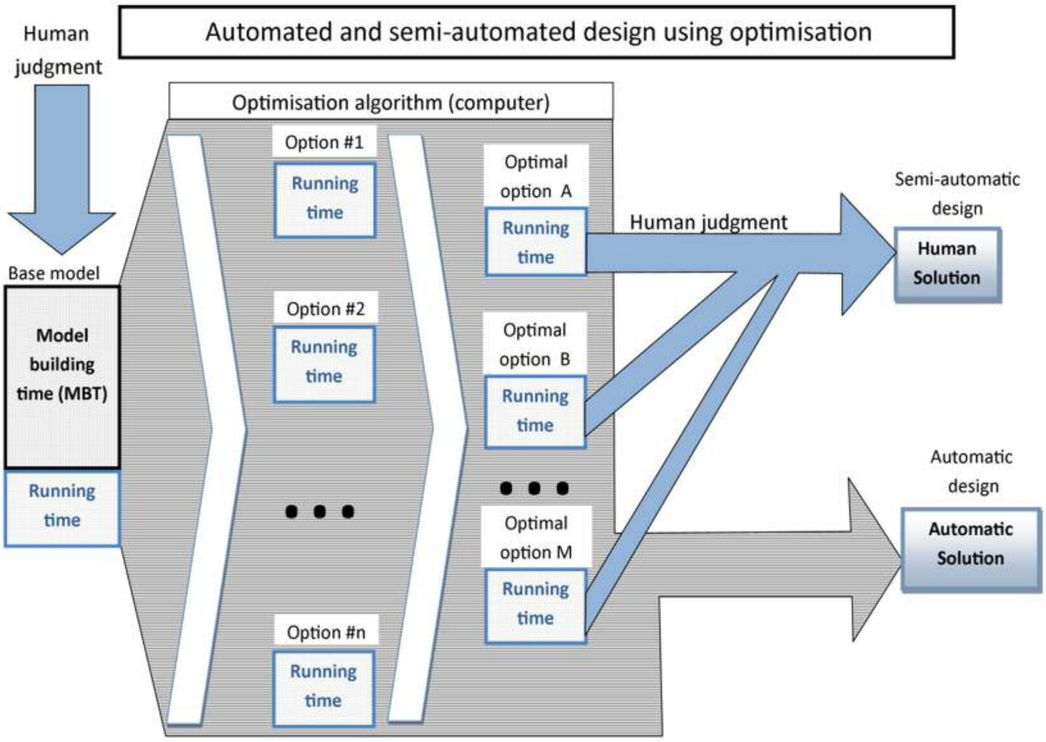

Figure 2.22 - Automatic and semi-automatic design.

This thesis shows two methods that improve the way of performing optimisation for automatic and semi-automatic building design.

As it was shown in this section, the optimisation can be applied to different questions of the design process at different stages. Each design question should be approached with a different strategy to make sure that the designer gets the most from the optimisation methods, but in any case, the algorithms presented in this thesis are beneficial.

Optimisation (or automatic design) has largely been used for building design in research, as shown in previous sections. The popularity of the optimisation methods for building design can also be seen in the availability of more “off the shelf” computational packages. There have been two scientific publications that give information about the *status-quo* of automatic design of buildings at the time of writing. These are the literature review of Evins (Evins, 2013), and the work of Attia et al. (Attia *et al.*, 2013) that includes a survey to building professionals about their use of optimisation for building design.

Attia et al. stated that most of the optimisations in the building design process are done during the early stages of the design (which is sensible as it is when most of the simulations are done, see above). The work of Attia et al. also showed that the two main technical obstacles for the deployment of optimisation in building design are:

1. The uncertainty of simulation model input and
2. The long computational time.

These are the two aspects that are treated in this thesis.

Chapter 4 will present an optimisation algorithm that accounts for the uncertainty of the occupants, and in Chapter 5 another that reduces computational times. The first algorithm could be used in a semi-automatic fashion if the designer is exploring the options in the pre-design stage. Using semi-automatic design, the designer will be able to use higher level information to select the best design. If the optimisation algorithm is being used at a later stage (design development) the algorithm should be used in an automatic fashion.

The second algorithm reduces computational times, and is aimed at the early step of the design stage (pre-design) where many options have to be evaluated leading to long computational times. This algorithm will make the evaluation of the options more feasible and allow for the production of near-optimal solutions that can be later evaluated by the designers.

2.5.4 Conclusion

Building design is an intellectual task that involves the selection of many parameters, and the compliance with many criteria. Optimisation algorithms can be a powerful tool to facilitate this task. The methods presented in this thesis go one step forward and improve traditional optimisation in two important aspects that have been seen to be two technical barriers: robustness and computational time.

2.6 Literature review

This section covers the relevant literature for this thesis.

2.6.1 Resistor Capacitor models of buildings

The representation of the building elements with RC-networks was the first attempt to model buildings dynamically. The work of Lorenz and Masy is an example of this approach (Lorenz and Masy, 1982 (in French)). Their work shows a way of representing multi-layered constructions of the building envelope with a 2 resistors 1 capacitor model (2R1C). This model was used by several authors in further years, but its limitations came out as well as its strength in later publications (shown below).

Achterbosch et al. developed another simple thermo-dynamic simulator based in RC-networks (Achterbosch *et al.*, 1985). In this work, Achterbosch et al. tackle the challenge of linearizing non-linear phenomena that occur in buildings (convection and radiation). This was solved with the application of standardised coefficients (linearization for normal conditions). This work also discusses the order of the models that are necessary to get an accurate response. The topologies shown in this paper can be seen in other publications.

Coley and Penman (Coley and Penman, 1992) used models based on RC-networks for data-driven simulation (see Chapter 3 of this thesis). Coley and Penman used these kinds of models because of their small number of parameters. The work by Coley and Penman consists on determining the values of the elements of the LPM that provides the most accurate outputs in comparison with a real building. One of the findings of their paper is that the element in the LPM that represents the thermal capacity of the air contained in the zone has to be four times larger than the actual heat capacity of the air. They conclude that this parameter has to be adjusted to include the thermal mass of furniture, partitions and other elements in the zone; this could have been sorted by including a specific element to represent partitions and furniture as in Achterbosch et al.

Tindale studied the possible topologies of LPMs representing buildings (Tindale, 1993). Although his work used the same number of elements to represent the building element as Coley and Penman, Tindale's work shows the limitation of second order models representing the whole building. He compared the results of these models with the results of the simulation using APACHE[12]. The limitations were seen to be especially true in heavyweight buildings. Tindale suggested adding an extra branch in the LPM, connected to the inside node, with one resistor and one capacitor in series. This seemed to have a positive effect in the accuracy of the model. However, after studying the rest of the literature in the topic, it seems that the reason of the loss of accuracy could be tackled in a better way by using a 3R2C network to represent the envelope (as seen in (Gouda *et al.*, 2002) or (Fraisse *et al.*, 2002). The branch suggested by Tindale does produce an improvement in accuracy but, because of its topology, it should probably be used to represent partitions and other thermal masses instead of tuning the capacitor representing the thermal mass of the air of the zone.

The works mentioned before used different techniques to find the most accurate LPMs of the buildings studied, in the work of Lorenz and Masy and Achterbosch et al. this is done with set of simple equations that allow the calculation of the LPM of any building with a trivial computational calculation. The rest of the authors used numerical methods to find the optimal parameters of the LPMs. Mathews et al. followed the philosophy of developing a methodology that does not use numerical methods for the creation of the LPMs (Mathews *et al.*, 1994). In their paper, the reader is provided with a set of simple equations to calculate the parameters of their LPM. The method shows the way of creating a LPM with four resistors and one capacitor (4R1C). The method developed by Mathews et al. is based in the calculation of the matrices of heat transfer coefficients of the building elements. The topology of the LPM created in this paper is too reduced, however, some of the methods to calculate the time constants of the complete models are accurate, and will be used in this chapter.

Gouda et al. published a comprehensive work about building models based on RC-networks, and also on the implementation of the energy systems to those models (Gouda *et al.*, 2000). Gouda used a 2R1C model for the walls of the envelope, a single resistor for the windows, and a 2R1C model for the partitions (they used a LPM for each zone, and connected them by the nodes representing the partitions). This work does not include qualitative changes in the LPM; however, it shows how these models can be used to perform more

[12] Finite differences simulation code.

comprehensive simulations of buildings by including the heating system and a basic solar radiation model. Gouda et al. (same co-authors) proved in (Gouda *et al.*, 2002) that the model used in the previous article (2R1C), is insufficient for the walls of the building envelope, and recommended a 3 resistor 2 capacitor (3R2C) model for this. Gouda et al. found the parameters of the LPM using optimisation methods. The limitations of the 2R1C model are shown prominently when the response of the model is evaluated under fluctuating internal gains.

Fraisse et al. developed a methodology to create LPMs of buildings by a set of equations obtained analytically (Fraisse *et al.*, 2002). In this method, the state space representation of the multi-layered construction is transformed to the Laplace domain and then the higher order terms are eliminated. In this way, the equations that are left can be identified with a state space system of order two that can be represented by a 3R2C. The method of Fraisse's et al. is rather complicated, and does not take into account the operational conditions of buildings, being the reduction that they suggested "blind" to the propose of the model.

The methodology shown by Fraisse et al. does not apply any numerical method to find the parameters of the LPM model that best represent the multi-layered construction, it is for that reason that it has been considered as an analytical method and therefore the only one that overlaps with the method presented in this thesis.

Another publication in which 3R2C models are used to represent the walls of the envelope is the work by Xu and Wang (Xu and Wang, 2007). In this work, genetic algorithms are used to find the optimal LPM of the constructions. The optimisation is done in the frequency domain, and the 3R2C model seems to be a good compromise between accuracy and simplicity to represent the walls of the building envelope.

The creation of lumped parameter models by abstracting the most thermally relevant elements of the buildings to a state space system has allowed several authors to develop their own building models coded into high level programing languages. An example of this is the work of Wetter in Modelica. Modelica is a dynamic systems solver that allows for the modelling of any process prior introduction of the differential equations that govern it. The module *ROOMS* developed by Wetter et al. is a simplification of the dynamics of the building using LPMs (Wetter *et al.*, 2011). The same principle is followed by Hudson using Matlab/Simulink to code a LPMs solver (Hudson, 1999).

This review of the previous work in reduction of building models shows that several authors have developed different methodologies; but more importantly, shows that the consideration of the normal operational conditions of buildings to develop a method for the creation of LPMs is not common (it has not been seen in any of the papers previously reviewed that use analytical methods to create the LPMs), and could be a strong modelling technique due to the cyclic nature of the inputs of the building (e.g. day and night affecting the weather, office hours affecting the gains).

2.6.2 Optimisation in building design

This section shows the state of the art of optimisation for low-energy building design.

2.6.2.1 Current optimisation packages for building design

Several researchers have created optimisation frameworks that can be used for building design. These packages are highly relevant to this thesis as what is presented here is not a complete software, but algorithms that could be implemented in these “ready to use” software packages.

Starting with the commercial software, IES-<VE> is developing “Optimise”, a new module that will be capable of performing single and multi-objective optimisation for a given design, after the user determines what variables will be optimised and which will be fixed. This module has been developed by Loughborough University among other industrial partners (Launched 5 September 2012).

Other researchers have created optimisation modules that operate with EnergyPlus, allowing the parameterisation of the models for the later optimisation in one or more objectives. One of these is the tool for Design Builder (graphical interface of EnergyPlus), developed in the research project ADOPT with De Montfort University with Yi Zhang as Principal Investigator (PI) (not launched at the moment of writing).

Michael Wetter has developed a variety of packages for optimisation of building design. The packages developed by Wetter are integrated in GenOpt and BuildOpt (Wetter, 2001) (Wetter and Wright, 2004) (Wetter, 2005) (Wetter and Polak, 2005). Wetter developed a framework in which the user can change the simulation engine and the optimisation algorithm allowing evaluating the optimal combination for each problem. The software developed by Wetter is more oriented to research as the usability is low and a substantial amount of knowledge about optimisation and basic programming is needed to operate it properly.

2.6.2.2 Optimisation algorithms used in building design. Literature review in Evolutionary Algorithms.

As mentioned before, EAs have gained a substantial popularity as function optimisers, and this has been reflected in their use to building design problems. The main papers in optimisation applied to building design using EAs can be divided into two categories: single-objective optimisation, and multi-objective optimisation. These are reviewed below.

2.6.2.2.1 Single-objective optimisation

Although most problems in building design are subject to a large number of objectives such as low energy demand, good lighting, thermal comfort, etc; there are some publications in which the authors use an optimisation algorithm to find the minimum or maximum of a single objective without taking into account any other implication of the design.

One of the first works published about optimisation of buildings, is the work of Wright and Farmani. They included three decision variables concerning the building fabrics among the variables to be optimised mainly focusing on the HVAC system (Wright and Farmani, 2001). Wright and Farmani used a genetic algorithm to perform this optimisation.

Another paper focusing in the shape and design of the envelope of the building is found in the work (Coley and Schukat, 2002) concerning the design of low energy buildings. Coley applied EAs to optimising the heating demand of a dwelling to a minimum by modifying the architectural parameters. The number of decision variables was small as Coley used a simple dynamic simulator. The simulator used by Coley also has the advantage of needing little time to run in the assessment of each solution. That made the work possible with limited computing resources (single core personal computer). Coley presented this methodology as a way of helping architects with their designs, but not as a way of finding a single optimum; architects will still need to assess the designs produced by the algorithm to find the best solution using other criteria difficult to assess by the computer, such as appeal.

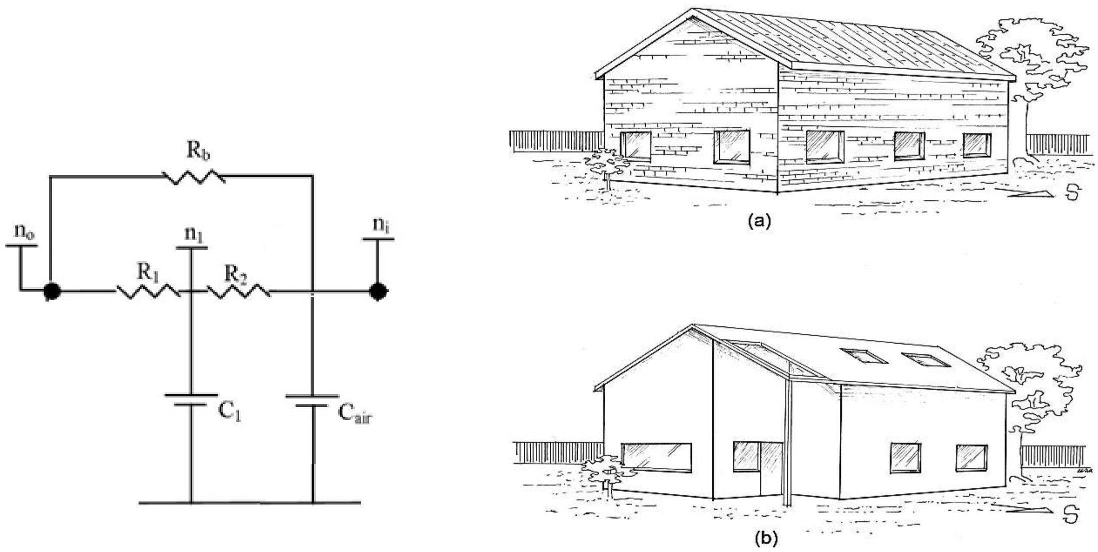

Figure 2.23. RC-network (left) representing the thermal model of the building optimised by Coley and Schukat and the artistic representation of two possible optimal designs (right) (recreated with the permit of the authors).

The work by Lee in optimisation of the indoor climate using GAs and CFD (Lee, 2007) presents certain interesting characteristics for this thesis. This application of GAs to a single objective optimisation problem is one of the few that consider the random variables (such as environmental conditions, occupants' behaviour, workmanship of construction, etc) affecting the optimisation. Although Lee does not consider the random variables as uncertainties in the optimisation problem (as in the classification of (Beyer and Sendhoff, 2007)), Lee produces a robust counterpart of the objective function using the probability distributions of the random variables.

Another example of single objective optimisation using EAs, and more specifically GAs, is the work by Ooka and Komamura (Ooka and Komamura, 2009). They used the versatility of GAs to find the best energy systems and the operational parameters of those, making the algorithm select the "energy solutions" as a whole. Ooka et al. used a Multi-Island Genetic Algorithm (MIGA), a modified GA that allows the development of different "species" separated in islands by isolating the individuals in clusters and allowing immigration and emigration of a limited numbers of them in every generation. Ooka would publish another paper as a co-author with Kayo as main author with similar methodology, but including the utilization of waste as a potential source of energy for cogeneration (Kayo and Ooka, 2010).

The publication by Kampf and Robinson (Kampf and Robinson, 2009) is an interesting application of Evolutionary Strategies to building design. Kampf developed an optimisation algorithm that is a combination of a CMA-ES[13] and a hybrid differential evolution (HDE) algorithm and used it for this work. This paper is an introduction of the new algorithm in addition to its application to the optimisation of land-use when planning the construction of a group of buildings with the maximum isolation. The algorithm itself is proven to be effective in this work, and its application successful.

Finally, the recent work of Tuhus-Dubrow (Tuhus-Dubrow and Krarti, 2010), shows an example of coupling a GAs with DOE-2 (see Chapter 3) as in the previous paper. In this case Tuhus-Dubrow studies the envelope size and shape, as the design of the envelope is usually a compromise between maximising solar energy access and minimising heat losses due to high ratios between envelope area and living space volume. The GA performs well in this application and allows finding the optimal design of the project.

2.6.2.2.2 Multi-objective optimisation

Multi-objective optimisation is a very attractive method for building designers for two reasons: they can optimise a design for any number of objectives; and, secondly, the result of a multi-objective optimisation is, by definition, a set of solutions.

Optimising several functions at the same time has a clear advantage: in building design, factors such as comfort, capital investment or energy use want to be optimised together for every design.

Providing a set of solutions, allows architects to select among a variety of designs applying higher level information difficult to assess by a computer such as appeal.

Chantrelle presented a work in which Multi-Objective Evolutionary Algorithms (MOEA) are used for low-energy building design (Chantrelle *et al.*,

[13] Covariant Matrix Adaptation Evolutionary Strategy

2011). Chantrelle used a Non-dominated Sorting Genetic Algorithm (NSGA), an algorithm that is based in the Pareto optimality of solutions (see Section 2.3.1.4); specifically, he used the so-called NSGA-II which is an elitist (maintaining the best individuals, see (Deb, 2001)) version of the NSGA (see (Srinivas and Deb, 1994)). The authors perform the optimisation firstly with two and secondly with three objective functions. Chantrelle compared the results when optimising the objective functions with single objective algorithms, then by pairs, and eventually as a group of three. As expected, the single objective optimisation give the boundary points of the two-objective optimisation Pareto fronts, and these the edges of the three dimensional Pareto front of the three-objectives optimisation. Chantrelle proved the validity of MOEAs for aiding decision making in building design with this work.

Another application of multi-objective optimisation used in building design can be found in (Caldas and Norford, 2003). In this paper, the building envelope is optimised for minimising heating and artificial lighting. This paper has been included in this review because the constraints of the problem, that force the shape of the envelope to fit in a real building site, make the optimisation problem closer to those that would be found in real life. Caldas used an algorithm based in Fonseca's algorithm (Fonseca and Fleming, 1998) and not the Pareto front (as in the NSGA). In Fonseca's algorithms the solutions obtain a fitness value inversely proportional to the number of solutions that dominate them.

Multi-objective optimisation allowed Wang to do a comprehensive optimisation in building design in his work (Wang *et al.*, 2005). Wang optimised the Life Cycle Cost (LCC) and the Life Cycle Environmental Impact (LCEI) together using multi-objective optimisation. Wang considered the LCC and the LCEI from the extraction of the materials from the natural resources to the demolition of the building. Wang used Fonseca's MOGA as in the work described in the previous paragraph. One of the interesting points in Wang's conclusions is how the Pareto front of this optimisation could be grouped in two clusters, making the clusters with solutions that are fundamentally similar. This is a common way of studying the Pareto front, or, in general, a set of multiple solutions (as in (Coley and Schukat, 2002)).

The work by Magnier (Magnier and Haghighat, 2010) shows one of the problems that can be faced when carrying on multi-objective optimisation for building design: computational times to evaluate the objective functions that are too long. Magnier used TRNSYS (see Chapter 3) to model the thermo-dynamic behaviour of the building (passive elements) and the HVAC system (active elements). TRNSYS can be a very accurate simulator; however, the time needed to carry out a simulation of the building for the whole year could be of the order of minutes. In an optimisation run where MOEAs are used, the populations may be as big as 200 individuals, and the number of generations carried out by the algorithm as many as 500 (700 in this work) to achieve convergence (depending on the number of decision variables), that means carrying out 10^5 (100000) simulations, if the evaluation of the objective function takes longer than 1 minute, the optimisation may become unviable (more than a week of computation) when performed in a standard personal computer (one core 3.0GHz). To work around this problem, Magnier used Artificial Neural Networks (ANNs). ANNs are able to produce a surrogate objective function that produces an approximate answer in a very short time; that way, some of the evaluations can be carried out in a short time. Magnier was then able to run a rather long (700 generation) optimisation using NSGA-II. Thermal comfort and energy consumption are maximised and minimised respectively in this work. One of the most interesting points extracted from the results of this work is how well the RSA generated by the ANN represented the objective functions with a few “real” evaluations of the objective functions, what can be understood as a proof of the “smoothness” of these functions.

Wright et al. compared the results of two multi-objective optimisation problems, one using a multi-objective algorithm; the other using a single-objective algorithm applied to a single objective function that is the result of doing the weighted summation of the objectives (Wright *et al.*, 2002)). This is a “sanity check” for the multi-objective EA that has not been seen in any other work in building design. Wright *et al*. also compare the differences in optimising building design with different test days of different seasons. Wright pointed out that the algorithm with 200 individuals and only 21 generations is able to produce close-to-optimal solutions. Another interesting point of this work is the comparison between single objective optimisation (using weight-vector) and multi-objective; precisely, how the multi-objective optimisation is able to obtain 119 more solutions than the single-objective optimisation, whilst only completing 2.5 times more evaluations of the objective function.

The work of Suga (Suga *et al.*, 2010) concentrates noticeably in the analysis of the results from the Pareto front. The optimisation problem considered in his/her work is a four objective multi-variant optimisation with the aim of designing the windows of an office block to maximize the uniformity of the luminance and the draught performance, and minimize the energy consumption and the glass cost. Suga discretized the decision space creating a grid for the vertices of the windows. This allowed the encoding of the evolutionary algorithm. As seen in (Wang *et al.*, 2005), Suga uses clusters to group similar solutions for the designer to understand the different options available.

Table 2.6 - Summary of the most relevant publications of multi-objective optimisation for this thesis.

Reference	**Highlights**
(Chantrelle *et al.*, 2011)	Algorithm: NSGA-II Comparison between single-objective and multi-objective optimisation
(Caldas and Norford, 2003)	Optimisation of building envelope constrained to fit in a real construction site. Fonseca´s evaluation of multi-objective optimality (Fonseca and Fleming 1998)
(Wang *et al.*, 2005)	Solutions presented in clusters: sets with solutions with similarities
(Magnier and Haghighat, 2010)	Objective function evaluated using TRNSYS Algorithm: NSGA-II Implementation of Artificial Neural Networks to reduce the computational time of the run
(Wright *et al.*, 2002)	Comparison between single-objective and multi-objective optimisation. Quantification of the difference of computational times between generating the Pareto Front with weighted-sum evaluation and a multi-objective algorithm
(Suga *et al.*, 2010)	The use of Genetic Algorithms force creating a discrete decision space.

2.6.3 Robust optimisation used in building design

The work of Lee (Lee, 2007) is one of the few examples of robust optimisation in the literature of building design. In the work of Lee the energy use of an HVAC system in an office is minimised. The decision variables define the configuration of the windows to reduce the load on the conditioning system, and determine the level of natural ventilation. Each solution is evaluated using Computational Fluid Dynamic (CFD) simulation. However, due to the long computational time needed to run a dynamic simulation for the whole year, Lee considered the outside temperature an uncertainty, and calculated the probability distribution of the air temperature for the location where the office is located. To be able to calculate the energy demand for the whole year, Lee picked 5 temperatures, and ran a CFD steady-state simulation with each of those temperatures. The energy needed to acclimatise the office under each of the temperatures was multiplied by the probability in the year of having that temperature outside (the five temperatures represent a range of temperatures so there are only 5 terms in the summation), the result of the summation of the energy demands per temperature multiplied by their probabilities was considered the total energy demand over the year.

Robust optimisation is used in Lee's paper exclusively to avoid the need to run dynamic whole year CFD simulations. However, he does not mention the variability that might exist due to different uses of the office i.e. different equipment, different schedules, different preferences in comfort etc.

Marjit presented a methodology in his Master's thesis consisting of an optimisation method that used meta-models to produce robust solutions (Marijt). The selection of the uncertain variables in this work is based on a previous work of Hopfe (Hopfe *et al.*, 2007) where she compared between 77 parameters to extract the most relevant ones when performing energy calculations. Behavioural patterns of the occupants are not considered by Hopfe the most influential, and therefore their influence was not tested in Marjit's thesis. Marjit selected physical parameters of constructions and infiltration as the source of uncertainties; leaving the uncertainties due to occupants out of the analysis.

The work in the thesis of Marjit considered only uncertainties due to occupants. And among these, only the ones relative to occupancy and electricity use. The use of windows and doors could be as influential, however, these factors were not considered as the implementation of those in the codes was complicated, and the availability of tools able to generate these patterns is limited[14].

2.6.4 Uncertainties in building design and building energy assessment

Uncertainties are found in any “real-world” system (see Chapter 5), and buildings are no exception. As early as 1978, Gero and Dudnik wrote a paper presenting a methodology to solve the problem of designing subsystems (HVAC) subjected to uncertain demands. After that, other authors have shown an interest in the uncertainties that are present in building design; the uncertainties were classified in this thesis in three different groups:

1. Environmental. Uncertainty in weather prediction under changing climate; and uncertain weather data information due to the use of synthetic weather data files: (1) use of synthetic years that do not represent a real year, and (2) use of a synthetic year that has not been generated from recorded data in the exact location of the project but in the closest weather station.
2. Workmanship and quality of building elements. Differences between the design and the real building: Conductivity of thermal bridges, conductivity of insulation, value of infiltration or U-Values of walls and windows.
3. Behavioural. All other parameters linked to human behaviour i.e. doors and windows opening use of appliances, occupancy patterns or cooking habits.

The type 1 from this grouping, have been divided here into two main groups: one concerning the uncertainty due to climate change; and the other concerning uncertainties due to the use of synthetic weather data files. Concerning the uncertainties due to climate change: buildings have long life spans, for example, in England and Wales, around 40% of the office blocks

[14] No tool has been found in the literature able to be coupled to EnergyPlus, and that controls the opening and closing of doors and windows with random patterns as those occurring in real buildings. Rijal, H.B., Tuohy, P., Humphreys, M.A., Nicol, J.F., Samuel, A. & Clarke, J., 2007. Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings,* 39**,** pp.823-836.

existing in 2004 were built before 1940 (30% if considered by floor area) (ODPM, 2005) and, 38.9% of English dwellings in 2007 were built before 1944 (CLG, 2007). This long life span makes buildings likely to operate with climates that might change due to global warming. De Wilde and Coley showed how important is to design buildings that take into consideration climate change and that are able to perform well in future weathers (de Wilde and Coley, 2012). These uncertainties have not been considered in this thesis. However, their importance is acknowledged and their implementation within the methodology presented in this chapter is feasible and suggested for further work.

Concerning the uncertainties due to the use of synthetic weather data files: Wang et al. showed the impact that uncertainties in weather data (among others) may cause in energy demand calculations (Wang *et al.*, 2012). The deviation in calculated energy use due to variability in the weather data were found to be different in different locations from a range of (-0.5% – 3%) in San Francisco to a range of (-4% to 6%) in Washington D.C. The ranges were calculated using TMY[15] as the reference. These deviations on the demand were smaller than the ones due to operational parameters. For those, the ranges were (-29% – 79%) for San Francisco and (-28% – 57%) for Washington D.C. The operation parameters were those linked with occupants' behaviour. The conclusion of this paper is that occupants will have a larger impact in energy calculations than the variability between synthetically generated weather data files.

The spatial resolution of weather data files was the concern covered by Eames et al. (Eames *et al.*, 2011). Eames showed how a low spatial resolution of weather data files can be the cause of disparities of up to 40% in the heating demand. Although this source of variability has a substantial impact on energy calculations, this source of uncertainties has not been considered in this thesis. The reason is that this uncertainty is not understood as an aleatory parameter but as an *epistemic*[16] uncertainty that can be solved with the appropriate

[15] Typical Meteorological Year

[16] Epistemic uncertainties are those caused by a lack of knowledge of the variable or input in opposition with aleatory uncertainties that represent the randomness (non controllable) nature of a variable. Swiler, L. & Giunta, A., 2007. Aleatory and epistemic uncertainty quantification for engineering applications. Sandia Laboratories.

improvement of the data resources or with specific weather data acquisition for each project.

In the work of Pettersen, uncertainties of group 2 (workmanship and quality of elements) and group 3 (behaviour) of the previous grouping were considered (Pettersen, 1994). This work shows how important occupants' behaviour is on the calculation of the energy demand of a building. Pettersen showed that the total energy use follows a normal distribution with a standard deviation of around 7.6% when the uncertainties due to occupants are considered, and of around 4.0% when considering those generated by the properties of the building elements.

A large study was carried out by Leeds Metropolitan at Stamford Brook. This project saw 700 dwellings built to high efficiency standards (Wingfield *et al.*, 2011). The results of this project show a significant gap between the energy used expected before construction and the actual energy use once the house is occupied. The workmanship is analysed in this work. The authors emphasise the importance of thermal bridges that were not considered for the calculations, and how those originated by the internal partitions that separate dwellings have the largest impact on the final energy use. The dwellings that were monitored in use in this study show a large difference between the real energy use and that estimated using SAP, with one of them giving +176% of the expected value when in use.

Hopfe has published several papers concerning uncertainties in building design. A more recent publication at the time of writing (Hopfe and Hensen) looks into uncertainties of group 2 and 3. In this work the uncertainties are defined as normal distributions. The random parameters are sampled to generate 200 tests that are sent to the simulator (VA114), the results from which will be analysed to check the uncertainties with the largest impact on the energy calculations. This work showed that the uncertainty in the value used for infiltration is the factor that is likely to have the largest influence on cooling and heating demands.

Another study performed by de Wilde and Wei Tian (de Wilde and Tian, 2009), compared the impact of most of the uncertainties affecting building energy calculations taking into account climate change. De Wilde and Tian used a two dimensional Monte Carlo Analysis to generate a database obtained with

7280 runs of a building simulator. A sensitivity analysis was applied to this database to obtain the most significant factors on the variability of the energy demand calculations. Standardised Regression Coefficients and Standardised Rank Regression Coefficients were used to compare the impacts of the uncertainties.

De Wilde and Tian agreed with Hopfe on the impact of uncertainties in the infiltration over energy calculations, but also introduced other factors, including uncertainties in: weather, U-Value of windows, and other variables related with occupants' behaviour (equipment and lighting). Their paper compares many of the uncertainties with a good sized database providing a realistic comparison for the scope of the sampling of the uncertainties.

The work of Schnieders and Hermelink (Schnieders and Hermelink, 2006) showed a substantial variability in the energy demands of low-energy buildings designed under the same specification (Passivhaus). See Figure 2.25.

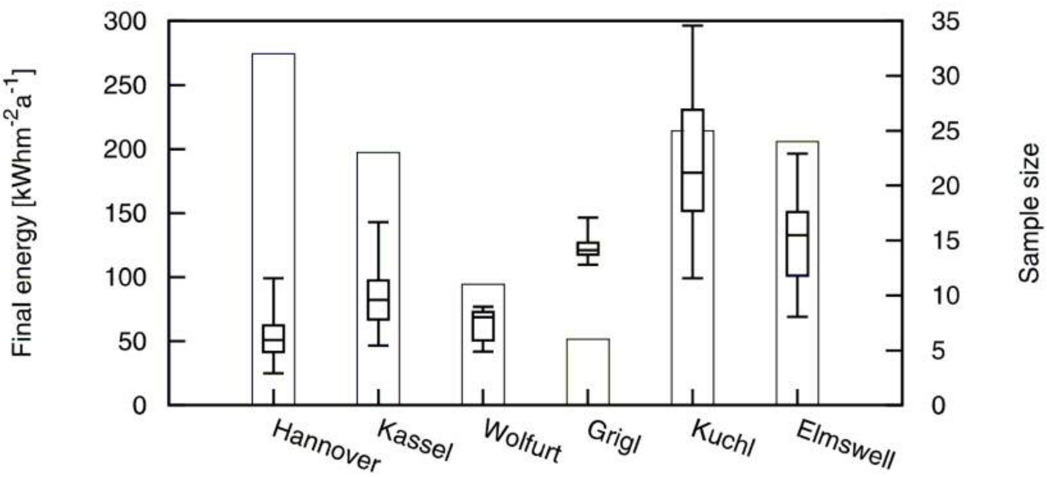

Figure 2.24 - Measured final energy consumption (candlesticks) of selected low-energy buildings (bars as sample size). The values contain all non-renewable energy supplies to the buildings, including household electricity and ancillary energy consumption. All data from the CEPHEUS data set (Schnieders and Hermelink, 2006) except the Elmswell data which is taken from Gill *et. al.* (Gill *et al.*, 2010).

Blight and Coley (Blight, 2012) showed that that variability can be occasioned due to variance in occupant behaviour (it should be noted that the use of windows and doors was included in this work). The work of Blight and Coley proves two things: (1) Occupants have a substantial influence on energy use; and (2) The model they used to generate occupants' behaviour is accurate for the creation of behavioural patterns of inhabitants.

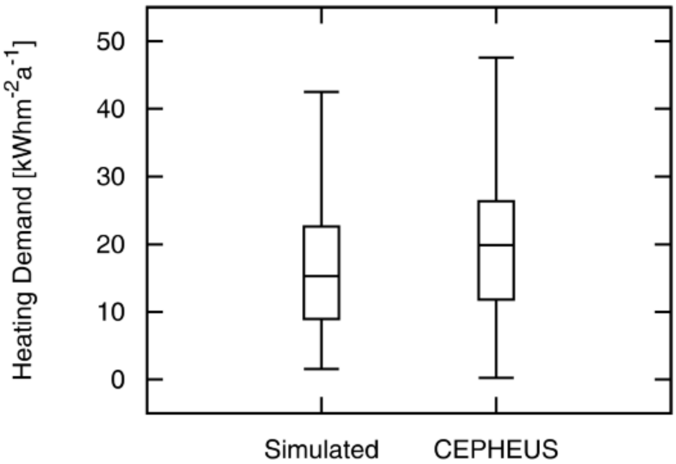

Figure 2.25 - Correlation between the data obtained by Blight and Coley (left) and real data from the study CEPHEUS (right).

The method used in the previous paper (Blight and Coley) to generate accurate profiles of occupants' behaviour was the one developed by Richardson et al. (Richardson *et al.*, 2008). The method was developed using the Time-Use Survey (TUS) of the United Kingdom as a reference of real behaviour of occupants, this database was elaborated after recording the activity of more than 6000 occupants in 24-hours diaries with a 10 minutes resolution[17]. Richardson's paper shows how the tool is able to generate behavioural patterns that correlate with the real data obtained from the TUS.

The availability of this tool allows computer scientist's to model the uncertainty of occupants' behaviour as a set of behavioural patterns that have been proven to correlate with real occupants' behaviour.

Concluding: standards and regulations are aimed at improving the energy performance of buildings (see Chapter 4). Those low-energy buildings will be more sensitive to occupants' behaviour as proved by (Schnieders and Hermelink, 2006) together with (Blight, 2012). This sensitivity should motivate a

[17] Ipsos-RSL and Office for National Statistics, United Kingdom Time Use Survey, 2000 (Computer File), third ed., UK Data Archive (distributor), Colchester, Essex, September 2003, SN: 4504.

deeper consideration of the uncertainties due to occupants when performing optimisation for building design. In this thesis accurate occupants' profiles are used to uncover robust building designs by including them in a modified optimisation algorithm that looks for robust solutions. As the computational time taken by the optimisation algorithm is one of the concerns of this thesis, the method introduced here was designed in such a way that it does not require much longer computational times than the methods used to perform optimisation without uncertainties.

This section has described the previous work in the impact of occupants' behaviour in energy demand calculations. In the following, a more comprehensive study of the literature is shown, where all the uncertainties that might affect energy demand calculations are assessed. This is done to justify why occupants were chosen as the uncertainty in this thesis, and the methodology here presented built around it.

It is worth mentioning that some authors have developed methodologies to deal with uncertainties intrinsically in the building simulator. This is the case of Brohus et al. (Brohus *et al.*) who developed a way of introducing the uncertainties in the heat balance equations by means of stochastic differential equations. The method allows one to obtaining the results of the simulation stochastically with confidence intervals.

Macdonald and Clarke implemented uncertainty handling in the building simulator ESP-r (Macdonald and Clarke, 2007). In his work, he considered uncertainties in the energy conservation equations to be able to quantify the effects of uncertainties. With this work, he was able to improve his previously published methodology: (Macdonald and Strachan, 2001) that was more computationally costly.

This section has discussed the uncertainties that are found when assessing energy performance of buildings. There have been several studies including these uncertainties in calculation methodologies, but in most cases, they are analysed using Uncertainty Analysis (UA) methods that require the re-evaluation of solutions for different scenarios (such as Monte Carlo Analysis or Latin Hyper cube Sampling). In this thesis, the propagation of uncertainties to find robust solutions will be embedded in the optimisation method to take advantage of the iterative nature of the algorithm to deal with the uncertainties.

More of this will be explained in Chapter 4 were the methodology is presented and applied to test functions and a building design application.

2.6.5 Surrogate models an applications in building design

The need to use complex assessment tools for the evaluation of potential solutions can render optimisation unfeasible. There is a standard procedure in engineering (Barthelemy and Haftka, 1993) to tackle this problem:

1. Create a simpler model of the objective function by:
   a. implementing a simpler model to assess the solutions, based on the physics of the problem
   b. creating an approximation of the objective function after evaluating a number of points within the objective function (meta-modelling)
2. Minimise the simpler model
3. Verify the optimality of the solution of the simpler model with the objective function

The creation of a simpler model based on physical principles is normally challenging. A quantitative change has to be done in the way that the system is modelled to obtain a model that requires less computation. This cannot be done in many cases due to the complexity of the system to be analysed or the nature of the problem (for example, search of natural modes of vibration).

Several works can be found in the literature where meta-modelling is used to create surrogate models for the optimisation, examples of these are (Booker *et al.*, 1999; El-Beltagy and Keane, 1999; Forrester *et al.*, 2007; Jansson *et al.*, 2003; Koziel *et al.*, 2009; Queipo *et al.*, 2005; Ong *et al.*, 2004) in mechanical engineering, and (Magnier and Haghighat, 2010) in building design.

The work of Jin et al. summarised the strengths and weaknesses of four of the most popular meta-modelling techniques, namely polynomial regression, multivariate adaptive regression splines, radial basis functions and kriging (Jin *et al.*, 2001).

One of the weaknesses of meta-models is that they suffer from the *curse of dimensions* (Ong *et al.*, 2004). This effect can be explained as follows: the number of points that are needed to create a realistic surrogate model of the decision space grows exponentially with the number of dimension of the objective function. As an example, if one wants to have 3 points per dimension in a decision space with 20 decision variables, one would need 3^{20} = 3486784401 points, if the problem had 3 decision variables, one would need 3^3 = 27 points. To create the surrogate model of the decision space the points need to be evaluated with the real objective function, and eventually be used to generate the surrogate model. Having a large number of decision variables has therefore a clear impact on the computational time needed to create the meta-models: the computational time to create a meta-model grows exponentially with the number of decision variables.

The method shown by Barthelemy and Haftka was considered by Booker et al (Booker *et al.*, 1999) as not ideal. In this report published by NASA, Booker et al. argues that the methodology of Barthelemy et al. violates a fundamental tenet of numerical optimisation: "*one should not work too hard until one nears the solution"*.

This was related to the need of constructing a surrogate model before knowing the shape of the decision space and performing an optimisation run of the surrogate model that might have been built with points that are not near the areas where the optimum or optima are located and therefore do not well represent the areas of high fitness. Booker et al. suggested a more efficient way of performing the optimisation: he used an on-line surrogate model that improves during the optimisation as more "true" points are selected and calculated in areas with high fitness.

In the paper of Booker et al., the framework is used to optimise the design of a helicopter rotor blade with 31 decision variables (the curse of dimensions would be clearly noticeable in this problem). The authors mentioned that the creation of simpler models that would be able to represent the objective (in this work: harmonics in flight mode) was not possible; therefore, they created a mathematical model (meta-model) by using the true points calculated with the objective function. Several optimisation algorithms are tested in Booker's work. A genetic algorithm is the only one used that belongs to the family of evolutionary algorithms.

El-Beltagy and Keane presented another framework for combining surrogate models and optimisation (El-Beltagy and Keane, 1999). In this case a

GA is investigated as function optimiser using surrogate models, but the way of creating the surrogate model is similar to the one described above (interpolation of true points). The method is proven with benchmark synthetic functions and a practical example of structural design, where the harmonics of a beam are searched.

The work of Ong et al. showed that Evolutionary Algorithms assisted with surrogate models can lead to optimisation with shorter computational times (Ong *et al.*, 2004). Ong et al. found in their investigation that a reduction of up to 95% in the computational time can be achieved when optimising a synthetic objective function (Rastrigin) using surrogate models, and up to 77% when the framework is used in a “real-world” problem (airfoil design).

Two other examples of the use of surrogate models to assist optimisation can be found in (Queipo *et al.*, 2005) and (Forrester *et al.*, 2006). The first paper gives a detailed description of optimisation using surrogate methods; the paper of Forrester et al. shows how using simulations that have not converged totally to build the surrogate model is a more efficient way of creating the meta-models than using results from fully-converged simulations; this is because more points can be evaluated for a given amount of time.

This short review on surrogate models to assist optimisation shows that these methods have been used in other disciplines. The work of Magnier and Haghighat (Magnier and Haghighat, 2010), was the only one found in the literature that uses surrogate models to make a more efficient optimisation in building design (Chapter 4). In the work of Magnier and Haghighat artificial neural networks and true points in the decision space are used to create a meta-model that is optimised.

Wetter used a technique similar to surrogate models in (Wetter, 2005). In this paper, Wetter used the accuracy with which the differential equations are solved in the building simulator to adjust the accuracy of the model and therefore the computational time to solve it during the optimisation. Although this technique does not belong to any of the ways of creating surrogates models defined before (Barthelemy and Haftka, 1993), it has been included here as it is relevant to the use of surrogate models in optimisation for building design.

The use of surrogate models has only been found in two of the papers reviewed in Chapter 4; however, Wetter and Wright suggested in their work

(Wetter and Wright, 2004), that the use of optimisation with surrogate models in building design is a promising area of research. No research has been found that uses optimisation for building design and the surrogate models created by simplifying the models themselves (type a in the listing of Barthelemy and Haftka).

The new measures to reduce carbon emissions in the building sector have increased the interest in producing low-energy designs, these being, buildings that need a fraction of the energy needed of a traditional building to create the same levels of comfort. Several software packages have been developed to aid building professionals in the design of low-energy buildings. These software packages (getting more and more complex with time) are able to evaluate the building physics and its energy systems in a very comprehensive manner. Among the phenomena that can be modelled with this kind of software one can find radiation, phase changing, humidity transfer, pollutant emissions, air movement, and many others. Although computers have become more powerful with time, this improvement does not overcome the growth on complexity of the building simulators, and therefore, the time needed to run a building annual simulation on a personal workstation. Those simulations can be of the order of hours, making the process of investigating several designs slow and tedious.

The fact that current dynamic simulators can assess the quality of buildings in term of energy efficiency, has motivated some building scientists to use optimisation algorithms coupled with these software tools to find low-energy designs (Tuhus-Dubrow and Krarti, 2010; GAMA, 2005; Chantrelle *et al.*, 2011), but the long computational times needed to run these optimisations can make the process unfeasible.

Other authors had used simplified building models to be able to run the optimisation in relatively short times (Coley and Schukat, 2002; Wright *et al.*, 2002). Although the results of these research works are enlightening, one could argue that due to the use of a basic simulator, only approximated optimisation for the early stage can be performed, and a more complex simulator should be used for refining the design.

Magnier and Haghighat had a different approach to the problem. Instead of using a simple simulator, they used and Artificial Neural Network (ANN) to create a Response Surface Approximation model (RSA), a type of surrogate model (meta-model). To create these meta-models a number of evaluations of the objective function is calculated at the beginning of the run to “educate” the ANN, and then that ANN is used to evaluate the objective function in the following. This method allows using complex simulators, and therefore, it can be apply at later stage of design where the systems and the architectural parameters are more detailed. Magnier and Hagnier pointed out that the ANN may produce results with errors up to 3.9 %, and these errors could be found in the solutions of the run, therefore implying a drawback in the method. Apart from that, ANNs suffer of the curse of dimensions (see Chapter 8, Section 2) as the number of points needed to train the ANNs grows exponentially with the number of decision variables of the optimisation problem.

Similar to the approach of Magnier et al. was the one of Eisenhower et al. (Eisenhower *et al.*, 2012). In this work, they used sensitivity analysis to obtain the parameters in building simulation that have the largest impact. With those parameters, they created a meta-model using a super computer for later using that meta-model to perform the optimisation.

The two cases above are examples of two ways of tackling problems that present unviable computational times can be solved: One, using a simple dynamic model to reduce the time of evaluating the objective function; or two, developing a surrogate model that will mimic the objective function and can be evaluated with short computational times.

On the one hand, the idea of training an ANN for the whole decision space is not ideal; on the other hand, using a basic building simulator may not provide the accuracy needed for a given problem. In this thesis, a different method is suggested.

The methodology that is presented in this thesis in Chapter 5 uses an evolutionary algorithm as a core of the optimisation; as the algorithm evolves, the solutions are assessed with different assessment tools that require different computational times.

This way of evaluating the objective function, can make some decision variables having no effect on the objective function when the simple assessment tools may not consider those decision variables (e.g. thermal mass of partitions in a steady-state calculation methodology). For this reason, the algorithm needs to be able to “catch up” on those decision variables when the assessment method becomes complex enough to interpret them. The algorithm should also maintain the values of the decision variables that were optimised in previous “cheaper” stages of the optimisation if the values are correct for further assessment tools.

2.6.6 Conclusion

This is a review of the literature available at the time of writing relevant to this thesis. It can be seen from this review that despite the fact that model fidelity has increased largely in the last 40 years there are a few questions that are still un-answered.

The importance of uncertainties in building energy assessment has been pointed out in several occasions. There are a few publications that rank those uncertainties and show the relative importance of each one in the overall energy use of the building.

This knowledge about the impact of uncertainties and the availability of optimisation techniques have motivated the merging of this two to create robust optimisation techniques that produce solutions that are less sensitive to uncertainties. The result of this is the algorithm in Chapter 4.

The use of simpler models in building assessment is also common in the scientific literature, but again, it has not been exploited in optimisation by creating those surrogate models not by numerical training of meta-models but using lower fidelity models that increase the fidelity as the optimisation progress. This is the principle of the algorithm developed in Chapter 5.

3 Resistor capacitor networks as thermo dynamic models of buildings

Contents

Nomenclature

T- Three dimensional time-dependent temperature field [K].

$\frac{\partial}{\partial t}$ – Derivative in time.

α – Thermal diffusivity [m^2/s].

k – Thermal conductivity [W/(mK)].

ρ – Density [kg/m^3].

Cp – Specific heat capacity [J/(kgK)].

q – Heat flow [W].

t – Thickness of a layer of material [m].

A – Area of a slab of material [m^2].

C – Capacitance [J/K].

R – Resistance [K/W].

h - Heat transfer coefficient (general)

f_{UB}- Upper bound of the range of relevant frequencies [s^{-1}].

f_{SN} – Shannon-Nyquist frequwncy [s^{-1}].

ω_{UB} – Angular frequency of f_{UB} [rad/s].

T_s – Sampling period [s].

τ_{LB} – Time constant for the lower bound of relevant frequencies [s].

f_{LB}- Lower bound of the range of relevant frequencies [s^{-1}].

ω_{LB} – Angular frequency of f_{LB} [rad/s].

s – Laplace variable of the frequency domain [rad/s].

Z – Impedance [h/(Ωrad)].

f_{24} – Frequency of a 24 hours period [s^{-1}].

R_{dom} – Resistance of the dominant layer [K/W].

C_{dom} – Capacitance of the dominant layer [J/K].

τ_{is} – Internal time constant of the first order lumped parameter model [s].

τ_{os}– Internal time constant of the first order lumped parameter model [s].

$R \quad _m$ - Summation of the resistances prior the dominant layer [K/W].

τ'_{in}- First internal time constant of the second order LPM [s].

τ''_{in} – Second internal time constant of the second order LPM [s].

τ'_{out} - First external time constant of the second order LPM [s].

τ''_{out}- Second external time constant of the second order LPM [s].

3.1 Introduction

This chapter describes a new methodology to create reduced dynamic models of buildings based in RC-networks. The method is a way of reducing a complex RC-network representing the passive elements of the building into a Lumped Parameter Model (LPMs). These models only consider the passive elements of the building, excluding any active energy system.

This chapter is an extension of the paper (Ramallo-González *et al.*, 2013).

It includes a new way of creating reduced models of multi-layered constructions; this is called the Dominant Layer Model (DLM), and it is one of the main contributions of this thesis. The methodology was created as a result of research on simple models of buildings. The Dominant Layer Model is a lumped parameter model, based on RC-networks, able to represent multi-layered constructions of any number of layers by reducing the layers to a model with two capacitors and three resistors.

The method to obtain DLMs is one of the steps of the complete methodology shown in this chapter; the complete methodology allows for the creation of LPMs that represent the whole building. The accuracy of the method is evaluated after being presented.

The creation of thermal models using RC-networks comes with the assumption that the non-linear phenomena can be linearized without losing a large deal of accuracy, because the heat transfer is dominated by conduction that is a linear phenomenon. This is something that can be subjective to discussion, however, most users of thermal models based in RC-networks, use them for their short computational times and simplicity.

There are several alternatives to this way of modelling. Building is dynamic systems that respond differently with inputs of different kind. The creation of building dynamic simulators that solve the numerical equations to provide with the thermal response of the building has motivated the creation of different ways of solving the dynamics of the building (Clarke, 2001).

A different but common way of dealing with the dynamic response of a system (in our case heat transfer) is making the simulated temperature a function of the inputs and all previous temperature values (USDoE, 2013a).

Using all the previous temperature values is far from computationally efficient. However, the similarities of higher order terms allow substituting them for historical flux calculations. These new terms are called Conduction Transfer Functions (CTF’s) and allow reducing the number of terms needed for obtaining an accurate solution. Using the state space formulation one can obtain the coefficients that have to be used in the time series that relate the simulated temperatures with the previous temperatures depending on the properties of the material (Ceylan and Meyers, 1980), but these can also be calculated using the Laplace transformation were the response in frequency of the system can be obtained (Hittle, 1979).

In this chapter, the description of the rational process that leads to the development of the methodology to reduce RC-networks to LPMs is described.

3.2 Hypothesis and aim of the work

The previous work in the topic shows that other authors have presented analytical methods to produce LPMs of buildings, but these had their limitations. These are: the model in (Lorenz and Masy, 1982 (in French)) or (Mathews *et al.*, 1994) being of low order and the model of (Fraisse *et al.*, 2002 158) making no use of the operational conditions of buildings, and being constituted by complex equations that make the method difficult to use.

The aim of this research was to find a method for creating reduced models of buildings (LPMs) without the need to use numerical methods. Also, these models have to be accurate for the normal operations of buildings i.e. when being use with realistic weather data files and real gains.

The hypothesis is that creating a method that is “aware” of the type of inputs that the model will have is a way of improving the accuracy of these reduced models.

3.3 RC-Networks and LPMs

3.3.1 Assumptions to create RC-networks representing buildings

The complexity of a mathematical model used to represent a real system can be as complicated as the modeller decides. However, the common practice when building a mathematical model is to adopt a compromise between fidelity to the real system and simplicity. In the same way, building scientists have to make several assumptions when modelling real buildings to make sure that only the most relevant components are included in the models so they can perform accurate but yet efficient simulations.

3.3.1.1 Thermal zones

Some authors have used several lumped parameter models to represent several thermal zones (rooms) in the building (Fraisse *et al.*, 2002). In this thesis, the lumped parameter model will be considered to represent a whole building, under the assumption that the rooms in the building have similar temperatures. This might lead to a substantial error depending on the use of the building, but this assumption has been taken in many cases when the speed of the simulation is prioritised (for example as in (Kampf and Robinson, 2007)).

3.3.1.2 Conduction through walls

The heat conduction through building elements such as walls and windows plays an important role in the overall energy balance of the building.

The equation of conduction in solids is:

$$\frac{\partial T}{\partial t} - \alpha \Delta \mathrm{T} = 0, \qquad \text{Eq. 3.1}$$

where *T* is the three dimensional time dependent field of temperatures (*T(t,x,y,z)*), α is the thermal diffusivity (or $\frac{k}{\rho Cp}$ with *k* the thermal conductivity [W/(mK)], ρ the density of the material[kg/m^3], and Cp its thermal capacity [J/(kgK)]) and Δ is the Laplacian operator. However, the heat transfer in buildings occurs in ways that enabled simplifications to be applied to Eq. 3.1.

The first assumption made in most building simulators is the consideration of one dimensional heat flow through walls (Clarke, 2001) (USDoE, 2013a). This assumption implies that the temperature along any direction perpendicular to the normal of the surface is the same. That changes Eq. 3.1 into:

$$\frac{\partial T(x)}{\partial t} - \frac{k}{\rho Cp}\frac{\partial^2 T(x)}{\partial x^2} = 0, \qquad \text{Eq. 3.2}$$

where *x* is the dimension along the normal of the surface.

In addition, the layers of material can also be discretized in the *x* direction as three nodes, two in the external faces of the layer, and one in the inside, as shown in Figure 3.1.

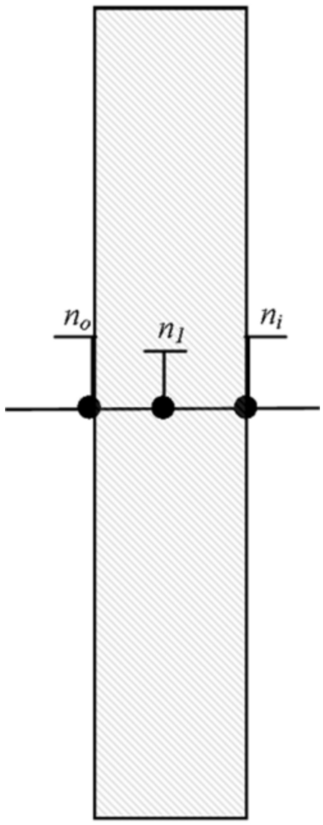

Figure 3.1 - Representation of a layer of material with three nodes, rather than as a continuous dimension.

This discretization in space allows a layer of material to be represented as the model in Figure 3.2, where C (= c_p x *area* x ρ x *thickness*) is the thermal capacity of the layer with unit J/K and R (= *thickness* / (k x *area*)) is its equivalent resistance with units K/W. This simplification is not used by most dynamic simulators (such as IES-VE or EnergyPlus) instead, they use by default the Conduction Transfer Function (CTF), The CTF uses a previously calculated finite time series to characterise the dynamic response of the construction (USDoE, 2013a). Using the CTF allows the simulators to calculate the temperatures and heat flows through walls dynamically at a low computational cost. However, this cannot be used when creating a building model based in RC-networks, as with the CTF the walls are not characterised by linear elements (resistors and capacitors) but by a set of coefficients that are used numerically by the engine of the simulator(see (ASHRAE, 2009).

The reduction of layers of material with a three nodes RC-network was studied in detail in (Barbaro *et al.*, 1986; Davies, 1982, 1983; Letherman, 1977). The reader is referred to those references to find a detailed discussion about the loss of accuracy that this simplification implies. However, the summary of that discussion is that the first order simplification might imply loss of accuracy in the model but only when representing single thick slabs of material.

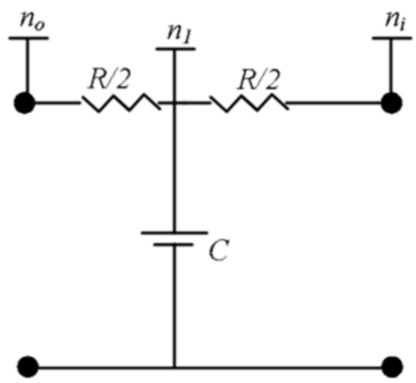

Figure 3.2 - First order representation of a single layer of material.

This first order approximation of a layer of material introduces errors in the model; however, it has been accepted by several authors (such as (Mathews *et al.*, 1994), (Xu and Wang, 2007), (Fraisse *et al.*, 2002) or (Gouda *et al.*, 2000)). This simplification has been used in this thesis as modern constructions tend to have more than two layers with different materials (ASHRAE, 2009; CIBSE, 2006), and seems to be the common practise in the literature; however, the author is aware of the errors that this assumptions might introduce to the method, and sees the need of further research to investigate the propagation of the error when the first order approximation of slabs is used in a multi-layered construction.

When Eq. 3.2 is applied to the model in Figure 3.2 i.e. single layer of material, the heat transfer equation becomes:

$$C\frac{dT_1}{dt} = \frac{1}{0.5R}(T_1 - T_o) + \frac{1}{0.5R}(T_1 - T_i) + q_i + q_o, \qquad \text{Eq. 3.3}$$

where T_x is the temperature at node *x*, the variables q_x are heat fluxes through the layer, and *C* and *R* are the equivalent capacitance and resistance of the layer respectively that are calculated by Eq. 3.5 and Eq. 3.4.

$$R = \frac{t}{kA} \ , \qquad \text{Eq. 3.4}$$

$$C = \rho c_p t A \ , \qquad \text{Eq. 3.5}$$

with R the equivalent resistance of the layer, t its thickness, *k* the conductivity of the material, *A* the area of the wall, *C* the equivalent capacitance, ρ the density of the material and c_p the specific thermal capacity of the material.

The simplifications taken up to this point allow one to convert the heat transfer equation Eq. 3.1 into a first order linear differential equation as the one in Eq. 3.3.

These are the simplifications applied to a single layer of material. However, the constructions used in walls have normally more than one material; instead, several layers are used to create a multi-layered construction.

RC-networks representing each layers of material, are connected in cascade (node n_i of one with node n_o of the next) to generate the complete RC-network of the construction an example is shown in Figure 3.3.

That results in several equations of the form of Eq. 3.3. This creates a set of first order differential equations to represent the heat transfer across the layers.

3.3.1.3 Homogeneous air conditions

The next assumption used in building simulators is to assume uniform air conditions over the interior of a modelled room (zone) i.e. the properties of the air in the whole zone are the same (USDoE, 2013a; Clarke, 2001). It is known that this is not true (see for example (CIBSE, 2006), Figure 5.2 page 5-5). However, the variability of air characteristics in rooms is usually dismissed to reduce computational times; a full CFD run would be needed to fully represent the spatial distribution of the air’s properties inside the zone, (see Section 5.10.3.2 of (CIBSE, 2006)).

3.3.1.4 Convection and radiation

Another assumption that needs to be taken to create accurate RC-networks of buildings is the linearity of convection and radiation.

Convection is the heat transfer mechanism produced by the movement of a fluid in contact with a solid at different temperature; it is represented by

$$Q = hA\Delta T, \qquad \text{Eq. 3.6}$$

where Q is the heat flow [W], A is the area affected by convection [m^2], ΔT is the difference of temperature between the surface of the solid and the temperature of the fluid in a point not disrupted by the solid [K], and h is the convective coefficient [$W/(m^2K)$]. If h were constant, convection would be a linear phenomenon. However, h is a number that depends on several parameters, mainly, the velocity of the fluid. To solve the problem of variable values of the convection coefficient, the convection can be modelled as a variable resistor (as in (Kampf and Robinson, 2007)). However, some authors have kept it constant using a standard empirical value (such as (Mathews *et al.*, 1994), (Hudson, 1999),(Gouda *et al.*, 2000), (Sebald, 1985)). These assumptions make it possible to include convection in RC-networks as simple resistors.

In the same way as convection, radiation can be linearized. Radiation is a non-linear physical phenomenon that cannot be included in the RC-network. However, a global convection-radiation factor can be used to represent this heat transfer mechanism as is shown in (CIBSE, 2006). These factors are empirical values that have been chosen to have the same effect on average as the real ones for a given weather and a given set up. These factors should be changed if the conditions are different (for example, in another country). In most cases, the U-Values of windows and constructions include the resistances due to convection and radiation, and therefore the linearization above is not needed.

3.3.1.5 Windows and infiltration

Windows and thermal bridges can be considered in the creation of LPMs of buildings to have negligible thermal mass compared with the thermal mass of walls and other structural elements, for that reason a simple resistor can be added to the RC-network of the whole system representing these elements.

Infiltration can only be included in the RC-network and maintain the linearity of the network[18] if it is considered constant during the simulation. Further sections will describe how to transform this infiltration value in a single resistor.

3.4 Creation of simple RC-networks to represent buildings

To create an RC-network type model of a building, the elements that contribute to the thermal behaviour of the building have to be represented.

The RC-networks representing all the thermally relevant elements of the building can be lumped into a simpler Lumped Parameter Model (LPM). The order of this model changes depending on the author: first order in (Mathews *et al.*, 1994), second order (Coley and Penman, 1992), or third order (Gouda *et al.*, 2000; Gouda *et al.*, 2002; Xu and Wang, 2007). In this section an LPM with high level of accuracy under the normal operations of buildings is investigated.

3.4.1 Reducing multi-layered constructions

The first step to create the LPM of a building is to create an LPM of the envelope; for that, the multi-layered constructions have to be reduced to a simple model. To create the complete representative network of a multi-layered construction, each layer of the construction could be considered as a two-port network with two resistors and one capacitor as shown Figure 3.2 (see Section 3.3.1.2). Adding several of these T-networks together produces a large RC-network with as many nodes as layers of material. A construction of n layers represented with an RC-network is solved by integrating the n differential equations that represent the RC-network. The integration of the n differential equations requires of the calculation of the n by n matrix $e^{A\Delta t}$ (the physical meaning of this matrix is explained below). The calculation of this matrix is performed only once for the whole simulation (the same is used in each time step) if none of the elements change along the simulation (no variable

[18] Variable resistors can be used for this propose; However, that would require the calculation of the matrices of the system in every time step (will be discussed in following section. Also those variable resistors can be linked to the variables of the system (make them proportional to internal temperature) but that makes the system non-linear.

resistances or capacitors); however, the calculation shown in Eq. 3.7 has to be carried out in every time step,

$$\boldsymbol{x}_{n+1} = e^{A\Delta t}\,\boldsymbol{x}_n + K\boldsymbol{u}, \qquad \text{Eq. 3.7}$$

where $\boldsymbol{x}_n$ and $\boldsymbol{x}_{n+1}$ are vectors of size *n* representing the temperatures of each layer, $e^{A\Delta t}$ is an *n* by *n* matrix that represents the response of the system without inputs, *K* is an *n* by *2* matrix that represents the effect of the inputs in the system and $\boldsymbol{u}$ is a vector representing the inputs (external temperature and gains in this case). The operations in Eq. 3.7 have an order of growth of n^2; as an example, the reduction of a multi-layered construction of 6 layer (6 nodes) to a simplified LPM with 2 nodes (like the one suggested in this thesis) will reduce the computational time of each time step by a factor of 9.

An RC-network of a multi-layered construction can be seen in Figure 3.3. The number of different layers *n* can be as large as those found in real buildings.

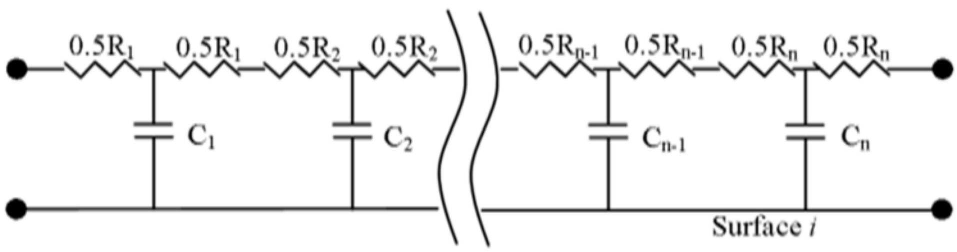

Figure 3.3 - RC network representing a construction with n layers.

3.4.1.1 Method of Fraisse et al.

The method published by Fraisse et al. is highly relevant for this thesis as it is the only alternative to the method that is proposed here (Fraisse *et al.*, 2002).

The paper by Fraisse et al. shows a methodology (from now on called Fraisse's method) to reduce multi-layered partitions to a 3R2C model among other methods. The methodology to reduce multi-layered partitions is described in this sub-section as it will be used in the validation of the method presented in this thesis in Section 3.5.

The first thing done in Fraisse's method is to calculate the transfer coefficients matrix of a 3R2C model. This matrix is as follows:

$$[\boldsymbol{H(s)}]_{3R2C} = \begin{bmatrix} \boldsymbol{1} & \boldsymbol{R_3} \\ \boldsymbol{0} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{1} & \boldsymbol{0} \\ \boldsymbol{sC_1} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{1} & \boldsymbol{R_2} \\ \boldsymbol{0} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{1} & \boldsymbol{0} \\ \boldsymbol{sC_1} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{1} & \boldsymbol{R_1} \\ \boldsymbol{0} & \boldsymbol{1} \end{bmatrix},$$ Eq. 3.8

following the same nomenclature as in Figure 3.9b, and with *s* the Laplace's variable representing frequency.

Each of the matrices in Eq. 3.13 represents the elements of the model (i.e. R_1, C_1, R_2, C_2, R_3) that are multiplied in reverse order as this are transfer functions matrices. The result of this multiplication is a 2 by 2 matrix with elements that are polynomials of order 2 in *s*. Equally, with a larger RC-network representing a multi-layered construction, one can multiply the transfer functions of all the elements and obtain a 2 by 2 matrix with elements that are polynomial of the order determined by the number of capacitors in the RC-network.

In Fraisse's method, the high order polynomials of the transfer functions matrix representing the multi-layered construction are truncated, eliminating the terms that are multiplied by s^3 or higher. Doing this allows to create 8 algebraic equations that relate the parameters of the LPM (3R2C) and the parameters of the complete RC-network. One of the equations is linearly dependent to the other 7; so the result is a set of equations with seven equations and 5 unknowns that gives (according to the Fraisse et al.) the best parameters for the 3R2C LPM.

The final equations provided by Fraisse et al. are as follows:

$$R_3 = \alpha_3 R_t, \quad R_2 = \alpha_2 R_t, \quad R_1 = \alpha_1 R_t,$$
$$C_2 = \beta_2 C_t, \quad C_1 = \beta_1 C_t,$$ Eq. 3.9

being the α's and β's variables introduced to facilitate solving the equations. The before obtaining these new variables another set is created by Fraisse's et al.:

$$R_tC_t(\alpha_2\beta_1 + \alpha_3) = m_1,$$ Eq. 3.10

$$R_t^2C_t^2(\alpha_3\ \alpha_2\beta_2\beta_1) = m_2,$$

$$\alpha_2\beta_2\beta_1 = o^2/(R_t{*}C_t^2),$$

$$R_tC_t(\alpha_2\beta_2 + \alpha_1) = p_1,$$

$$R_t^2C_t^2(\alpha_1\ \alpha_2\beta_2\beta_1) = p_2,$$

With those parameters then one has to solve the following equations:

$$\xi = 1 - \frac{m_1}{RC}\left(1 + \frac{p_2}{m_2}\right),$$ Eq. 3.11

$$\Delta = \left[o_2\left(1 + \frac{p_2}{m_2}\right) - RC^2\xi\right]^2 + 4RC^2\xi o_2\frac{p_2}{m_2}$$

And with then these:

$$\beta_3 = \frac{-o_2\left(1+\frac{p_2}{m_2}\right)+RC^2\xi+\sqrt{\Delta}}{2RC^2\xi},$$ Eq. 3.12

$$\beta_1 = 1 - \beta_3,$$

$$\alpha_2 = \frac{o_2}{RC^2\beta_2\beta_1},$$

$$\alpha_3 = \frac{m_1}{RC} - \alpha_2\beta_1,$$

$$\alpha_1 = 1 - \alpha_2 - \alpha_3$$

These equations used with Eq. 3.9 provides with the parameters of the 3R2C LPM. It can be seen from the description how complex Fraisse's method is, not only that, it has been seen in this research that the equations above do not have a solution.

3.4.1.2 Study of inputs of multi-layered constructions

The response of a dynamic system such as a wall is different depending on the frequency of the inputs. Dynamic systems/models can be studied in the frequency domain by using the Laplace transform: a linear operator that makes it possible to transform differential equations into algebraic ones (for more information about this transform see (Ogata, 2002)). For example, Eq. 3.3 (the equation to model the heat transfer through a layer of material) takes the form of Eq. 3.13 in the time domain.

$$C\frac{dT_1(t)}{dt} = \frac{1}{0.5R}(T_1(t) - T_o(t)) + \frac{1}{0.5R}(T_1(t) - T_i(t)) + q_i(t) + q_o(t). \quad \text{Eq. 3.13}$$

If the Laplace transform is applied to this equation, the result is Eq.3.14.

$$sCT_1(s) = \frac{1}{0.5R}\left(T_1(s) - T_o(s)\right) + \frac{1}{0.5R}\left(T_1(s) - T_i(s)\right) + q_i(s) + q_o(s),^{19} \quad \text{Eq.3.14}$$

where *s* is the Laplace variable, sometimes represented as *jω* with *j* the imaginary unit, and *ω* the angular frequency.

In this representation, the independent variable *s* is a complex number and therefore has amplitude and phase. The variables also become complex and are represented by a vector or phasor. Eq.3.14 is the representation of a linear system in the frequency domain. The outputs of linear systems have the same frequency as its inputs once the steady-state regime is reached. In the case of a construction, a sinusoidal oscillation of the outside temperature produces a sinusoidal oscillation of the inside surface of the construction with the same frequency, but with different amplitude (gain) and different phase (lag).

That condition allows studying dynamic linear systems as black boxes that modify amplitudes and phases of their inputs depending on their frequency; as the frequency of the output is known to be the same as the frequency of the input, it is possible to reconstruct the outputs completely in the time-domain knowing the change in amplitude (gain) and lag with respect to the input (phase).

The main inputs for models that represent constructions are the time varying temperature and heat flows that occur at the boundaries of the wall or

---

19 Normally the functions that are passed into the frequency domain are assigned capital letters (f(t) -> F(s)) to show that the expression of this function changes. However here, the functions representing temperatures have not been changed as temperature is normally assign the capital letter ‘T’ to distinguish it over ‘t’ (time). The function T(s) in Eq.3.14 should be considered as a different function than T (t).

partition. These inputs are not sinusoidal. Instead, they will be more complex time-series but with some periodicity (such as daily cycles). These inputs can be decomposed into harmonics using a Fourier transform for a given interval. With the Fourier transform, the inputs can be represented by a sum of sinusoidal functions with different frequencies. The Fourier coefficients provide a measure of the contribution of each harmonic to the overall input; these coefficients are called the spectrum of the input.

As the inputs of the model will be the sum of a set of harmonics, the aim of the methodology shown in this thesis is to create an accurate model for those harmonics. The accuracy of the model for sinusoidal inputs with frequencies that are not likely to be found in the real inputs of constructions are irrelevant (for example fluctuations in outside temperature over 0.01 seconds is unlikely to be relevant).

The inputs at the boundary of the walls are the inside and outside temperature, and the heat flow through the outside and inside surface. The outside temperature and the outside heat flow (mainly solar radiation) are read from a weather file. The heat flow and temperature of the inside depend on the calculations carried out within the simulation and on heating systems triggered by internal temperature or changes in temperature due to different conditions such as windows opening.

In a two-port RC-network (as in Figure 3.2), two of the variables can be obtained from the other two. For this work, the outside temperature and the heat flow through the inside surface have been used as inputs. The aim was to create a methodology that produces accurate reduced models that truthfully predict the temperature of the internal surface of the construction i.e. the one in contact with the air of the zone. The motivation of this is that the temperature of the internal surface of the wall is crucial for a correct determination of the air temperature in the zone. Modelling properly the air in the zone comes with a realistic behaviour of the thermostat and therefore a well predicted heating demand, whereas the external temperature of the construction is normally not a relevant output for energy related calculations.

Summarizing: The method that was investigated had to be accurate for a *relevant* range of frequencies that are the most significant in the spectrum of the inputs; the relevant inputs are the outside temperature and internal heat gains. The output is the temperature of the internal surface of the construction.

In this methodology, a range of frequencies have been searched, that will represent the band where the main harmonics of the inputs can be found. The hypothesis is that developing a method that forces the accuracy of the models created in that range of frequencies, will result in a method that creates accurate models under real conditions. This range has been called the *Range of Relevant Frequencies* (RoRF). The following paragraphs show how the bounds of this range were chosen.

In a building simulation, the heat gains are calculated during the simulation and therefore they are different for every case. However, the outside temperature normally comes from a weather file with a specific sampling period (such as (DoE, 2011)).

Using the sampling period of the inputs, the higher bound of the RoRF can be defined by the Shannon-Nyquist theorem (Shannon, 1949). This theorem establishes that a continuous function can be totally determined from a discrete time-series only if the original function has no harmonics higher than a frequency half the sampling frequency (f_s) of the discrete series. As a result, it is possible to introduce the upper bound for the RoRF as:

$$f_{UB} := f_{SN} = \frac{1}{2T_s} = \frac{1}{2}\, h^{-1}\ , \ and,\ \omega_{UB} = 2\pi f_{SN} = \pi\, radh^{-1}\ , \qquad \text{Eq. 3.15}$$

where f_{UB} is the upper bound frequency, f_{SN} is the Shannon-Nyquist frequency, ω_{UB} is the upper bound angular frequency, and T_s is the sampling period of the weather file.

With this equation the higher bound of the RoRF is defined for the variables that come from a weather data file. The next paragraph investigates a possible equivalent for the gains.

Eq. 3.15 defines the upper bound of the RoRF for the variables read in weather files with a sampling period of 1 hour. However, that upper bound might not be appropriate when considering the internal heat gains. The internal gains come from different phenomena such as solar radiation from windows, electrical appliances or the metabolism of occupants. The gains due to solar radiation could go under the assumptions in the previous paragraph as they are read from the same weather file. However, the gains due to metabolism, electric appliances and heating systems are very different; the sampling of those time series will depend on the accuracy specified by the user; also, most of them present square shapes (on/off control) what introduce high order harmonics in the spectrum of the inputs.

The Fourier coefficients of step functions decrease as the frequency grows. In addition, the use of appliances and heating systems, normally present a certain daily periodicity because of working routines (office hours) and environmental parameters (day and night).

To have an estimate on how the harmonics could decrease in frequencies higher than the 1/24 h^{-1} (daily), the continuous unit step function with a period of 24 h was considered as a reference. For the step function the Fourier coefficients are inversely proportional to the frequency (see for example (Ogata, 2002)). That means that if the harmonics of a step function with a period equal to 24 hours are calculated, the harmonic with frequency two times larger than the frequency of the daily cycle will have an amplitude that is half the one of the main harmonic at 24 h^{-1} (see Table 3.1) and that reduction will continue as the frequency grows.

It has been assumed that the internal gains in a real building can be discomposed into a main daily harmonic, and harmonics with higher frequencies with amplitudes that decrease proportionally to the inverse of their frequency. To see the validity of this assumption a real case has been studied.

A building was modelled with realistic gains coming from metabolism, appliances and solar irradiation through windows (the schedules were created using benchmark values from (CIBSE, 2006)), to evaluate the spectrum of the gains. The internal gains of the zone were written to a file with a sampling period of 1 minute to ensure that the reporting period was not masking high frequency harmonics. A Discrete Fourier Transfer was applied to the time-series to extract its spectrum that is shown in Figure 3.4 and transcribed in Table 3.1. The harmonics are shown together in this table, with the equivalent ones of a continuous step function.

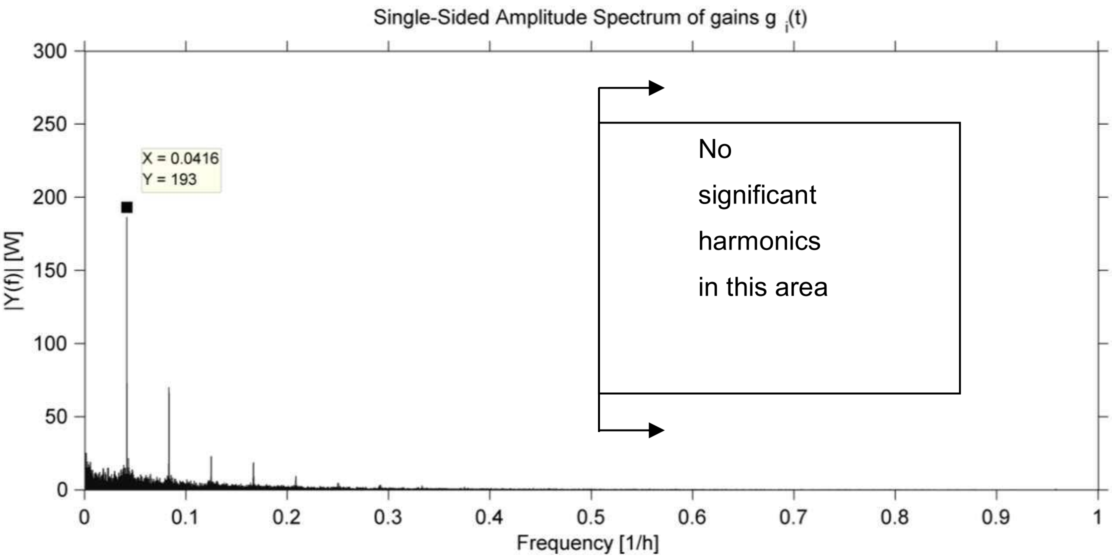

Figure 3.4 - Representation of the harmonics of a time series of internal gains in a building simulation from data sampled at a resolution of 1 minute. Note the peak representing the harmonic with the largest amplitude with a 24 hours period.

Table 3.1 - Harmonics found in the time series of the internal gains of a simulated building compared with harmonics of a step function with period 24 h.

Frequency	Amplitude (real gains)	Amplitude (square function)
0.0416 (daily)	193	193 (reference)
0.0832 (x2)	79.2	96.5
0.124 (x3)	22.9	64.3
0.166 (x4)	18.8	48.2
0.208 (x5)	10.0	38.6
0.2496 (x6)	5.2	32.2

It can be seen in Figure 3.4 and Table 3.1 that the harmonics get smaller with frequency more rapidly in the spectrum of the real gains than those from the square function. Although this does not prove the non-existence of high-frequency harmonics in the gains of buildings, the narrow band in which harmonics are found in this study (0.0416 - 0.4 h^{-1}), suggests that the upper bound defined before with the Shannon-Nyquist theorem (0.5 h^{-1}) is unlikely to leave relevant harmonics of the internal gains out of the RoRF. Also, it can be seen in Figure 3.4 that the harmonic at 24 h^{-1} is the one with the lowest frequency (it should be noted that there was no harmonic found in the harmonic corresponding with the year period frequency 1.14x10^{-4} h^{-1}).

The spectrum of the gains does not show significant harmonics over the value of 0.5 h^{-1}, and this is consistent with the real understanding of the meaning of this graph: a peak over the 0.5 h^{-1} value would represent a heat source that turns on and off every hour during the whole year. This is unlike in a system as a building. No one would expect a heating system driven by a thermostat, that turns on an off consistently with periods smaller than half an hour, instead due to the thermal inertia of the building and the hysteresis of the thermostat, it is likely that the heating system will stay on for longer.

Also, the gains have to heat up the air of the zone before affecting the walls, (this section talks about creating LPM of constructions), therefore, the air will work as a damper that smooth the gains with high frequency, making their effect in the construction smaller.

The previously selected upper bound of the RoRF obtained using the Shannon-Nyquist theorem seems to be conservative enough to include all the harmonics of the internal gains. This upper bound will be used as the upper bound of the RoRF of the inputs temperature and gains.

To select the lower bound of the RoRF a frequency was searched at which the response of the construction can be considered as steady state. To determine this, the time constant of the construction was used. The time constant is a measurement of the order of magnitude of the time that a construction needs to “react” to a temperature change (see a general book about building simulation such as (Clarke, 2001). In this case, the time constant can be estimated by summing the thermal capacity of the layers of the construction and summing their resistance. The time constant can then be calculated by multiplying these two sums. This was done to make sure that the highest possible value is used. The time constant, and lower bound are calculated with the expressions in Eq. 3.16

$$\tau_{LB} = \sum_{k=0}^{n} R_k \sum_{k=0}^{n} C_k \,, \qquad f_{LB} = \frac{1}{2\pi} \frac{1}{\sum_{k=0}^{n} R_k \sum_{k=0}^{n} C_k}, \qquad \text{Eq. 3.16}$$

$$\omega_{LB} = \frac{1}{\sum_{k=0}^{n} R_k \sum_{k=0}^{n} C_k}.$$

where τ_{LB} is the time constant [s], f_{LB} is the frequency of the lower bound [Hz], ω_{LB} is the angular frequency of the lower bound [rad/s], R_k is the resistance of the k^{th} layer of the construction, n is the total number of layers and C_k is the thermal capacity of the k^{th} layer.

With the definition of the lower bound, the RoRF can be defined as the range defined by $(\omega_{LB}, \omega_{UB})$

After studying the inputs and outputs of a possible model representing a construction, it can be concluded that it would be ideal to create a methodology that generates reduced models of constructions that are accurate in the range defined by the Eq. 3.16 and the Eq. 3.15 i.e. the RoRF.

In the following section, the way to find the topology of that model was investigated.

3.4.1.3 Topology of the model

The topology of a dynamic model determines its number of parameters and its degrees of freedom; but also, the computational time that is requiered to solve it. Selecting an adequate topology with the appropiate number of elements was an important part of this research.

The simplest dynamic model of a multilayered construction is the one created by Lorenz and Masy (Lorenz and Masy, 1982 (in French)). The topology of this model can be seen in Figure 3.5. This topology was later used by other authors (Coley and Penman, 1992; Hudson, 1999; Dewson *et al.*, 1993; Gouda *et al.*, 2000; Tindale, 1993). However, this topology does not offer enough degrees of freedom to have an accurate response for the RoRF when evaluated with real constructions, as proved by Gouda et al. (Gouda *et al.*, 2002). Gouda showed that first order models of constructions are accurate in representing the effect of outside temeprature on internal temepratures, but are especially inaccurate when excited by internal gains.

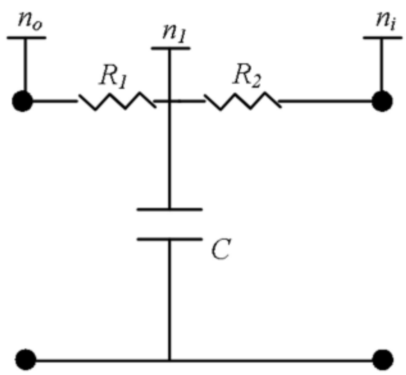

Figure 3.5 - Lorenz and Masy's first order model.

The topology of the 2R1C model (as suggested by Lorenz and Massy (Figure 3.5)) is simple enough to allow the calculation of the differential equations that caracterise the model. Therefore a quick study of its characteristics was done to verify if it is a topology that will result in accurate models. This is done in the following.

In dynamic systems, the transfer function describes the relationship between the output and the input in the frequency domain. If the equations of the first order model in the frequency domain are obtained, the transfer function that relates the inside temperature (output) and outside temperature (input 1) can be calculated as:

$$\frac{T_i(s)}{T_o(s)} = \frac{1}{sCR_1} \qquad \text{Eq. 3.17}$$

where $T_i(s)$ is the inside temperature in the frequency domain, $T_o(s)$ the outside temperarature in the frequency domain, and *s* the Laplace variable. Similarly, the transfer function for the same output (inside temperature) and internal gain (input 2) is represented in as:

$$\frac{T_i(s)}{q_i(s)} = \frac{R_1R_2 + sCR_1R_2}{1 + sCR_1} \qquad \text{Eq. 3.18}$$

with $q_i(s)$ the heat gains in the frequency domain.

The calculation of the transfer functions allows an understanding of the dynamic behaviour of the model. Modern control techniques allow to analyse the dynamic response of the system by the study of the so called poles and zeros of the transfer function (Ogata, 2002) (the poles and zeros of a dynamic system determine the dynamic behaviour of that system).

The transfer function shown in Eq. 3.17 has a pole (where the denominator is zero) when $s = -1/R_1C$. The position of the pole means that the model acts as a low pass filter with a cut-off frequency equal to $-1/R_1C$. This means that with this model, there will be a frequency after which inputs with higher frequencies will be atenuated. To visualise this, one can think of a solid stone wall in a building: due to the heavy weight of the material, rapid changes in the outside temperature will not have any effect in the inside surface of the wall as the swing in temperature has to be slow to allow enough time to heat up its thermal mass.

The transfer function in Eq. 3.18 shows one pole and one zero (where the numerator is zero) with values $s = -1/R_1C$ and $s = -(R_1 + R_2) / (R_1 R_2 C)$ respectively. In this case, the pole and zero mean the following: the system works as a low-pass filter after the cut-off frequency defined by the pole, but this effect is eliminated at frequencies that correspond to the position of the zero and higher.

The first interesting point extracted from the caluclation of zeros and poles is that the construction shows a filter effect for the outside temperature and for the gains, but this model assumes the same cut-off frequency for both.

The cut-off frequency is a key parameter of the behaviour of a system because it determines the frequencies at which the attenuation of the inputs will start. In the first order model the poles of both transfer functions (Eq. 3.12 and Eq. 3.13) have the same value ($s= -1/R_1C$). This means that there is not combination of parameters that allows different cut-off frequencies for each transfer function. However, there is no guarantee that the cut-off frequencies for the outside temperature and internal gains are going to be equal for a given construction. A counter-example has been used to shown that the cut-off frequencies of the two transfer functions can be different. The Bode diagram of a construction can be seen in Figure 3.6 where the cut-off frequencies for the two inputs applied to the same construction are different (note: the construction is extracted from the tests performed further in this thesis where it is called “sandwich 2”).

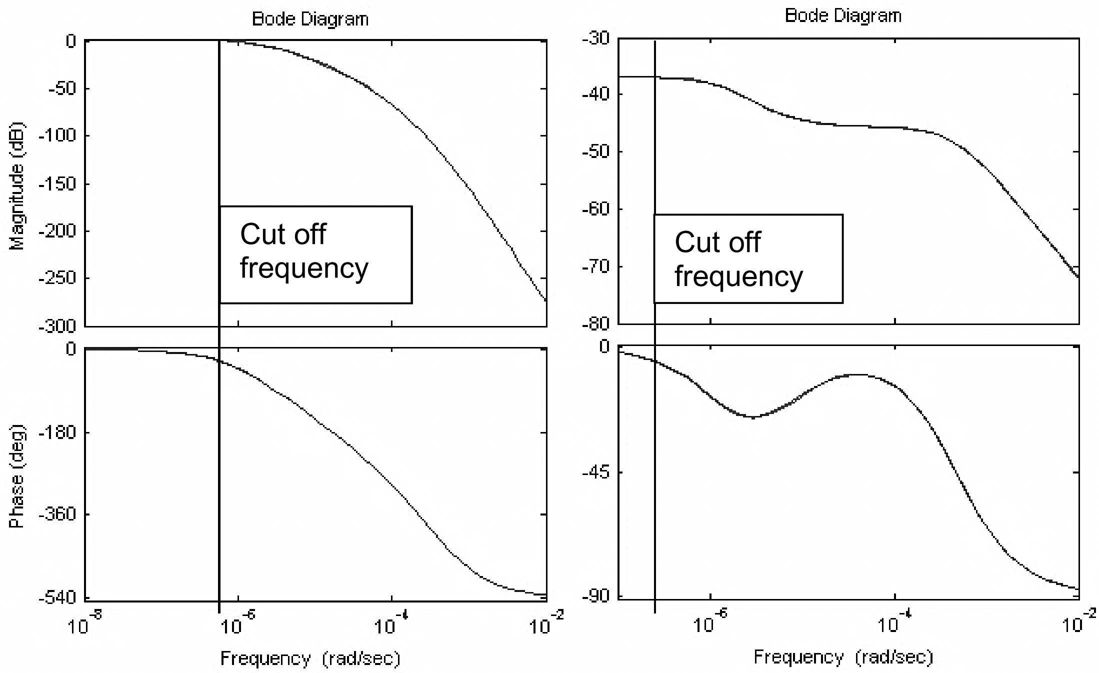

Figure 3.6 - Bode diagrams of a construction. Cut-off frequencies at different locations for the left pair (system under outside temperature) and right pair (system under gains).

The fact that the first order model has not enough degrees of freedom to model accurately multi-layered constructions with two inputs (outside temperature and heat gains) agrees with the experimental work of Gouda (Gouda *et al.*, 2002).

The literature on the topic and the study of the first order model just presented has motivated the adoption of a second order model to be used as the basis for the methodology suggested in this thesis, the second order model has the topology shown in Figure 3.7.

The second order model (3R2C) has been chosen as the previous model (2R1C) has been proven to not represent the dynamics of some walls properly. However, no study has been done evaluating the improvement that adopting a 4R3C model would produce. This has not been studied in this thesis as the 3R2C gave good results on the cases studied but should be evaluated in further work.

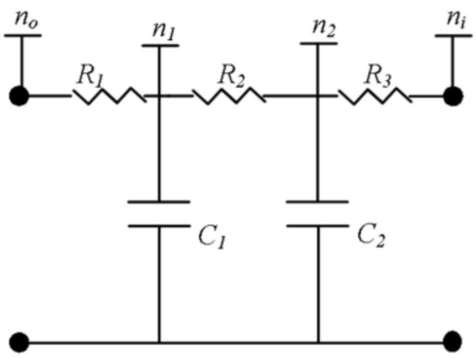

Figure 3.7 - Second order RC-network for representing constructions.

Once the topology of the model is selected, it is necessary to create a methodology that produces values for the elements of the model i.e. provides the parameters of the system. Although other authors (such as (Gouda *et al.*, 2002), (Xu and Wang, 2007) or (Coley and Penman, 1992)) have used numerical methods to find optimal parameters of LPMs, this research aims to produce a method that does not need any computationally expensive numerical algorithm. Instead, a simple algebraic set of rules that provide the value of the parameters of the model was considered ideal.

3.4.1.4 Values of the parameters

As already said, a multi-layered construction can be represented using first order models for each layer of material (see Section 3.3.1.2). Adding those T-networks together results in an RC-network like the one shown in Figure 3.3.

The linearity of the elements of the RC-network that represents a construction allows the application of superposition. When the dynamic model of the construction is considered, the temperature of the internal surface of the construction can be calculated as the sum of two responses from two models (or circuits) each one with only one input: one the outside air temperature, and another the internal gains (g_i), the external gains (mainly radiation in the outside of the wall, has been neglected). This has been shown in Figure 3.8.

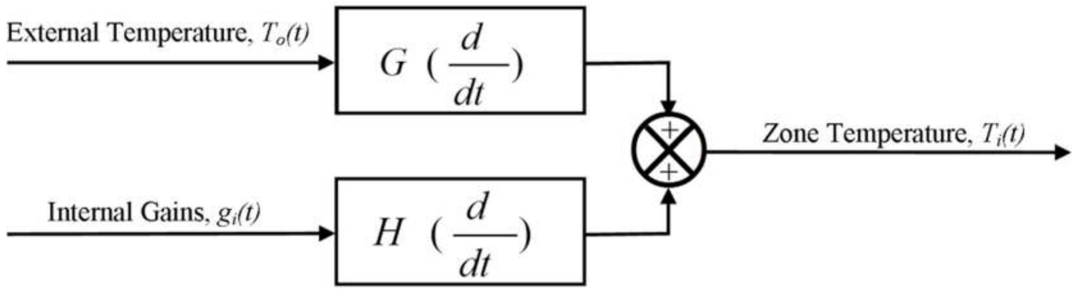

Figure 3.8 - Internal temperature as the sum of the response of two linear systems.

Firstly, the model with incidental gains was considered (*H*(*d*/*dt*) in Figure 3.8). This model has a heat gain applied to the node that represents the internal surface of the construction, and the node that represents the outer layer of the construction is considered to be earthed, i.e. the external voltage/temperature set to zero[20] (zero is selected to make possible the superposition of the two outputs).

The first equation of this system is obtained by considering steady-state conditions i.e. the capacitors have infinite impedance and the circuit is reduced to a set of resistances in series. This produces the first requirement for the LPM:

$$\sum_{Construction} R_i = \sum_{LPM} R_j, \quad \text{Eq. 3.19}$$

where R_i are the equivalent resistances of the different layers in the complete model (Figure 3.3) and R_j are the resistances in the LPM (Figure 3.9b). This equation forms the first condition (the steady-state condition) for the creation of the LPM.

The next equation to be derived will be obtained from studying the dynamic response of the system. To represent the dynamic behaviour of the construction the most significant dynamic characteristics of the complete network have to appear in the LPM. The cyclical nature of gains causes the heavy weight layers to have a much larger contribution to the dynamic response of the construction than lighter ones. If the construction is considered from the

[20] As the model is maintained linear at all times, the temperatures can be considered Degrees or Kelvin as soon as there are all considered in the same scale.

inside out (from n_i to n_o), one is likely to find a layer of material that will store and release the majority of the heat during the repeated heating cycles. This *dominant layer* plays an important role in the dynamic response; the LPM presented in this paper is designed to represent this layer and therefore its effect on the dynamic response at the expense of other less important layers. The assumption that was made in this thesis is that including this layer of material directly in the LPM will improve the accuracy.

The dominant layer is found from the consideration of the influence of each layer in the overall response under the RoRF. The vertical branches of the circuit in Figure 3.3 represent the heat capacity of the layers within the construction. The impedance of each branch to the heat flow (current) injected at the surface of the last construction (the inside node: n_i) could be considered as the impedance of the capacitor plus the sum of the resistances from the node of the branch to the inside node. This impedance depends on the frequency; however, an *influence value* was created that is a measurement that averages the impedance for the range of angular frequencies of interest (i.e. RoRF from ω_{LB} to ω_{UB}). The influence value (with units *h/(Ωrad)*) of each branch is defined as:

$$Inf_k = \left(\int_{\omega_{LB}}^{\omega_{UB}} \left(\left|\frac{1}{j\omega C_k} + \frac{R_k}{2} + \sum_{l=k+1}^{n} R_l\right|\right) d\omega\right)^{-1}, \qquad \text{Eq. 3.20}$$

where ω_{LB} and ω_{UB} are the lower and upper bound of the RoRF, ω is the integration variable, R_k is the resistance of the k^{th} layer of the construction, n is the total number of layers, and C_k is the thermal capacity of the k^{th} layer.

The influence value of the branches is an indicator of the dominant layer; the higher its value, the larger the current that will pass through it, and thus, the impact of this branch on the dynamic response for the RoRF. The dominant layer is such that:

$$Inf_{dominant} = \max_n Inf_k. \qquad \text{Eq. 3.21}$$

Although this method of finding the dominant layer was successful (it will be seen in the validation) further investigation demonstrated that in all the constructions used, the dominant layer defined by Eq. 3.20 gives the same results as when calculating the layer with smallest impedance (in module) for a frequency equivalent to the daily cycle (0.042 h^{-1}). The fact that the results are the same is not surprising. The frequency equivalent to the 24 hours period will always be part of the range of RoRF. In addition, after studying the inputs in the previous section, it can be seen that the accuracy of the model for this frequency is crucial and should be tuned to achieve accuracy. Tindale did this in his work (Tindale, 1993) for the estimation of the parameters of a whole building model with constructions modelled with first order models, although he used a numerical method.

The calculation of the dominant layer can therefore be done applying the simple formula:

$$|Z|_{dominant} = min\left|\frac{1}{j2\pi f_{24}C_k} + \frac{R_k}{2} + \sum_{j=k+1}^{n} R_j\right|. \qquad \text{Eq. 3.22}$$

with $|Z|_{dominant}$ denoting the module of the impedance of the dominant layer, and f_{24} the frequency corresponding to the 24 hours period (0.0417 h^{-1}).

To include the dynamic effect of the dominant layer, the last capacitor and the last resistor (the ones in contact with the inside node) of the LPM are defined to represent the dominant layer. This is achieved by making the last capacitor of the LPM have the same value as the capacitance of the dominant layer and the last resistor of the LPM to have the same value as the sum of the resistances of the layers between the dominant layer and the inside node. This is seen in Eq. 3.23 and Eq. 3.24.

$$R_3 = 0.5R_{dom} + \sum_{i=dom+1}^{n} R_i, \qquad \text{Eq. 3.23}$$

$$C_2 = C_{dom}, \qquad \text{Eq. 3.24}$$

with R_3 the third resistor of the DLM, C_2 the second capacitor of the DLM, *dom* the position of the dominant layer, *n* the total number of layers, and R_i the resistance of layer *i*.

The explicit consideration of a dominant layer, as introduced in this thesis, is the key element of the methodology; as such the LPMs obtained with this methodology have been called Dominant Layer Models (DLMs).

For the second model (or circuit, *G*(*d/dt*) in Figure 3.8), the time-varying outside temperature is incident on the node representing the external surface (n_o in Figure 3.3) of the construction and the internal gains are eliminated.

This RC-network is a set of T-networks in cascade, and each of those networks is a low pass filter as the input and output are respectively the temperature in the left and the right side of the T-network and each of the layers of material will stop high frequency changes of the outside temperature influencing the inside temperature. As the two elements closest to the inside node are already fixed, the rest of the methodology aims to create a first order model of the components that are left in the complete RC-network that will maintain the accuracy of the LPM.

It is, therefore, possible to calculate the *cut off* angular frequency for each layer, which is given by $\omega_c = 1/RC$, and obtain the time constant $\tau=RC$ (where C is the capacitance of the layer of material and R is half of the resistance). However, the different layers are connected in cascade, and therefore, each of the layers will have a resistance from the other layers on both sides (except for the external layers). According to the methodology of Mathews et al. (Mathews *et al.*, 1994), one can calculate two time constants for each of the layers that will relate with the cut off angular frequencies from the inside and from the outside of each (n_i and n_o respectively in Figure 3.3). The time constant of each layer for the outside (τ_{os}) is therefore calculated by summing the value of all the resistors previous to the layer (from the outside in) and multiplying this by the capacity of the layer, and the time constant for the inside (τ_{is}) is calculated by summing the values of all the resistors after the layer (from the outside in) and multiplying them by the capacity of the layer.

Matthews et al. showed that the most accurate first order model under outside temperature can be obtained by calculating the summation of the time constants from the inside and outside of each layer. As the dominant layer and the layers after this (from the outside in) are already in the LPM, the equations to calculate the summation of the time constants are:

$$\tau_{is} = \sum_{j=1}^{dom-1} C_j * \left(\frac{R_j}{2} + \frac{R_{dom}}{2} + \sum_{k=j+1}^{dom-1} R_k\right), \qquad \text{Eq. 3.25}$$

$$\tau_{os} = \sum_{j=1}^{dom-1} C_j * \left(\frac{R_j}{2} + \sum_{k=1}^{j-1} R_k\right), \qquad \text{Eq. 3.26}$$

$$R_{tot-dom} = \frac{R_{dom}}{2} + \sum_{j=1}^{dom-1} R_j \ , \qquad \text{Eq. 3.27}$$

where τ_{is} and τ_{os} are the time constants relative to the two sides of the circuit (inside and outside respectively) and C_j and R_k are the capacity and the resistance of the j^{th} and k^{th} layer respectively, *dom* represents the position of the dominant layer starting from the outside and $R \quad _m$ represents the sum of resistances up to the dominant layer. The summation of the time constants has to be equal to the time constants of the first order model. Therefore we know that:

$$R_1 = \frac{R_{tot-dom} * \tau_{os}}{\tau_{os} + \tau_{is}}, \qquad \text{Eq. 3.28}$$

$$R_2 = \frac{R_{tot-dom} * \tau_{is}}{\tau_{os} + \tau_{is}} \text{ and} \qquad \text{Eq. 3.29}$$

$$C_2 = \frac{\tau_{os}}{R_1} = \frac{\tau_{is}}{R_2}. \qquad \text{Eq. 3.30}$$

The steps followed up to here fix the topology of the LPM as a 3 resistors 2 capacitors (3R2C) model (Figure 3.9b). Given the topology of the simple model defined by Figure 3.7, and the set of equations above it is straightforward to obtain the DLM of a given construction:

1 Find the dominant layer using Eq. 3.21.
2 Assign the capacitance of the dominant layer to C_2.
3 Obtain R_3 with Eq. 3.23.
4 Obtain R_1 with Eq. 3.28.
5 Obtain R_2 with Eq. 3.29.
6 Calculate C_2 with Eq. 3.30.

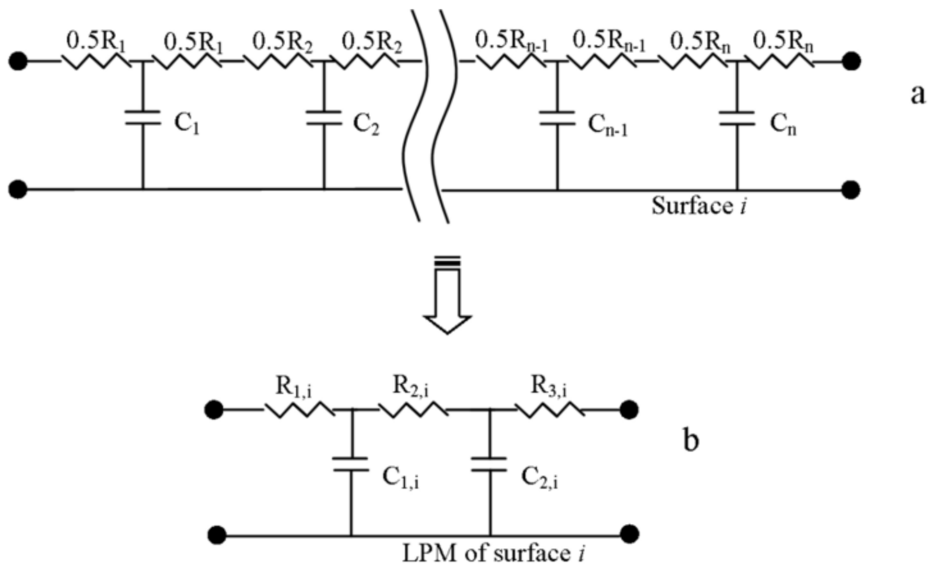

Figure 3.9 - Reduction of multi-layered construction to 3R2C LPM.

3.4.2 Aggregation of parallel multi-layered surfaces

After each multi-layered surfaces of the envelope have been reduced to a 3R2C LPMs, it is necessary to further reduce the several surfaces forming the envelope into a single 3R2C LPM as in Figure 3.10.

Several authors have develped methodologies to agregate LPMs of multi-layered constructions to a single LPM (Mathews *et al.*, 1994) (Fraisse *et al.*, 2002). Fraisse shows a method in (Fraisse *et al.*, 2002) to reduce several 3R2C LPMs to a single 3R2C model. However, this method made use of only 2 characteristic time constants of the 3R2C models, and that could imply limited accuracy to describe such complex models. After studying the work of Mathews (Mathews *et al.*, 1994), in this thesis, it was considered that it could be more accurate to extend the equations of Mathews et al. for their second order reduction to generate four time constants for each 3R2C LPM. This novel approach has been followed in this thesis and is explained in this chapter.

Similar to the reduction of the multi-layered construction, the steady-state response must be maintained in the simplified model. In this case the summation of the total conductance of the LPM is equal to the sumation of the total conductance of the surfaces in the complete model. In this case the walls are connected in parallel as shown by Figure 3.10 and the condition is given by:

$$\sum_i R_{i,LPM} = (\sum_j \frac{1}{R_{1,j}+R_{2,j}+R_{3,j}})^{-1},$$ Eq. 3.31

were $R_{i,LPM}$ is the resistance number *i* of the LPM that represents all the walls, and $R_{x,j}$ is the resistance number *x* of the 3R2C LPM that represents the surface number *j*.

The dynamic behaviour of the full model must also be maintained in the reduced model. To achieve this, the time constants of the complete RC-network must be maintained. Mathews et al. obtainned the time constants of a 3R2C RC-network (Mathews *et al.*, 1994) with the cross products of capacitors and resistances to reduce multi-layered constructions to first order models, here it will be used to reduce paralel surfaces to a single 3R2C LPM. Each RC-network is characterised with the four time constants: τ'_{out}, τ''_{out}, τ'_{in}, τ''_{in} and these can be calculated using:

$$C_{1,LPM}R_{1,LPM} = R_{total}\sum_j \left(\frac{C_{1,j}*R_{1,j}}{R_{t,j}}\right) = \tau'_{out},$$ Eq. 3.32

$$C_{2,LPM}(R_{1,LPM} + R_{2,LPM}) = R_{total}\sum_j \left(\frac{C_{2,j}*(R_{1,j}+R_{2,j})}{R_{t,j}}\right) = \tau''_{out},$$ Eq. 3.33

$$C_{2,LPM}R_{3,LPM} = R_{total}\sum_j \left(\frac{C_{2,j}*R_{3,j}}{R_{t,j}}\right) = \tau'_{in} \text{ and}$$ Eq. 3.34

$$C_{1,LPM} * (R_{2,LPM} + R_{3,LPM}) = R_{total} * \sum_j \left(\frac{C_{1,j}*(R_{2,j}+R_{3,j})}{R_{t,j}}\right) = \tau''_{in}.$$ Eq. 3.35

here $R_{x,LPM}$ and $C_{x,LPM}$ is the resistor and capacitor number *x* of the LPM that represents all the surfaces, and $R_{x,i}$ and $C_{x,i}$ is the resistance and capacitor number *x* of the LPM that represents surface number *i*, with τ'_{out} and τ'_{in} the first time-constants from the outside and the inside respectively, and τ''_{out} *and* τ''_{in} the equivalent second time constants. The time constants have been weighted with the total resistance of the surface $R_{t,i}$. Rearranging, the parameters for the reduced LPM are given by:

$$R_{1,LPM} = R_{total} * \left(\frac{\tau'_{out}}{\tau''_{in}+\tau'_{out}}\right),$$ Eq. 3.36

$$R_{2,LPM} = R_{total} * \left(1 - \frac{\tau'_{out}}{\tau''_{in}+\tau'_{out}} - \frac{\tau'_{in}}{\tau''_{out}+\tau'_{in}}\right),$$ Eq. 3.37

$$R_{1,LPM} = R_{total} * \left(\frac{\tau'_{in}}{\tau''_{out}+\tau'_{in}}\right), \quad \text{Eq. 3.38}$$

$$C_{1,LPM} = \left(\frac{\tau''_{in}+\tau'_{out}}{R_{total}}\right) \text{ and} \quad \text{Eq. 3.39}$$

$$C_{2,LPM} = \left(\frac{\tau''_{out}+\tau'_{in}}{R_{total}}\right). \quad \text{Eq. 3.40}$$

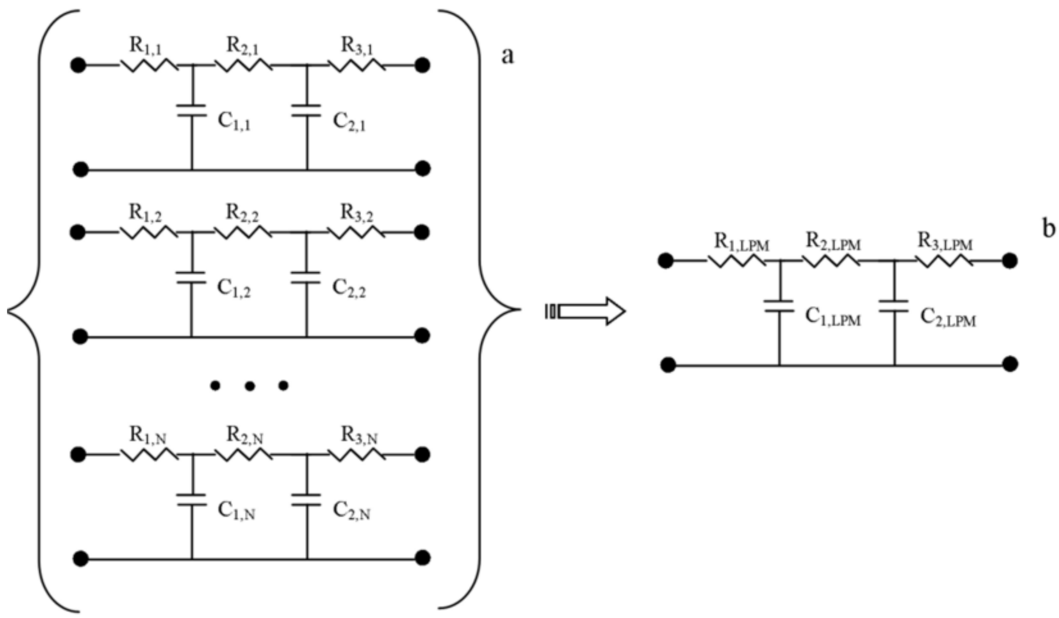

Figure 3.10 - Reduction of several 3R2C LPMs of several surfaces of the envelope to a single 3R2C LPM.

3.4.3 Adding partitions and internal mass

Partitions and heavy internal elements (such as furniture) in buildings can modify their thermodynamic response by becoming heat buffers within the zones studied. The interaction of the internal mass with the internal air can be represented by a first order branch connected to the air node in LPMs according to Tindale (Tindale, 1993). Several partitions and internal masses with different properties will be present in the building; therefore, another exercise of model reduction needs to be carried out to reduce those internal masses into a single branch in the LPM of the building.

Internal masses are only affected by the internal temperature and the internal gains of the building and not by the outside temperature. In this work, the constructions of the partitions have been considered symmetric for the sake of simplicity, but modifications could be done to the method to include asymmetric partitions.

Because the layers of the partitions are symmetric, and both outer surfaces are connected to the inside node, the RC-network as shown by Figure 3.11a can be reduced to the network shown by Figure 3.11b by simply applying symmetry.

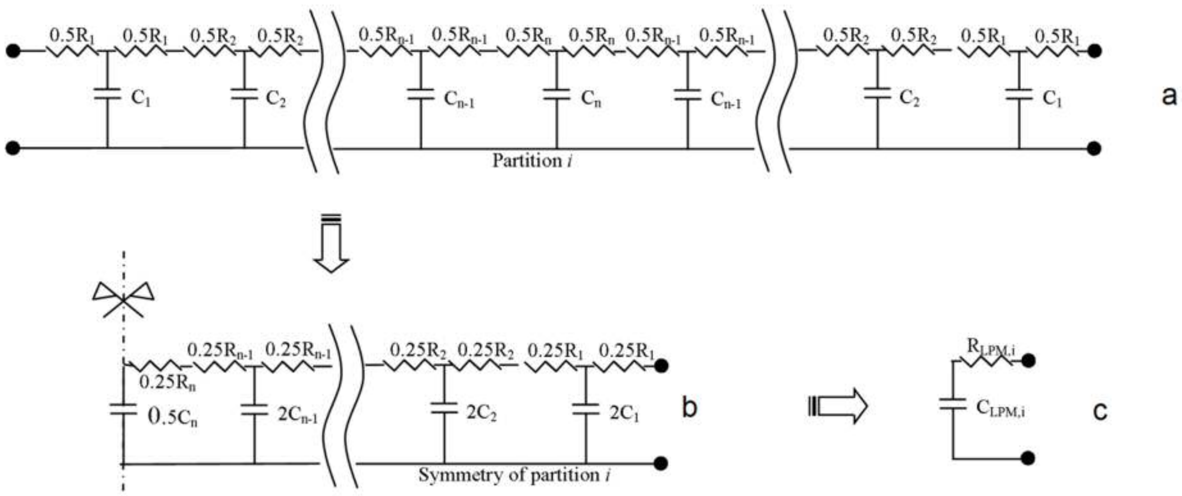

Figure 3.11 - Symmetry applied to a partition with multi-layered construction, and posterior LPM reduction.

To achieve the simplified 1R1C LPM from the multi-layered partition, the RC-network of Figure 3.11b , has to be reduced to a branch with a resistor and a capacitor in series as shown in Figure 3.11c (Tindale, 1993).

The multi-layered partition (Figure 3.11b) must first be reduced to a single first order RC-network. Extending Eq. 3.25 and Eq. 3.26 for the construction of the partition, the time constants of the full partition are given by:

$$\tau_{is,i} = \sum_{j=1}^{n}(C_j(\frac{R_j}{2} + \sum_{k=j+1}^{n} R_k), \text{ and} \qquad \text{Eq. 3.41}$$

$$\tau_{os,i} = \sum_{j=1}^{n}(C_j(\frac{R_j}{2} + \sum_{k=1}^{j-1} R_k) \; . \qquad \text{Eq. 3.42}$$

The resistance and capacitance can then be obtained by:

$$R_{tm,i} = R_t(\frac{\tau_{os,i}}{\tau_{os,i}+\tau_{is,i}}) \text{ and} \quad \text{Eq. 3.43}$$

$$C_{tm,i} = \sum_j C_j , \quad \text{Eq. 3.44}$$

where $R_{tm,i}$ and $C_{tm,i}$ are the capacitance and resistance of the branch of the internal thermal mass number *i* that represents the multi-layered internal partition with resistance R_j and capacitance C_j.

The next stage requires the first order 1R1C branches to be reduced to a single 1R1C branch equivalent to the sum in parallel of all the partitions: Figure 3.12. To perform this reduction, Eq. 3.25 to Eq. 3.30 are used again. The branches of the different thermal masses are connected in parallel, so the time constant of each branch is weighted by its resistance, as was done in summing the surfaces. The overall time constant can be calculated by:

$$\tau = \sum_i R_{tm,i}C_{tm,i} * (\frac{R_{total}}{R_{tm,i}}) = \sum_i C_{tm,i} * R_{total}), \quad \text{Eq. 3.45}$$

with:

$$R_{total} = (\sum_i \frac{1}{R_{tm,i}})^{-1}. \quad \text{Eq. 3.46}$$

The resistance and capacitance of the 1R1C branch is then given by:

$$R_{tm,LPM} = R_{total} \text{ and} \quad \text{Eq. 3.47}$$

$$C_{tm,LPM} = \frac{\tau}{R_{total}} = \sum_i C_{tm,i}. \quad \text{Eq. 3.48}$$

This demonstrates that the equivalent branch is given by simply summing the total resistance and capacitance of the individual branches.

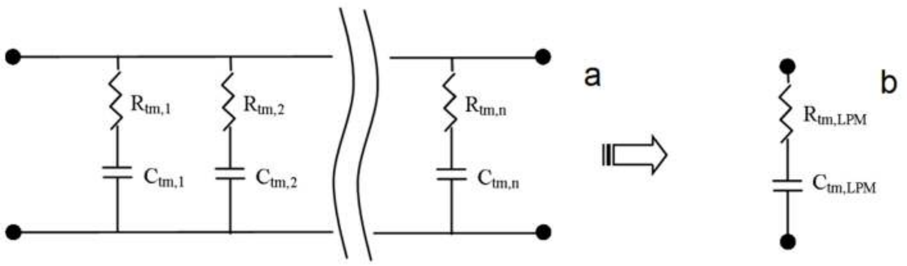

Figure 3.12 - Reduction of *n* branches representing different thermal masses of the building into a single 1R1C branch.

3.4.4 Elements with larger conductance than heat capacitance

Some elements such as windows, thermal bridges and infiltration are modelled as simple resistors in LPMs. This is because the mass of the elements is not taken into account as the large diffusivity makes the heat storage negligible (imagine the heat transfer through a steel beam compared with the heat transfer through a 200 mm concrete block). The conductances resulting from windows, thermal bridges and infiltration are summed together to create a single conductance and then represented as a resistor (inverse) in the LPM. The sum of resistors in series or in parallel does not imply any loss of accuracy.

Windows are modelled in RC-Networks as single resistors as they are considered to not have significant mass compared with the heavy elements (walls and partitions). This has been done in the work of (Goyal and Barooah, 2011; Fraisse *et al.*, 2002; Hudson, 1999; Coley and Penman, 1992; Tindale, 1993; Mathews *et al.*, 1994) and all other works referenced in this chapter. To calculate the equivalent resistor of windows, the U-Value of each of the windows is multiplied by their area, and that provides their conductances. The inverse of the conductance is the resistance value that is used in the RC-network.

Achterbosch modelled the thermal bridges as resistors in his work (Achterbosch *et al.*, 1985).

It is also common practice to model constant infiltration (averaged ach over the year) as a single resistor. This infiltration is sometimes defined as the design value infiltration, and represents a constant flow of air during the year (USDoE, 2013a). If infiltration is supposed to have a constant value of flow (as in designs with fixed air changes per hour), then the heat that leaves or enters the room can be calculated as:

$$Q = q\rho C_p \Delta T \,, \qquad \text{Eq. 3.49}$$

where Q is the rate of energy leaving the room [W], q is the air flow [m^3/s], ρ is the density of the air (here considered constant) [kg/m^3], C_p is the thermal capacity of the air (also constant) [J/(kgK)]and ΔT is the temperature difference between the air that leaves the room and the air that gets into the room from the outside[K]. If we take:

$$R_{infiltration} = \frac{1}{q\rho C_p} \,, \qquad \text{Eq. 3.50}$$

then $R_{infiltration}$ can be integrated in the RC-network of the building as a resistor connecting the outside and the inside nodes. Infiltration is considered this way as constant and therefore the LPM does not change during the simulation with the consequent saving in the computational time. The ventilation, that does change, can be modelled as a voltage (temperature) dependent current source connected to the inside node. This is described further in Section 5.4.2.

The fact that windows and infiltration are single resistors connected to the same pair of nodes allows them to be summed as a set of resistors in parallel without the addition of any imprecision.

To finish, Coley and Penman (Coley and Penman, 1992) showed that the capacity of the air of the building has to be included in the model as a capacitor connected to the internal node.

Summarising, the methodology presented in this thesis, provides a method of reducing the building envelope to a 3R2C RC-network, the internal mass and partitions to a 1R1C model, windows, infiltration and thermal bridges to a resistor and the thermal capacity of the air in the room to a capacitor. The LPM that includes all this elements is shown in Figure 3.13, and is the one used in Chapter 5.

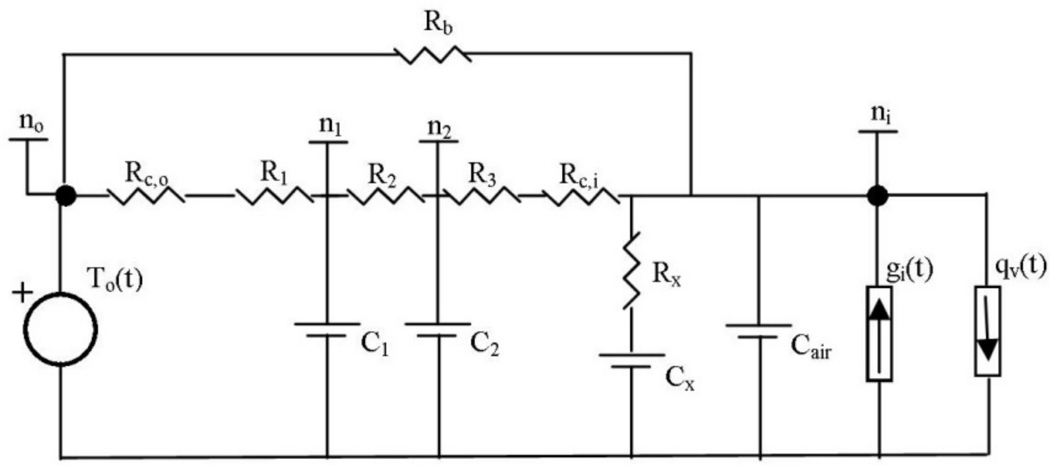

Figure 3.13 – The proposed lumped parameter model of a building.

3.5 Validation

In this chapter, the methodologies presented before are assessed and their performance and accuracy tested.

In Section 3.4 a methodology to create LPMs of RC-networks representing buildings was shown. The method presented there used the operational conditions of the building to create the Dominant Layer Model, the other reduction steps in the methodology used the time constants of the different sub-circuits to characterise each of the LPMs created.

First, the validation of the Dominant Layer Model (DLM) is done with a few examples of real constructions, and then the whole procedure of creating LPMs of buildings is evaluated in each of its steps with an automatic framework that generates a variety of case studies for each run.

The common practise to validate models in building simulation is to use (1) Analytical solutions, (2) Empirical data, or (3) results from other tools. The methodology described in this section consists on creating an RC-network that has a similar dynamic response to a larger RC-network that represents truly all the elements of the building. Due to the nature of the method, the validation used has been slightly different to the common practise. This is for the following reasons:

To validate the accuracy of the method by comparing analytical solutions, the transfer function of the full RC-network and the LPM would need to be calculated and compared. This is equivalent to comparing the Bode diagrams of the full RC-network and the LPM and will be done in this section.

In the case of empirical data, the validation for this methodology is more complicated. The fact that the method provides a LPM that represents the dynamic of the building, does not mean that that LPM is possible physically, and therefore cannot be replicated in real life, which makes the validation not possible with empirical data.

To make sure that the order of magnitude of the responses obtained with the complete RC-network and the LPM are of the right order of magnitude, curves in the time domain have been generated using EnergyPlus (validation using other tools). However, it should be taken into account that the methodology shown here is a method to reduce large RC-networks representing buildings into LPM's. The fact that the curves given by EnergyPlus are different than those by the LPM and the RC-network is because the model fidelity of EnergyPlus is much larger than that of the RC-networks and LPMs.

3.5.1 Detailed validation of the Dominant Layer Model for real constructions

The Dominant Layer Model has been tested for several constructions in detail. This evaluation of accuracy has been done studying the response in frequency of the DLMs and the complete thermal models represented with RC-networks, this validation is also to be found in (Ramallo-González *et al.*, 2013).

For numeric modelling, a simplified model has the aim of representing real constructions while reducing the computational time. To demonstrate the accuracy of the DLM, six multi-layered constructions have been modelled.

The layers of material used in the test constructions were transformed to T-networks with values from Table 3.2. The constructions are defined in Table 3.3. This table shows that the constructions used to validate this method have similar materials and topologies to those in real buildings, except for the last two (*proof* and *all heavy*).These were included to check the method's accuracy in extreme cases, yet keeping real construction materials.

Fraisse presented a way of obtaining the parameters of a LPM with the same topology as the DLM, also in an analytical way, but using a different method (Fraisse *et al.*, 2002). As the DLM is an alternative to Fraisse's approach, the two are compared in the following. Although Fraisse's methodology uses an analytical approach, it must be noted that the computational time to obtain the DLM is shorter and the method more intuitive.

Table 3.2 - Resistance and heat capacitance values for a $1m^2$ layer of the materials used.

Material	Thickness (mm)	Resistance (K/W)	Capacitance (J/K) x3600
Air gap	n/a	0.1500	n/a
Brick	101.6	0.1142	42.80
Concrete	300	0.1538	168.0
Gypsum	19	0.1187	4.602
Insulation	125	4.1667	1.806

Table 3.3 - Constructions.

Light	Outside – gypsum – insulation – gypsum – Inside
Heavy	O. – brick – ins. – concrete – gypsum – I.
Sandwich1	O. – brick – air – brick – I.
Sandwich2	O. – brick – air – brick – insulation – I.
Proof	O. – gypsum – ins. – gypsum – conc. – gypsum – brick – air – brick – gypsum – I.
All heavy	O. – gypsum – conc. – gypsum – brick – conc. – brick – gypsum – I.

To evaluate the accuracy of the DLM, Bode diagrams and time-domain responses were generated. Bode diagrams represent the relationship between the outputs and the inputs in magnitude and phase for different frequencies. The Bode diagram of magnitude shows how much the input will be amplified or reduced at the output depending on the frequency of the input. The Bode diagram of phase shows the lag between an oscillation at the input and the corresponding response at the output depending on the frequency of the input, (for more information about Bode diagrams and frequency response of dynamic systems (see (Ogata, 2002)).

It was described previously that the response of the construction can be studied independently, affected only by outside temperature and only by internal gains due to the linearity of the system, and then considering the total output as the summation of both. The accuracy of the reduction method presented in this paper has been tested for both inputs separately. The response (internal temperature) was analysed under fluctuating outside temperature (T_o), and internal gains (g_i). The results are two separate sets of Bode diagrams like the ones in Figure 3.15. The accuracy of the models under both inputs was tested in the time domain with the Bode diagrams for both inputs and compared with the model that truly has all the layers, called here complete.

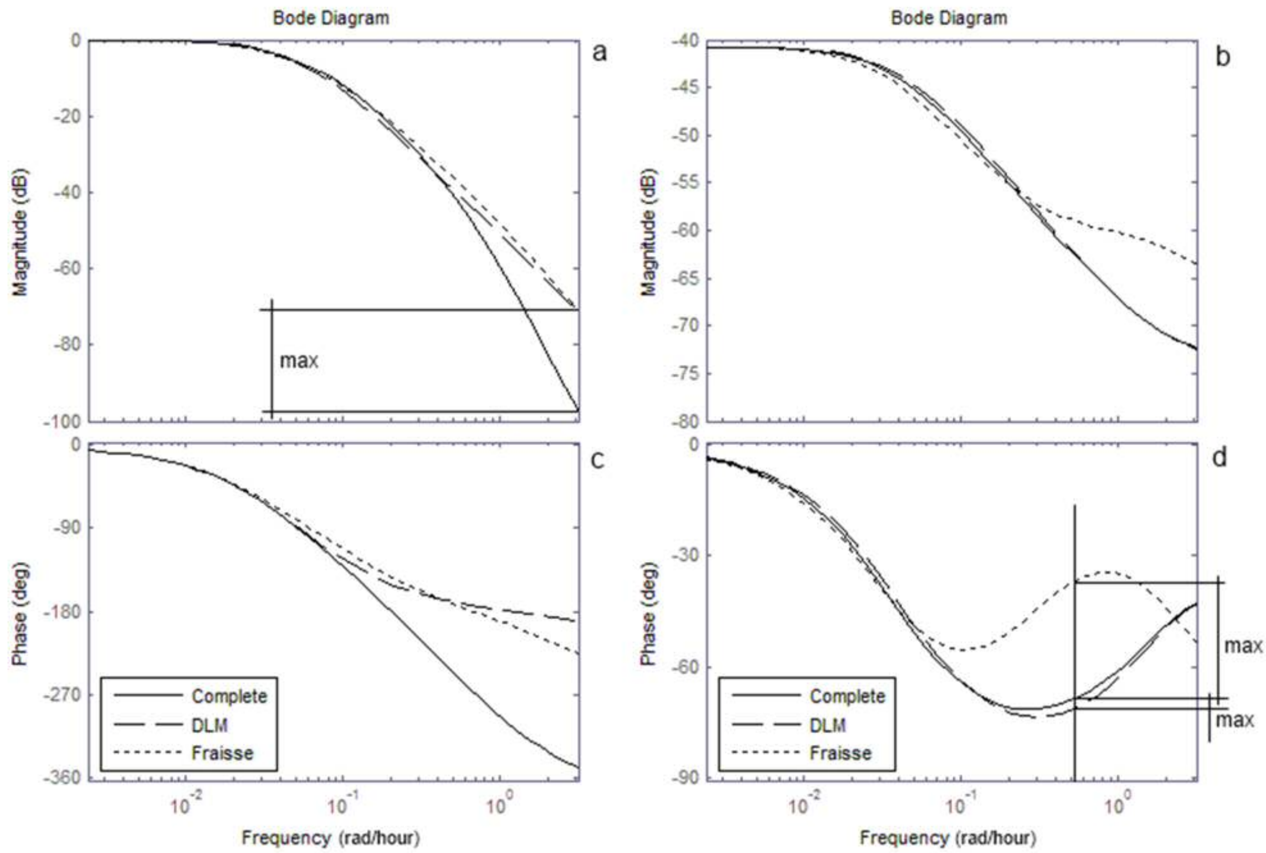

Figure 3.14 - Example Bode diagram for the construction named *sandwich 2*. Input: external temperature (T_o) (left pair); internal gains (g_i) (right pair). Solid line: complete model; dashed: DLM; points: LPM obtained with Fraisse's method.

Figure 3.14 shows example Bode diagrams comparing the complete model with the DLM and the LPM with parameters obtained by Fraisse's methodology. In plots *a* and *c* of Figure 3.14 the system is driven by a sinusoidal varying outside temperature; in plots *b* and *d* by sinusoidal varying internal gains. These Bode diagrams were obtained for every construction. However, for simplicity, the discrepancy in these diagrams has been shown by the values of the curves at the angular frequency at which the differences between models are largest Figure 3.15 and Figure 3.16. For example Figure 3.14 shows that Bode diagrams present the maximal differences at 3.14 rad/h for diagram *a*; two pair of bars will be shown with values: -97.4 (complete) with -71.3 (DLM) and -97.4 (complete) with -71.3 (Fraisse). This shows that both models are similar for this construction. When representing the plot *d*, the values will be shown as two pairs of bars with values: -68.8 (complete) with -71.4 (DLM) at frequency 0.52 rad/hour and -68.8(complete) with -36.8 at the same frequency. For this case the DLM clearly outperforms Fraisse's model and so is shown in the bar diagrams (Figure 3.15 and construction *sandwich 2*).

The first response studied in the frequency domain was under outside temperature.

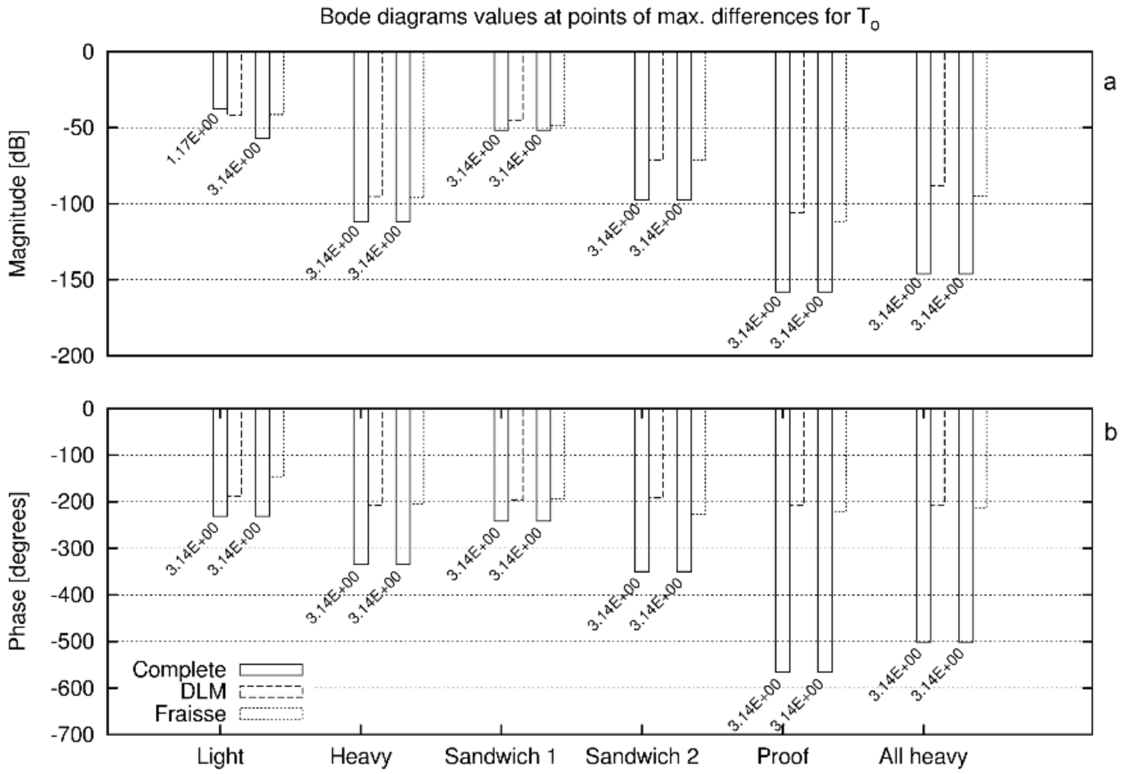

Figure 3.15 - Values of magnitude and phase for the three models when using T_o as input. The pairs of bars show the value of the Bode diagram for the complete and the reduce model (DLM or Fraisse's) and the angular frequency at which the maximum difference is found (the angular frequency is in rad/hour).

Figure 3.15 shows pairs of bars representing the values of the curves in the Bode diagrams at which the differences between the complete model and the DLM and the Fraisse model were the largest. The plot has been *generated* for the six constructions and for magnitude and phase, considering T_o as the input; this means that the magnitude shown in Figure 3.15a is calculated by $20\log(T_{out}/T_{in})$, and T_{in} = 1([21]). The number under the bars represents the angular frequency at which the maximum difference is found.

The first conclusion from Figure 3.15 is that, in the magnitude plot, the values are very small. A magnitude value of 100 dB in the Bode diagram represents a reduction by a factor of 10^5. As an example: if the construction *sandwich 2* is considered, it is seen that the value of magnitude at which the maximum difference is found is around 100 dB. A change of outside temperature of 1 degree C, will contribute to a change in internal temperature of 10^{-5} degree C which can be considered negligible for a building simulation. Performing the comparison between the two models (completed and any of the LPM) for the same example (*sandwich 2*), a change of temperature in the outside temperature of one degree C is translated in a change in inside temperature of $10^{-4.87}$ degree C for the complete model and $10^{-3.56}$ degree C for the DLM or Fraisse's model, this implies an absolute difference of: 0.000262 degree C for the worst case scenario.

If one considers the construction *light*, as it has the smallest attenuation of the input; 1 degree C oscillation at the angular frequency of Figure 3.15a will lead to: $10^{-2.85}$ degrees for the complete model and $10^{-2.06}$ degrees C for Fraisse's model in internal temperature, this results in an absolute difference of 0.00730 degrees C. Therefore, the differences seen in these Bode diagrams are substantial, but they occur at frequencies where the response have been reduced enough to be considered negligible.

The graph in Figure 3.15a also shows that the models generated with the DLM have in general the same differences with the complete model as the ones generated with Fraisse's methodology, but in constructions *sandwich 1*, *proof* and *all heavy* the model created with Fraisse's methodology have smaller error than the DLM (with a difference between the two of: 6.07%, 3.68% and 4.72% respectively). The DLM outperforms the model created with Fraisse's method for construction *light*, with the difference between complete and reduced model of 27.65% for this method and 10.91% for the DLM.

Figure 3.15b shows the values of the Bode plot of phase at which the differences were the largest for outside temperature. As in Figure 3.15a, the

[21] Degree Celsius has been the scale used in this work.

deviations for both Fraisse’s and the DLM with respect to the complete model are similar. The only construction that produces a significant difference is *light*. For this construction the DLM shows a smaller maximum difference with the complete model than the model created with Fraisse’s methodology. However, it can be seen that for constructions *sandwich 2*, *proof* and *all heavy*, Fraisse’s model is slightly better than the DLM, with relative improvement over the DLM of 9.75%, 2.57% and 1.28% respectively compared with the complete model. The difference between the two in heavy and *sandwich 1* are negligible and for *light*, the DLM is an 18% closer to the complete model than Fraisse’s model. The impact of these discrepancies in real simulation (time-domain) will be studied further in this section.

Figure 3.15 shows that the differences in the Bode diagrams of the complete and the reduced models can be large. However, the maximum differences are found at points where the input has been reduced greatly. It will be shown that because of this differences happening when the inputs are negligible, the reduced models perform well despite those.

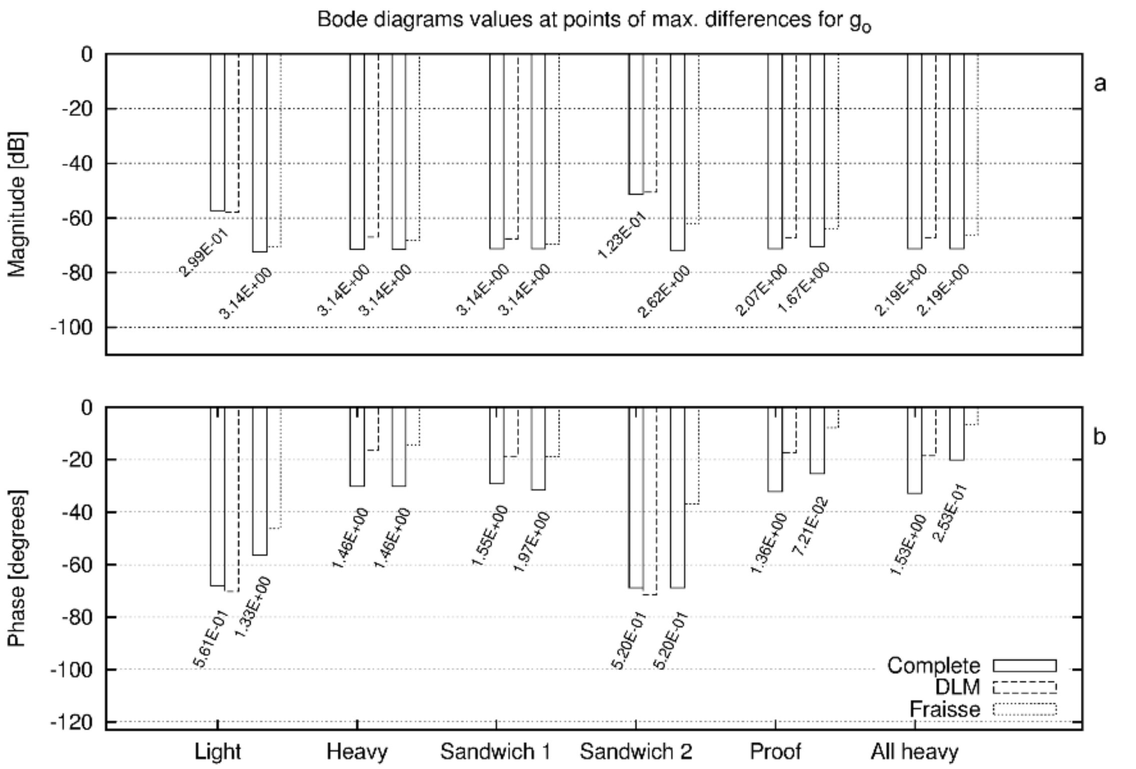

Figure 3.16 - Values of magnitude and phase for the three models when using g_i as input. The pairs of bars show the value of the Bode diagram for the complete and the reduce model (DLM or Fraisse's) and the angular frequency at which the maximum difference is found (the angular frequency is in rad/hour).

Figure 3.16 shows the values of the curves of the Bode diagrams at which the differences between the three models were largest for internal gains. The DLM equals or outperforms Fraisse's model in almost all constructions. Although the order of the magnitude plot (Figure 3.16a) implies a reduction of the input as high as the one shown by Figure 3.15a, one should consider that the input for this graph (internal gains) has variations that are normally between one to two orders of magnitude larger than variations in outside temperature (see the profile of realistic gains and outside temperature in Figure 3.17).

Under varying gains, the magnitude Bode diagrams of the DLM are similar to those of the complete model. The reduced model generated with Fraisse's method outperform the DLM in constructions *heavy* and *sandwich 1* by a small amount (1.53% and 2.62% respectively, this percentage is in the reduction of the input as it is a logarithmic scale). The Fraisse method works well for most constructions in magnitude. However, the error for construction *sandwich 2* is larger than in any other with a 13.5% deviation.

Figure 3.16b shows the value of the Bode diagrams where the largest differences are found between models for phase. Constructions *light* and *sandwich 2* show a substantial difference between the complete model and Fraisse's model, the difference is smaller than the difference between the complete model and the DLM. For constructions *heavy, sandwich 1*, *proof* and *all heavy*, the reduced models are not able to follow accurately the complete model and that is shown in substantial differences in the Bode diagrams of the reduced and the complete models. Although both models show substantial differences, the DLM outperforms Fraisse's model in constructions proof and all heavy.

After comparing the discrepancies in the frequency domain, three periods of 48 hours have been simulated in the time domain, to show the implication of the disparities in the Bode diagrams are in the time-domain response. The three periods are from 100 to 148 hours, from 2000 to 2048 hours and from 4000 to 4048 hours where the hour is the hour in the weather file and hour = 0 is the first of January 00:00. With this we aim to visualise the response in winter, spring and summer to show the accuracy of the models for three different periods of weather. This is relevant because the resistances taken in the models based in RC-networks to represent convection and radiation were fixed, and we know that those will take different values depending on the weather conditions. The constructions were used to create a simplistic building model consisting of a box of 10x10x5m that was simulated with the outside temperature given by a weather file for London (DoE, 2011) and a modulating realistic gain (see Figure 3.17). With this, it is possible to visualise the effect of the discrepancies in the Bode diagrams.

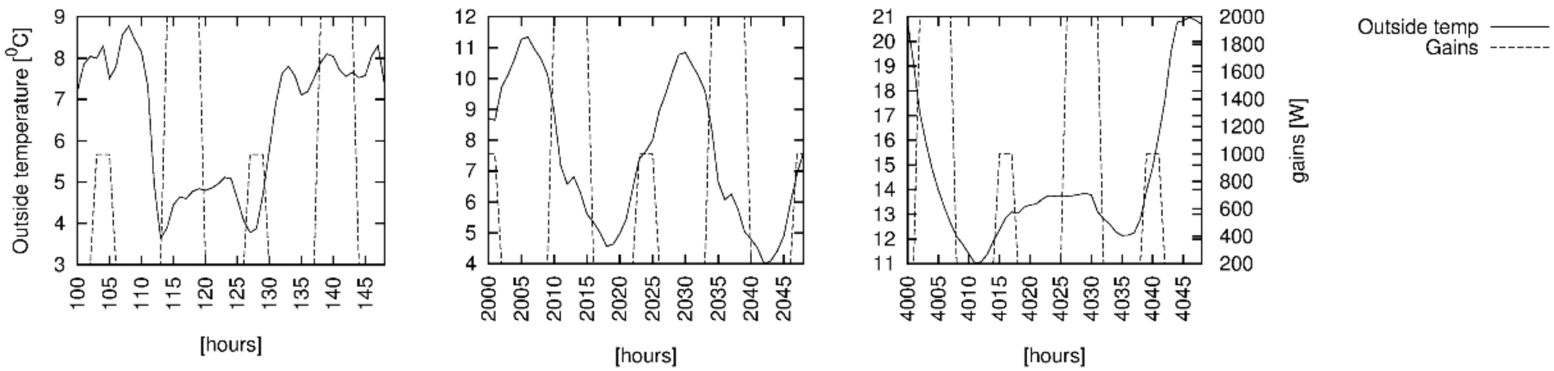

Figure 3.17 - Inputs of the dynamic models. Outside temperature and heat flow for three 48 hours periods in winter, spring and summer.

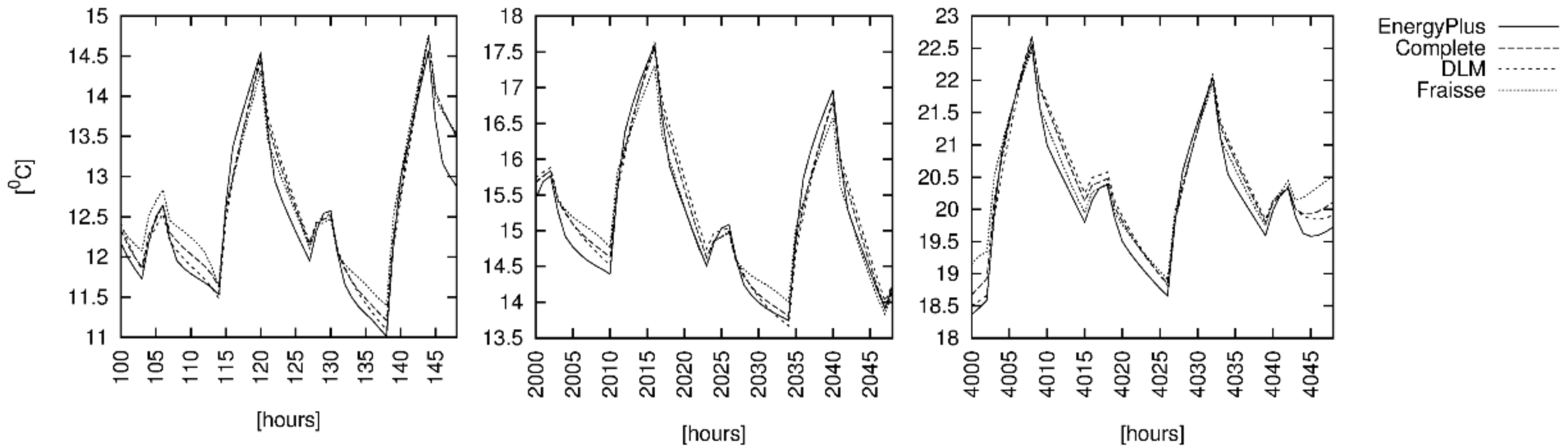

Figure 3.18 - Temporal response for the models of construction "Light".

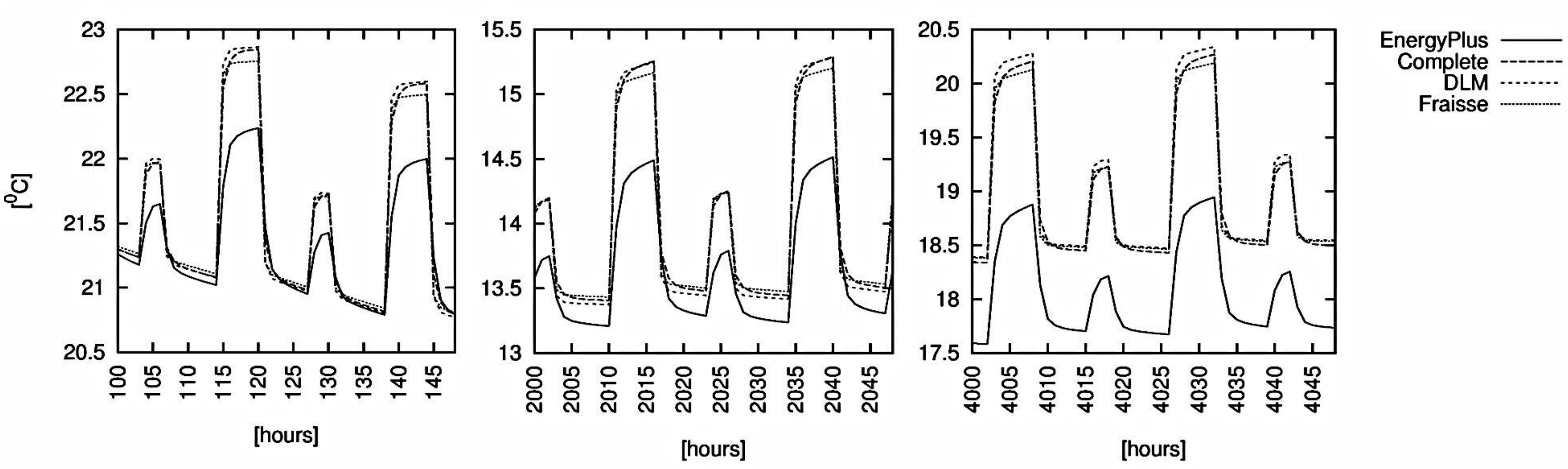

Figure 3.19 - Temporal response for the model when using construction "Heavy".

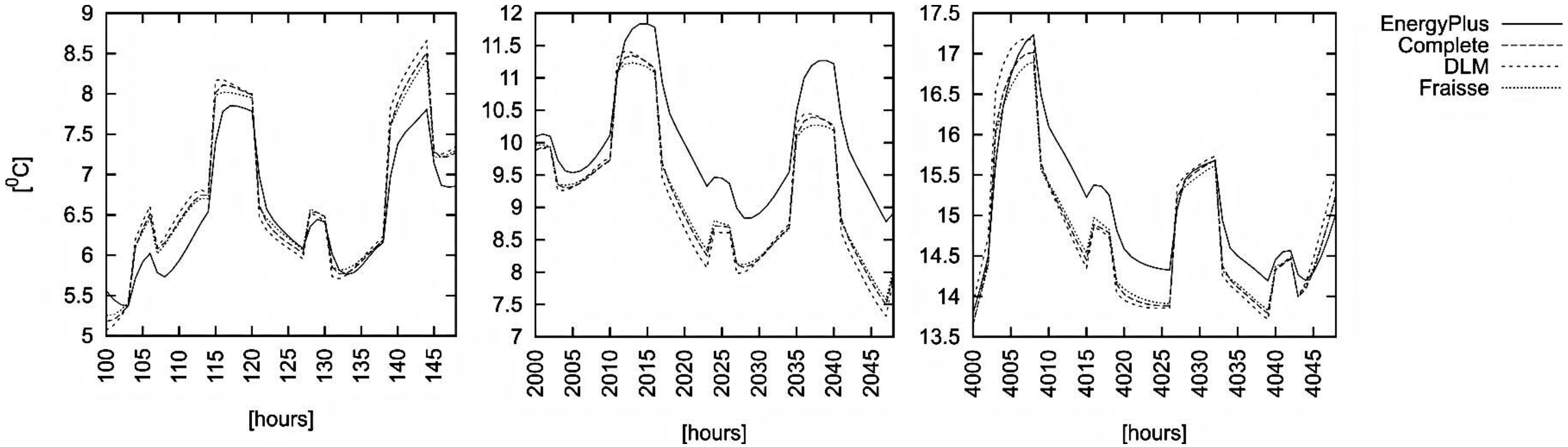

Figure 3.20 - Temporal response for the model when using construction "Sandwich 1".

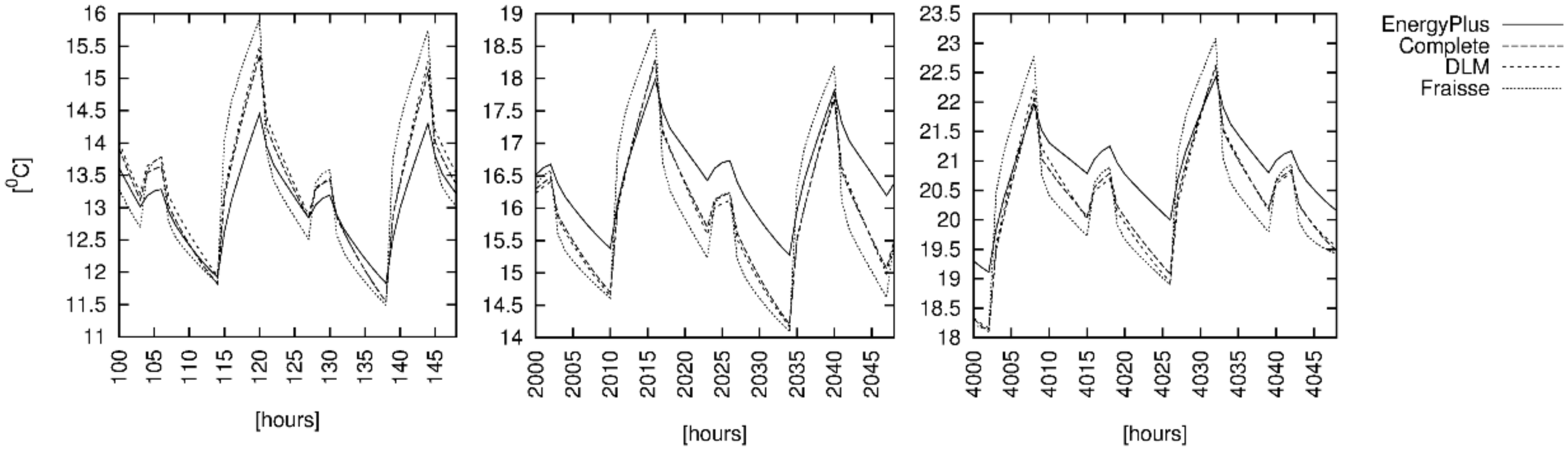

Figure 3.21 - Temporal response for the model when using construction "Sandwich 2".

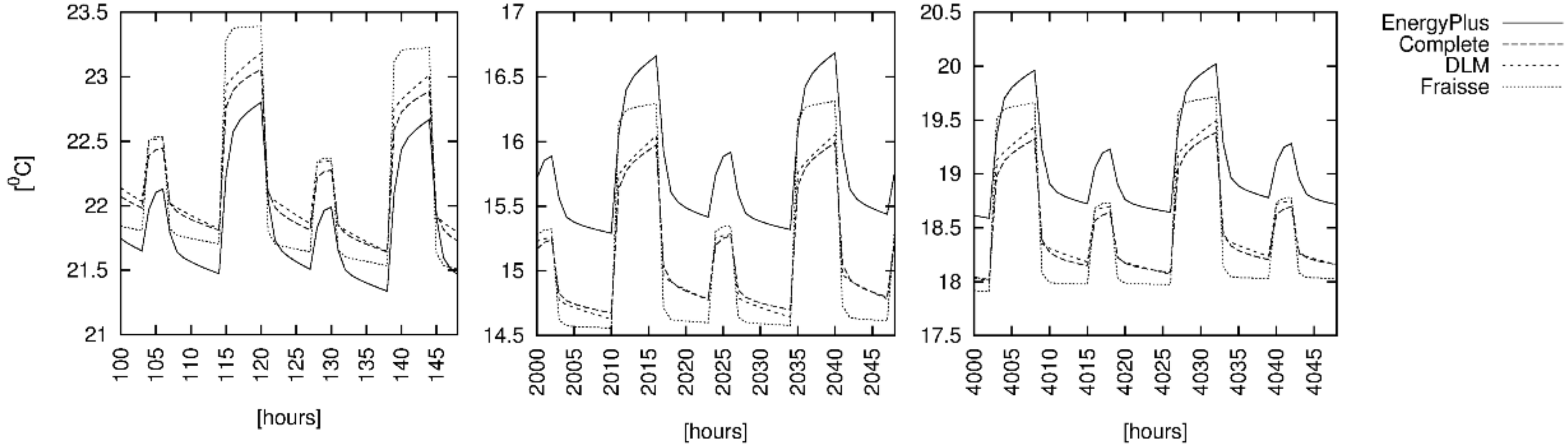

Figure 3.22 - Temporal response for the model when using construction "Proof".

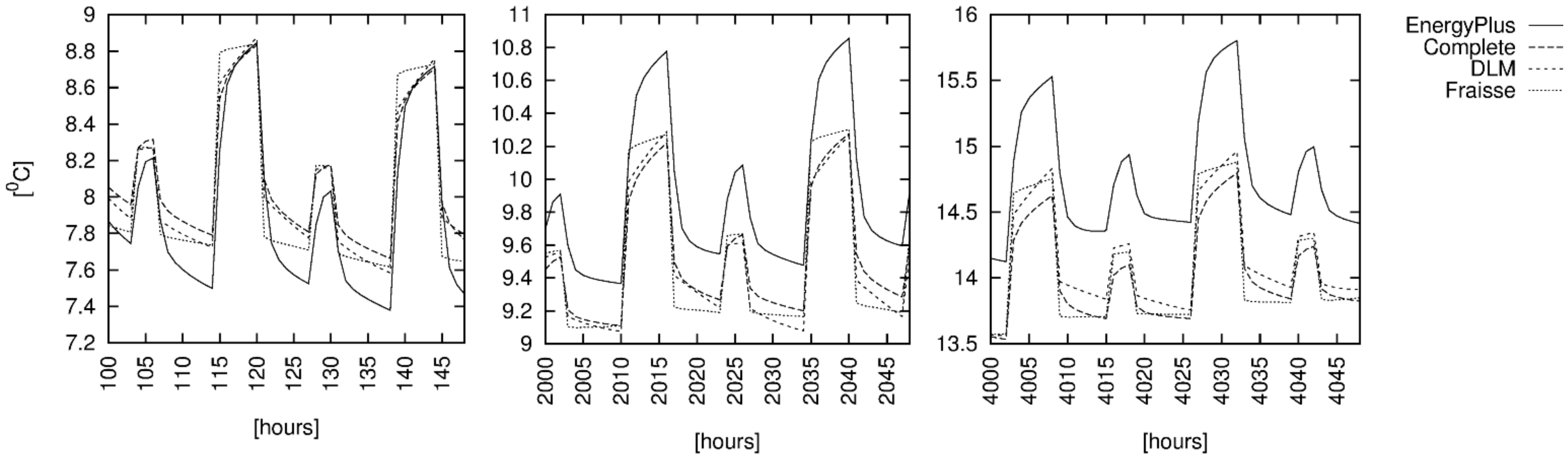

Figure 3.23 - Temporal response for the model when using construction "All heavy”.

A series of figures have been generated with the temporal responses from the simulations described in the previous paragraph. However, to reduce the number of figures, only the most significant have been included here. In these simulations, the response using EnergyPlus was included as a reference. The models based in RC-networks have been assigned an initial temperature equal to that one used in EnergyPlus, calculated with the pre-warming period of the simulation.

The bar diagrams in Figure 3.15 and Figure 3.16 show little difference in the frequency domain between the models (complete, DLM, Fraisse's) for the construction *light*. Figure 3.18 confirms this for the time domain.

The internal temperature of the construction *light* under the input in Figure 3.17 is shown in Figure 3.18. The responses of the three models and EnergyPlus are in general similar. It should be noted that Fraisse's model seems to over predict the response slightly. This difference is particularly noticeable around the periods 2025-2035 hours and 4045-4048 hours. These differences could be related to the significant difference found in Figure 3.16 in phase for this construction, but in general the differences are small.

The plots of the responses of the three models representing constructions *heavy* and *sandwich 1* were similar to those in Figure 3.18. In the three plots, there is a clear difference between the output of EnergyPlus and the outputs of any of the models based in RC-networks. This could be because some phenomena are not taken into account in the models based in RC-networks (non-linear phenomena such as radiation and convection). The difference between the response of the LPM's and EnergyPlus is expected and does not imply that the model is poor. One should bear in mind that these models are used when fidelity is compromised to get shorter computational times (around 1000 times faster).

However, the response of the models based in RC-networks is similar despite the fact that there are small differences in the Bode diagrams of these constructions. For the first three constructions, the internal gains seem to have the same effect in the three models as there are no clear differences with respect to the heating cycles. Although some differences were observed in the frequency domain of the three models representing these constructions, the discrepancies seem not to influence in the temporal response of the models greatly.

The temporal response of *sandwich 2* is been shown in Figure 3.21. The response of the models in this case highlights a greater accuracy of the DLM compared with Fraisse's model. This lack of accuracy of Fraisse's model seems to be particularly visible in the heating cycles. As shown by Figure 3.16, this construction shows the highest difference between the complete model and Fraisse's model for phase under g_i. The angular frequency at which the highest difference is found is one of the lowest at 0.52 rad/hour (close to the angular frequency for the daily cycle: 0.26 rad/hour), making this difference in the Bode diagram more influential in the time domain under realistic inputs.

Figure 3.22 and Figure 3.23 show the temporal response to the constructions *proof* and *all heavy.* The differences from the Bode diagrams predict an overestimation of the effect of the heating cycles in the internal temperature for construction *proof*, and *all heavy* using the model obtained with Fraisse's method. The differences between the Bode diagrams are found at low angular frequencies in the case of the model generated with Fraisse's methodology (0.072 rad/ hour and 0.25 rad/hour for *proof* and *all heavy* respectively), this implies a lack of accuracy in the representation of the internal temperature under the heating cycles, the shape of the curve that represents the internal temperature in these two cases is found to be inaccurate when using Fraisse's model. The DLMs for these two constructions are accurate when compared with the complete model; this improvement in accuracy under internal gains is much larger than the reduction of accuracy of the models under outside temperature (see Figure 3.15). The response of the DLM is very accurate in the construction *proof*. However, the DLM for the construction *all heavy* seems to lose accuracy in the third period (summer) and the outputs becomes as inaccurate as the output from Fraisse's model, although the DLM outperforms Fraisse's model for winter and spring. This lack of accuracy in this specific period shows a lack of consistency in the accuracy of the DLM, although it is not seen that the DLM produces a response in the time domain that is worse than a response from Fraisse's model.

3.5.2 Validation of the complete reduction method

In Section 3.4.1, the dominant layer model is part of a full reduction methodology to create LPMs of RC-networks representing buildings. In this research, the DLM was validated independently as was shown in the previous section; however, the rest of the methodology was also validated and the results are presented here.

To validate the methods, a testing framework was created in Matlab where 500 different RC-Networks were synthetically[22] created to representing 500 different buildings. These networks include multi-layered constructions for the envelope of the building and for surfaces of the partitions. Windows, infiltration and thermal bridges have been excluded in this analysis.

To create the RC-networks with realistic values, but not being constrained by a limited number of constructions, the values of thickness, conductivity, thermal mass and density of the layers of the constructions were generated randomly. The constructions of the envelope were determined by sampling a random number that takes values from the ranges shown in Table 3.4. The constructions of the partitions were generated using the ones in Table 3.5. These ranges have been determined after studying those in real construction materials (CIBSE, 2006). The thickness and the product $c_p\rho$ of materials in partitions have been assigned a smaller range as these constructions do not require the structural function that surfaces in the envelope do.

[22] They do not represent real buildings. They represent buildings that have been created by sampling random numbers that define their environmental parameters.

Table 3.4 - Ranges of the three variables that define the properties of a layer of a construction.

Property for envelope	Range
Thickness [mm]	10 - 500
Conductivity [W/m]	0.02 - 2.00
c_p * ρ [J/m^{3}K]	2e4 - 2e6

Table 3.5 - Ranges of the three variables that define the properties of a layer of a construction.

Property for partition	Range
Thickness [mm]	2 - 50
Conductivity [W/m]	0.02 - 2.00
c_p * ρ [J/m^{3}K]	2e4 - 2e5

The values in these tables were intentionally made extreme as that is equivalent to have a broader range of buildings to test.

The buildings has been considered to have a fixed geometry with 80 m^2 floor area and each surface f the envelope is formed by a different constructions with a number of layers that can go from 2 to 6. The model has also partitions and each one has different constructions with a number of layers of two or three. The layers of material have been generated by sampling a uniformly distributed random number with the limits defined in Table 3.4 and Table 3.5. As a result, 500 complex RC-networks were generated in each of the tests and each having 8 to 46 nodes. The reduction from a system with 46 nodes to a system with 4 (suggested in this methodology) implies reducing the computational time that depends on the number of nodes of the original complete model but goes from 75% to 99% reduction.

The accuracy of the reduction was analysed by studying the response in frequency of both systems: the complete RC-network and the LPM. The complete model and the LPM are evaluated when driven by varying outside temperature, and varying internal gains. Although these two driving forces are always present, they can be studied separately because of the linearity of the RC-networks. The model will be found accurate if, for the two driving forces, the output is similar for the complete model and the reduced model.

The output selected for the RC-networks was the inside temperature. The inside temperature will determine the most relevant output in the case of performing an energy building simulation as this temperature determines the behaviour of a potential thermostat, and determines the comfort of the occupants.

The response of the systems (complete and reduced) was analysed in the frequency domain. This is done by applying a sinusoidal unitary input as the driving force of the RC-network (this will be for outside temperature and internal gains), and then capturing the difference in amplitude (gain) and phase (lag) of the output (inside temperature).

Each one of the synthetically generated RC-networks was modelled by truly representing all the elements in it, and then it was reduced by using the methodology presented before into a LPM. The two models (complete and reduced) were analysed in frequency for the two driving forces (outside temperature and internal gains). The differences between the two responses (complete and reduced) were measured at each frequency for amplitude and phase and each of the driving forces (outside temperature and internal gains). The differences vary depending on the frequency; therefore, it is represented as a series of values. It should be noted that the differences were not calculated as a ratio ($T_{complete}/T_{reduced}$) but as the absolute difference ($T_{complete} - T_{reduced}$): this was done to capture the fact that the input at high frequencies will have a small impact in the output because of the nature of the RC-network, and therefore losing accuracy at those high frequencies has a small impact on the overall temporal response.

Each graph shown in this section corresponds with a test of accuracy of the LPM representing the complete model for one of the driving forces for 500 different buildings. Each graph is built with four sub-plots representing respectively: (a) a boxplot of the amplitude of the output from the complete RC-networks to show the variability that might exist between the 500 different RC-networks of the 500 different buildings, (b) a boxplot of the differences on amplitude between the output of the complete RC-network and the output of the LPM to compare the previous variability with the order of magnitude of the error in the outputs from the models created with our methodology, the equivalent for phase is shown in subplots c and d.

The steps of the methodology were tested independently to assess their specific accuracy.

The first test was carried out including only multi-layered partitions in the surfaces of the envelope, but the same construction was used for all surfaces. No internal partitions were considered. The results of this test can be seen in Figure 3.24 and Figure 3.25.

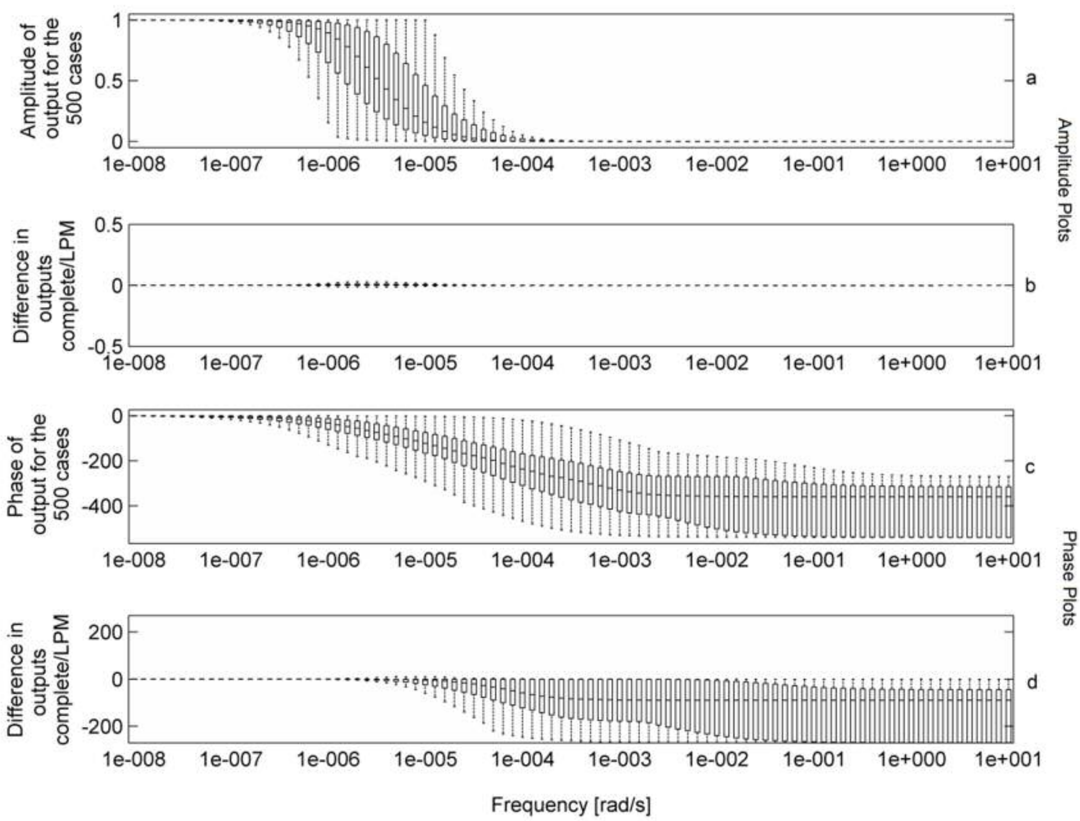

Figure 3.24 - Absolute values of the output and differences in the outputs produced with the LPM. Reduction of the multi-layered constructions. Outside temperature.

Figure 3.24 and Figure 3.25 show that the reduction of multilayer constructions into 3R2C models introduces the first loss of accuracy. The method seems to reproduce well the amplitude of the output for both inputs (outside temperature and internal gains). However, the phase seems to have the largest differences.

The first noticeable fact extracted from Figure 3.24 is that variations in outside temperature with frequencies larger than 1e-3 rad/s have negligible effect in the output, as the amplitude is too small to have a substantial effect in the output. The same can be said with Figure 3.25 for frequencies higher than 1e-2 rad/s. Errors in the output of the LPM for frequencies larger than those previously noted are irrelevant as the contribution to the output for these large frequencies can be neglected.

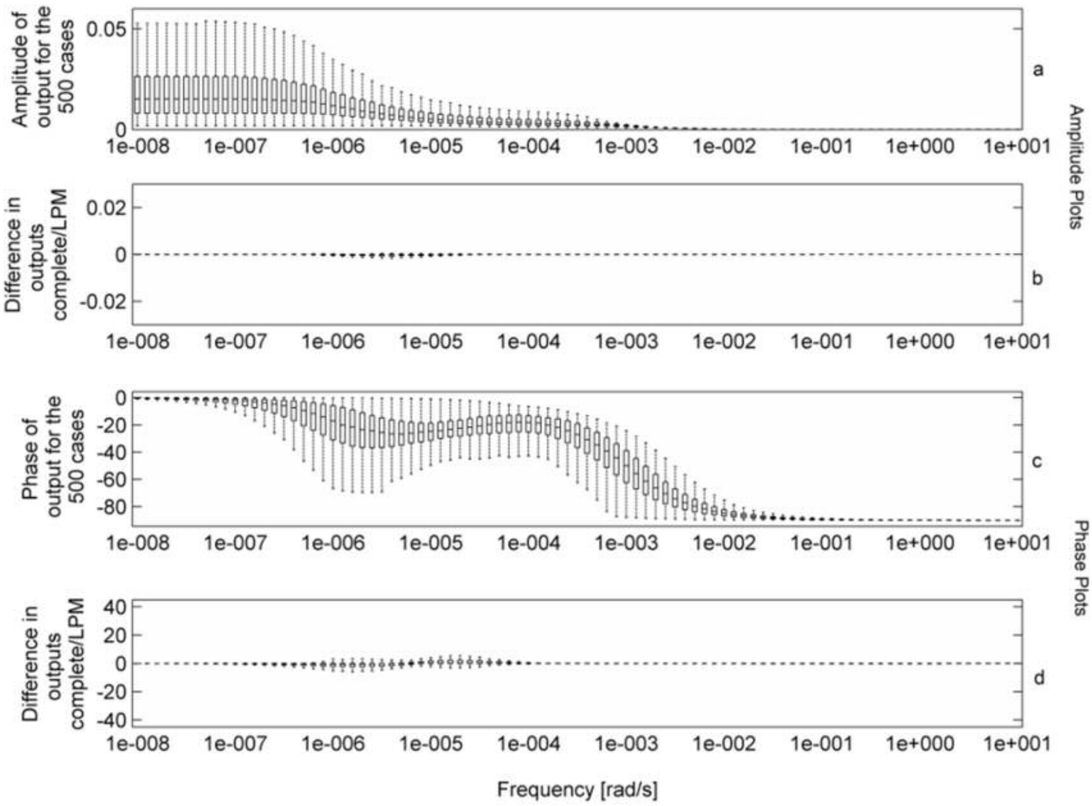

Figure 3.25 - Absolute values of the output and differences with the outputs produced with the LPM. Reduction of the multi-layered constructions. Internal gains.

In the case of the outside temperature (Figure 3.24), the LPM will always underestimate the lag of the output. This lack of accuracy is only relevant for the interval from 1e-6 rad/s to 1e-3 rad/s as after that frequency the model reduces greatly the amplitude of the input Figure 3.24a and therefore will have very little effect in the output.

The error in predicting the amplitude and phase of the output when internal gains are the input is also substantial (Figure 3.25c and d). The error when predicting the amplitude is seem to be small for this case (Figure 3.25b), and the error in phase is always smaller than the 35% (Figure 3.25d).

The next test was performed considering only the surfaces in the envelope having different constructions, but having these constructions two layers only so there was no error due to the reduction of multi-layered constructions to a 3R2C model. This will measure the loss of accuracy that results from adding surfaces with different constructions to a single 3R2C model. The results can be seen in Figure 3.26 and Figure 3.27.

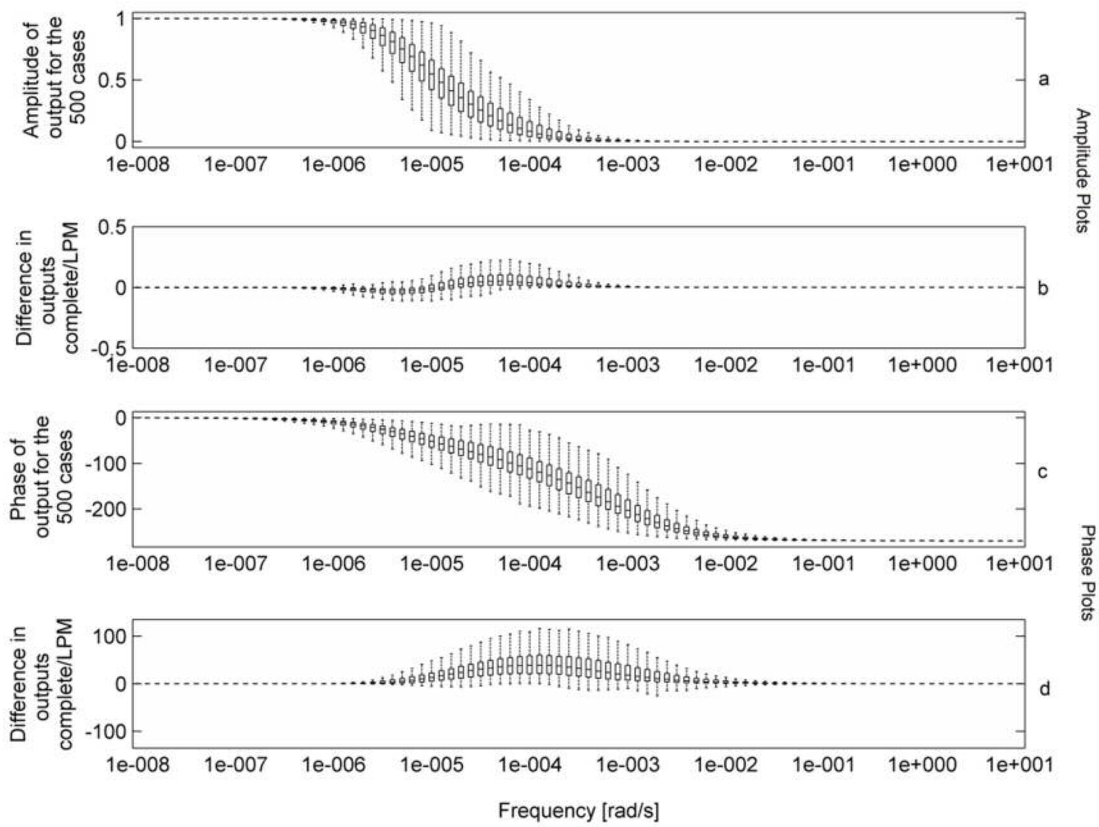

Figure 3.26 - Absolute values of the output and differences with the outputs produced with the LPM. Reduction of parallel surfaces only. Outside temperature.

When reducing several surfaces to a single LPM, the loss of accuracy is substantial in amplitude and phase for both driving forces.

Figure 3.26 shows the outputs of the models and the errors with the outside temperature as input. In this case the errors are as big as the differences between the models generated for the testing in amplitude and phase. The error is particularly large in the 1e-6 rad/s to 1e-3 rad/s interval.

That band includes the daily cycle (1.15e-5 rad/s) and that might result in large differences when the models are used for simulation in the time domain.

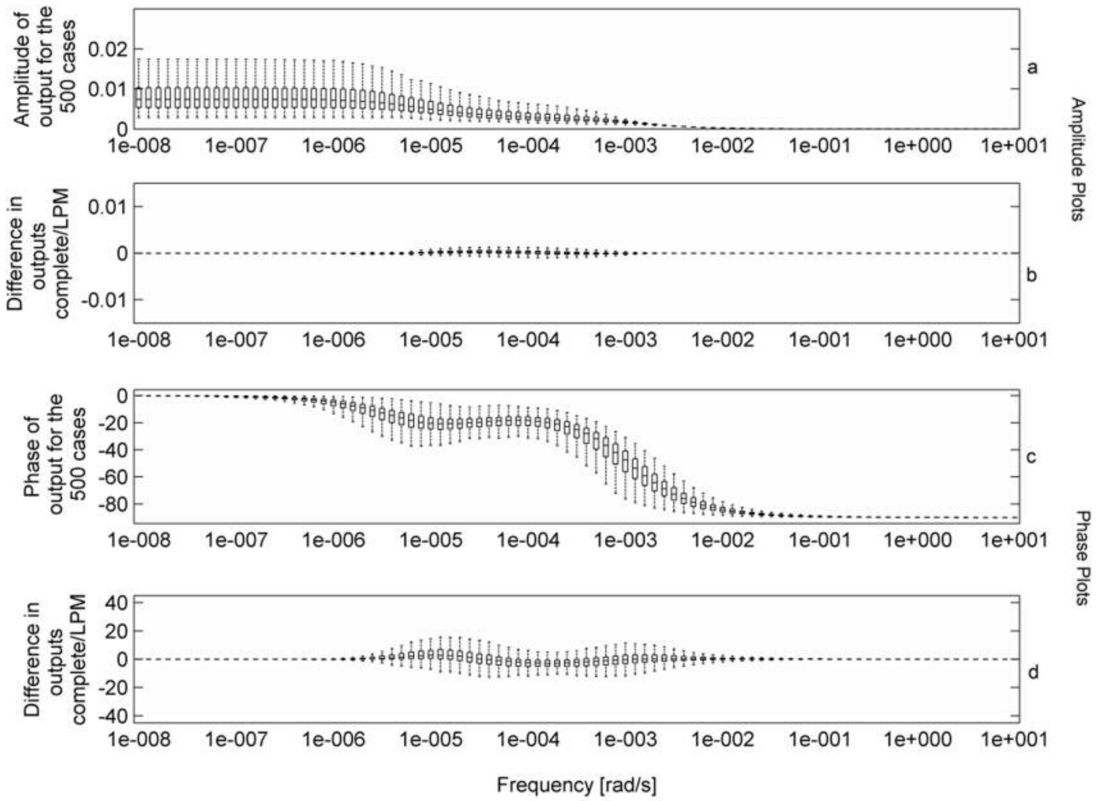

Figure 3.27 - Absolute values of the output and differences with the outputs produced with the LPM. Reduction of parallel surfaces only. Internal gains.

Only the amplitude plot when the driving force is the internal gain shows reasonable accuracy (Figure 3.27). However, the phase differences (Figure 3.27d) present deviations as big as those between cases (buildings).

The next step in the validation was the evaluation of the reduction of multi-layered partitions of the complete RC-networks. To isolate the effect of this reduction, these RC-networks were generated with 3R2C models as surfaces with all surfaces of the envelope the same 3R2C. This test produced the graphs shown in Figure 3.28 and Figure 3.29.

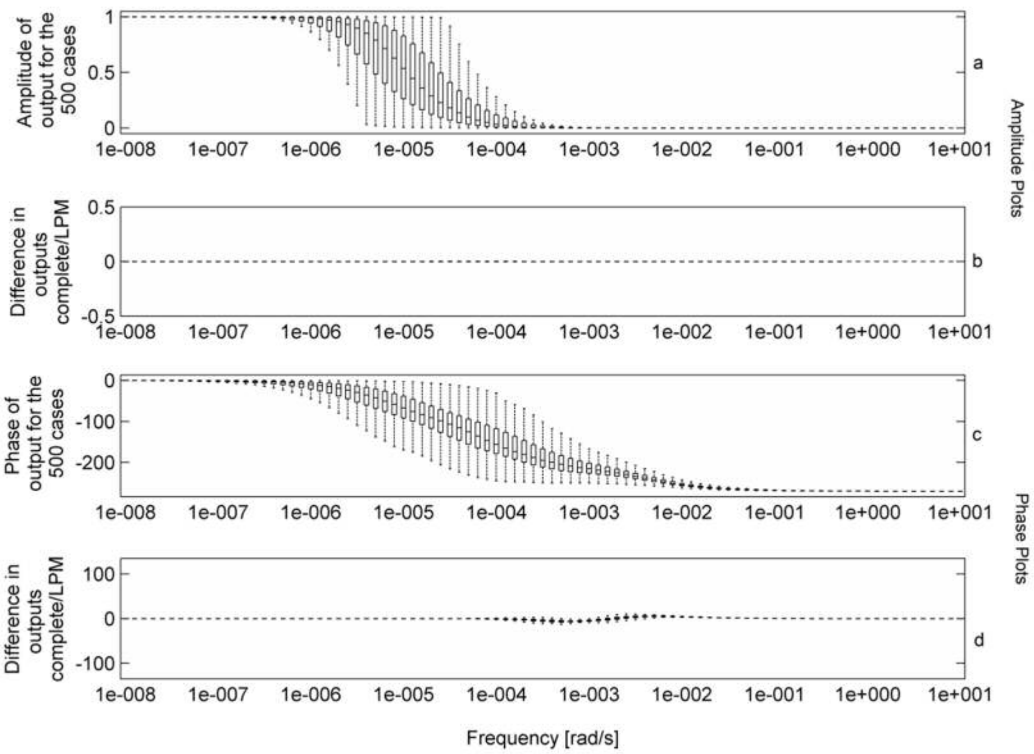

Figure 3.28 - Absolute values of the output and differences with the outputs produced with the LPM. Reducing partitions to LPM. Outside temperature.

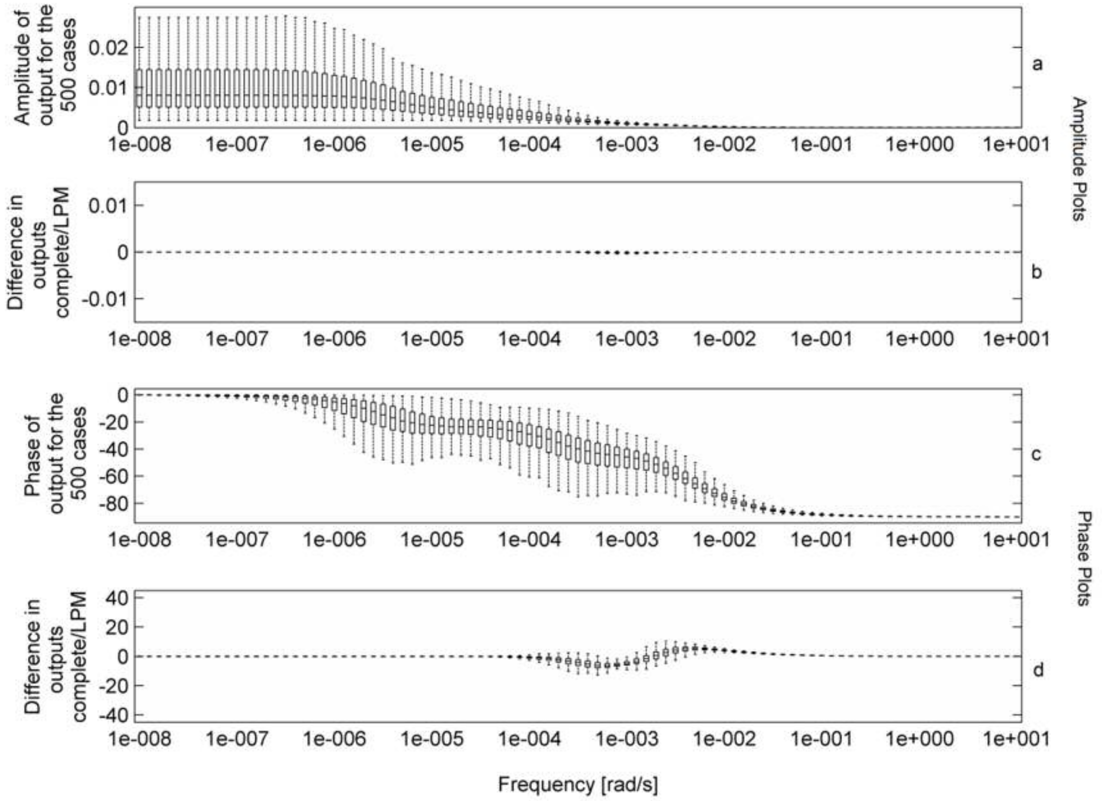

Figure 3.29 - Absolute values of the output and differences with the outputs produced with the LPM. Reducing partitions to LPM. Internal gains.

For outside temperature (Figure 3.28), the reduction of partitions to the 1R1C branch in the LPM does not imply a large reduction in accuracy. This reduction shows small differences of amplitude and phase when the outputs from the complete model and the LPM are compared.

For internal gains (Figure 3.29) the deviations in amplitude are smaller than any of the previous. The deviations in phase are substantial; however, it is smaller than that when reducing parallel surfaces, and shows a good accuracy at frequencies corresponding to daily cycles (7.3e-5 rad/s).

Finally, the methodology was tested considering all the possible reductions; this test produced the plots shown in Figure 3.30 and Figure 3.31.

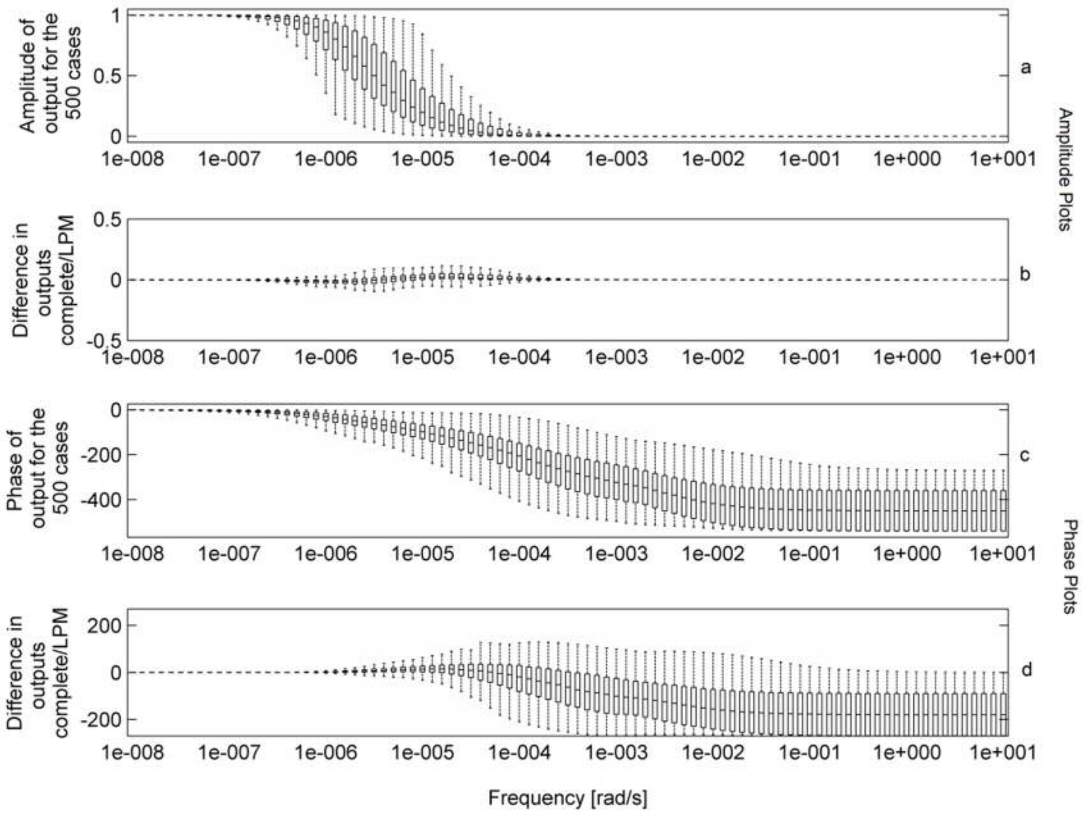

Figure 3.30 - Absolute values of the output and differences with the outputs produced with the LPM. All reductions. Outside temperature.

The plots in Figure 3.30 and Figure 3.31 show that the errors do not reduce or increase when including all the reduction steps. Instead, these figures show that the differences between the outputs generated with the complete model and the LPM are similar of those when considering the maximum of each reduction i.e. the envelope of the errors in the previous cases.

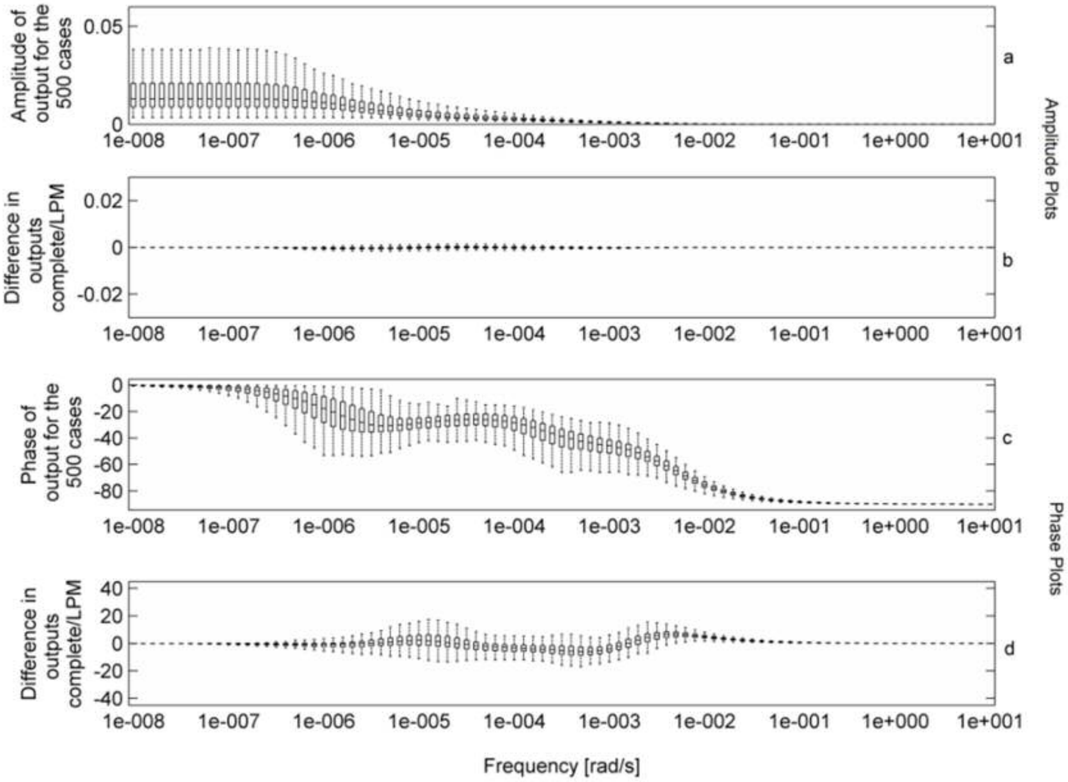

Figure 3.31 - Absolute values of the output and differences with the outputs produced with the LPM. All reductions. Internal gains.

After seeing that the largest errors were introduced when adding several surfaces of the building envelope together i.e. when modelling a building where each wall has a different construction, another test was completed including all the reductions except for this one i.e. all walls are identical. This test was performed to verify that the model will be able to provide reasonably accurate LPMs taking into account the assumption that all the walls of the envelope have the same construction; this can be considered as a reasonable assumption as most buildings have the same constructions in all the walls of the envelope excluding the roof and the floor. The results are shown in Figure 3.32 and Figure 3.33.

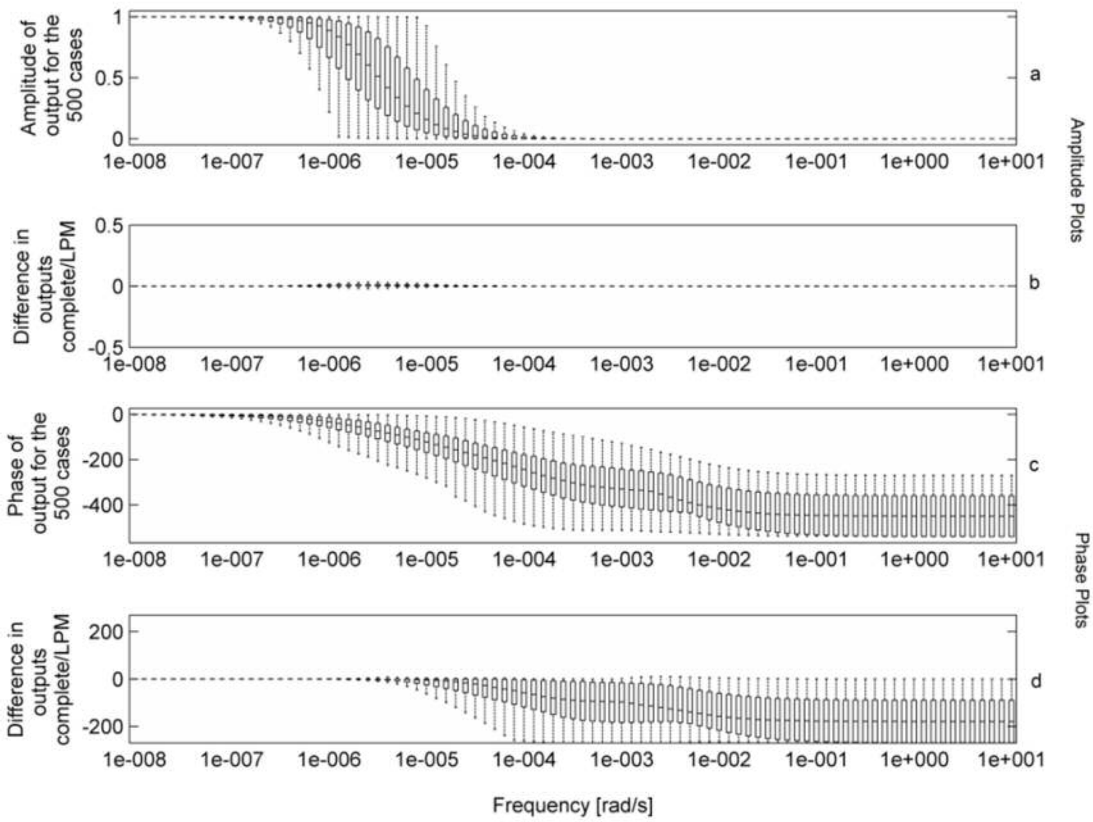

Figure 3.32 - Absolute values of the output and differences with the outputs produced with the LPM . Same construction in all the walls of the envelope. Outside Temperature.

These last figures show that when the building has the same constructions in all the walls of the envelope, the LPM generated with the methodology suggested in this paper represents the response of the complete model in amplitude, and presents an acceptable correlation in phase, although the lag of the outputs is always underestimated by the LPM.

The accuracy is maintained particularly well when considering internal gains as the input. This is especially true for a frequency of 7.3e-5, the frequency equivalent to the daily cycle. This is not surprising as the method in Section 3.4 focused on ensuring high accuracy for this frequency.

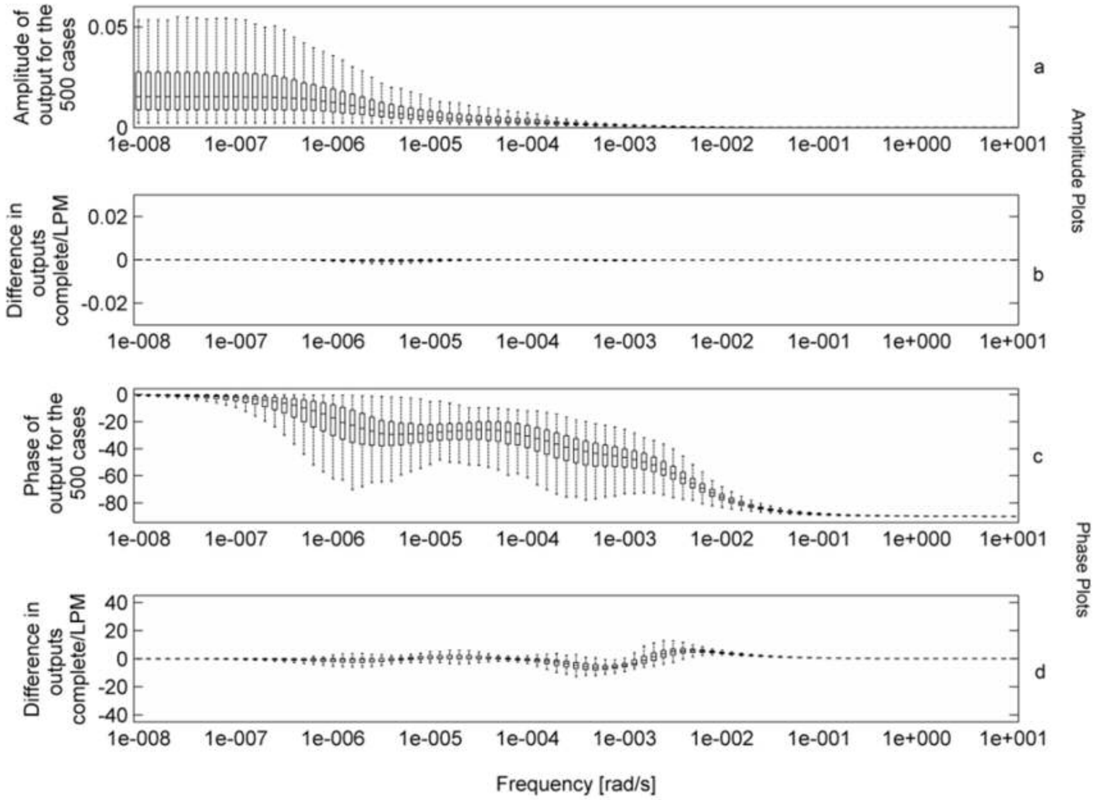

Figure 3.33 - Absolute values of the output and differences with the outputs produced with the LPM . Same construction in all the walls of the envelope. Internal gains.

3.6 Conclusions

Accurately modelling the dynamic behaviour of buildings can require long computational times; being able to reduce this computational time will allow models that run multiple representations of a design, or of driving forces, to be completed more rapidly; for example in automatic optimisation algorithms or when being use to complete sensitivity analysis.

This work presents a new analytic way of reducing complex RC-networks representing thermally-relevant elements of buildings to LPMs. The method is especially accurate in reproducing the magnitudes of the internal temperatures of a building subjected to variable outside temperature and heat gains. However, the response of the reduced model obtained with the methodology of this paper has been shown to give outputs with different phase than the outputs produced with the complete model. This is particularly prominent when the outside temperature is considered as the driving force. However, this underestimation is consistent and can be considered when analysing the results of these models.

The DLM outperforms the alternative in the literature and proves that the hypothesis is true: namely using information of the operational conditions of buildings can improve the accuracy of the LPMs created.

The complete reduction method seems to work particularly well when the original model presents the same constructions in all the walls of the envelope. This is a common case for the wall; however, the roofs will almost always have different construction to the walls, this suggests that the appropriate approach to take to reduce these models is to create two 3R2C RC-networks, one for representing all the walls of the envelope and another to represent the roofs and not to reduce this networks any further.

The methodology presented does not require numerical methods or complex calculations; instead, the LPM can be generated with a trivial computational effort, and will provide a response very similar to the model represented by the complete RC-network.

Having access to simple (but-still-accurate) simulation methods will allow designers to run models that represent multiple variations of a design rapidly (for example when performing automatic optimisation algorithms (Peippo *et al.*, 1999)).

4 Basic Robust Optimisation Method for Building Design: The Changing Environment Evolutionary Strategy

Contents

Nomenclature

$\Delta(t, i)$ – Michalewetz's mutation operation function.

HD – Heating demand [J].

$\Delta\overline{T_{\iota-o}}$ – Monthly average temperature difference between inside and outside [K].

G_{walls} – Total thermal conductivity of walls [W/K].

G_{roof}- Total thermal conductivity of roof [W/K].

G_{win} - Total thermal conductivity of windows [W/K].

G_{inf}- Total thermal conductivity of infiltration [W/K].

$\Delta\,\overline{T_{\iota-g}}$ - Monthly mean temperature difference between inside and outside [K].

G_{floor}- Total thermal conductivity of floor [W/K].

α – Scaling factor to account for the dynamics of the gains [1].

$gains$ – Gains [W].

Δt – Time period [s].

$UValue_a$ – U-Value of walls [W/(m^{2}K)].

$UValue_{roof}$ - U-Value of roof [W/(m^{2}K)].

$UValue_{floor}$- U-Value of roof [W/(m^{2}K)].

t_i- Thickness of layer *i* [m].

k_i – Conductivity of material *i* [W(mK)]

4.1 Introduction

The use of optimisation methods for building design was introduced in Section 2.3. In this chapter, a modified evolutionary algorithm capable of producing robust solutions at low computational cost is described. This algorithm was created to uncover robust low-energy building designs.

It was shown in Section 2.3 how optimisation methods can be used to generate optimal designs. Also, it was briefly discussed in the Introduction (will be described further in this chapter) that optimisation problems concerning building design are subjected to uncertainties. These uncertainties have, in many cases, a substantial impact in the design as they can influence important characteristics of the building such as energy demands (Schnieders and Hermelink, 2006).

Several robust optimisation methods were described in Section 2.4. It was stated that Evolutionary Algorithms (EAs) are the most popular algorithms used to generate robust solutions; however, some of those robust algorithms require some extra sampling of the solutions to solve the problem generated by the uncertainties. The re-sampling comes with an increase in the computational time.

This chapter shows an evolutionary algorithm that is expected to find robust solutions against different environmental parameters. The algorithm enhances the capabilities of EAs of generating robust solutions, with the aim of generating robust solutions for dynamic environments (Section 2.4). To create this algorithm several modifications have been done to the canonical form of Evolutionary Strategies (ESs) (Section 2.3). The Changing Environment Evolutionary Strategy (CEES) was created with the aim of producing robust solutions given environmental uncertainties[23] without the need of resampling each possible solution under all environments.

This chapter presents the characteristics of that algorithm, which has been called the CEES, its validation and application will be shown further in this chapter (section 4.9). First the description of the algorithm itself, and the rational process that leads to the definition of its characteristics, are shown. After that, the way the algorithm deals with the constrains of the problem is explained. This is followed by an outline of the algorithm in code form, its comparison with the three canonical forms of EAs and finished with conclusions and references.

[23] Uncertainties of Type A under Beyer and Sendhoff classification: Beyer, H.G. & Sendhoff, B., 2007. Robust optimization - A comprehensive survey. *Computer Methods in Applied Mechanics and Engineering,* 196**,** pp.3190-3218.

4.2 Aim and hypothesis

The aim is to create an optimisation method that is able to produce robust solutions without the need of re-evaluating them under different environments. Therefore this work was done under the hypothesis that it is possible to create an optimisation algorithm (or to modify an existing one) that will produce robust solutions without extra computational time for re-sampling.

More specifically, it was assumed that evolutionary computational methods are able to cope with uncertainties *per se*, along the lines with the opinions found in the reviews of robust optimisation methods: (Jin and Branke, 2005) and (Beyer and Sendhoff, 2007).

Following these principles the hypothesis was that it is possible to create an evolutionary algorithm capable of using different environmental conditions along the optimisation to produce robust solutions. This is equivalent to natural evolution on Earth, where the conditions changed greatly along the different eras, but some species survived to all these changes: the most robust species.

This algorithm was designed with the aim of solving optimisation problems to produce low-energy buildings, the main topic of this thesis; more specifically, the problem of optimising building designs to obtain low-energy solutions that perform under different occupants and occupants' behaviours.

The way the objective function changes depending on the occupants is not known until the design is evaluated under different scenarios. It is assumed that there exist designs that are less sensitive to the different uses of the building that is consequence of different users or different habits of those. The algorithm presented in this chapter aims to find those designs.

The occupants are an environmental parameter if one considers the classifications of uncertainties done by Beyer and Sendhoff (Beyer and Sendhoff, 2007). How that environmental parameter changes the shape of the objective function is unknown; therefore, the algorithm was created to find robust solutions of functions in which the effect of the environmental uncertainty can be any.

4.3 Working principle of the CEES

The main idea for the creation of the CEES, is to develop an algorithm that uses a set of solutions per iteration (i.e. a population based algorithm), and that evaluates the solutions in each iteration with a different value of the environmental parameter.

The algorithm will have much in common with the canonical forms of the Evolutionary Strategies (ESs) ESs and Genetic Programing (GP). However, the main aim is to have a population of solutions that are evaluated using a different value of the environmental parameter in each generation, the solutions that have lost fitness[24] with that evaluation will be left out, and their slots filled with individuals that are modifications of the fittest survivals. How close these individuals will be to their “parents” will be determined by the stage of the algorithm (will be explained in section 4.4.2).

The characteristic of forcing a change in the environmental parameter in every generation is the most noticeable feature of the algorithm presented in this thesis therefore the algorithm was given the name: The Changing Environment Evolutionary Strategy or the CEES.

To make this algorithm work, it requires a “slow” evolution i.e. the individuals do not change rapidly in each generation. That way, the population stays long enough in a certain area of the decision space to be tested under different values of the environmental parameter.

In the following section the main mechanisms of the CEES are described.

4.4 The CEES: Encoding and operators

Evolutionary algorithms have specific ways of tackling the problem of optimisation depending on their encoding and their operators. This section explains the encoding and operators that were chosen for the CEES and the reasons why they were found the most appropriate for the problem at hand.

4.4.1 Encoding

The first step was to select an appropriate encoding of the decision space; the encoding represents the way in which the decision space is “seen” by the algorithm. There are two main streams in the literature (see Chapter 2.3 of this thesis):

1. Binary encoding
2. Real encoding

[24] Fitness is a term used in EAs to denote the quality of the solution.

The encoding determines how the values of the decision variables are stored in the algorithm. Binary encoding is the most used encoding in Genetic Algorithms (Holland, 1975; Goldberg, 1989; Bäck, 1996). However, binary encoding implies a lost on accuracy of the algorithm because the decision space is discretised in points. The algorithm can only evaluate, and ultimately choose an optimum, among those points.

As mentioned in Chapter 2.3, binary encoding is that integrating step-wise mutation in algorithms with this encoding is not straight forward.

The real valued encoding is the form of encoding of the canonical forms of ESs and GP. This encoding uses the real values of the decision variables; therefore, there is no limitation on accuracy as any point of the decision space can be evaluated and chosen as optimum. Also, the real encoding facilitates the implementation of step-wise mutation mechanisms. For these reasons and the limitations of binary encoding, real encoding was used for the CEES. With this encoding, each solution will be represented as a set of real numbers, being the values of its decision variables.

4.4.2 Mutation

The mutation mechanism is the main exploratory operator for ESs and GP. The exploration of the decision space is done by modifying the value of the decision variables of the individuals in each generation.

There are two main groups of mutation mechanisms, those with random scope and those with controlled scope, or step-wise mutation mechanisms.

With a random mutation operator, areas of the decision space that have been explored and dismissed by the algorithm due to poor fitness could be re-explored as the mutation operator might “send” one of the solutions to that area.

This effect might not be desirable when the environmental condition is changing the shape of the objective function in every generation. Although an individual located in a “dismissed” area might have a large fitness for that generation with that value of the environmental parameter, it is likely that most of the individuals of that area were eliminated because they lose fitness with other values of the environmental parameter at that location of the decision space.

The CEES uses a mutation mechanism that ensures that the decision space is explored and examined completely but in a controlled way going from a gross search to a fine search. With this, the algorithm maintains solutions that have survived for a number of values of the environmental parameter but does not keep those that have great fitness by chance due to a specific value of the environmental parameter.

A mutation operator with the characteristics shown above is the one introduced by Michalewicz (Michalewicz, 1996). This mutation mechanism has a scope that depends in the progress of the algorithm. The operator works in the following way: First the scope of the mutation is calculated for the generation:

$$\Delta(t,i) = \left(x_i^U - x_i^L\right)\left(1 - \frac{t}{T}\right)^b \qquad \text{Eq. 4.1}$$

where $\Delta(t,i)$ defines the scope (step-size) of the mutation and depends on the generation number *t* and the decision variable *i* for which it is being evaluated, x_i^L and x_i^U are the lower and upper bound of decision variable number *i*, *T* is the maximum number of generations, and *b* the parameter determining the degree of non-uniformity. Then the mutation of an individual is calculated by doing:

$$x'_i = x_i + \Delta(t,i) * (r - 0.5) \qquad \text{Eq. 4.2}$$

$$if\ x'_i < x_i^L \rightarrow x'_i = x_i^L \qquad \text{Eq. 4.3}$$

$$if\ x'_i > x_i^U \rightarrow x'_i = x_i^U, \qquad \text{Eq. 4.4}$$

for each decision variable, where x'_i is the new value of decision variable number *i* in the mutated solution, x_i^L and x_i^U are the lower and upper bound of decision variable, $\Delta(t,i)$ the step-size of the mutation, *r* a random number with flat probability distribution in the range [0, 1] and *t* the generation number.

The function $\Delta(t,i)$ is used as the control of the step size of the mutation. This can be considered as a uniform operator in the sense that the step size decreases equally for all the decision variables as the algorithm evolves (with a scaling factor to adjust the scale). Weicker and Weicker demonstrated that uniform mutation performs well for problems with changing landscapes due to environmental parameters in (Weicker and Weicker, 1999).

4.4.3 Crossover

The crossover mechanism creates new individuals that share some characteristics from those in previous generations.

In EAs, the crossover operator is a way of exploring the decision space. The mechanism is found to act in different ways depending of the algorithm. In GAs, crossover plays an important role in the convergency of the algorithm according to the *Schema theory* (Goldberg, 1989). Following this theory, the crossover helps with the preservation of patterns in the genotype (binary string containing the set of decision variables encoded in binary code) that are present in all individuals with high fitness.

In ESs the crossover mechanism has been seen to accelerate the convergency of the optimisation for some cases (Schwefel, 1977). If a crossover mechanism had to be used in the CEES that would be the crossover mechanism of ESs for being these operators suitable for real encoding (Section 2.3.3.3). However, no crossover operator was included in the CEES, because a crossover operator makes the evolution of the individuals faster, eliminating the possibility of evaluating them extensively with different environmental parameters.

Also, some crossover operator in real-encoded EAs produce intermediate solutions from the parents that do not necessarily mean an improvement; this is true when the objective function is not unimodal[25]. An example of a multimodal function is shown in Figure 4.1, in this figure an intermediate combination of two high fitness parents does not have high fitness.

The lack of crossover operation is a substantial difference of the CEES with the canonical form of ESs and GAs and a point of similitude with the canonical form of GP.

[25] Functions in which the second derivative is always positive or always negative.

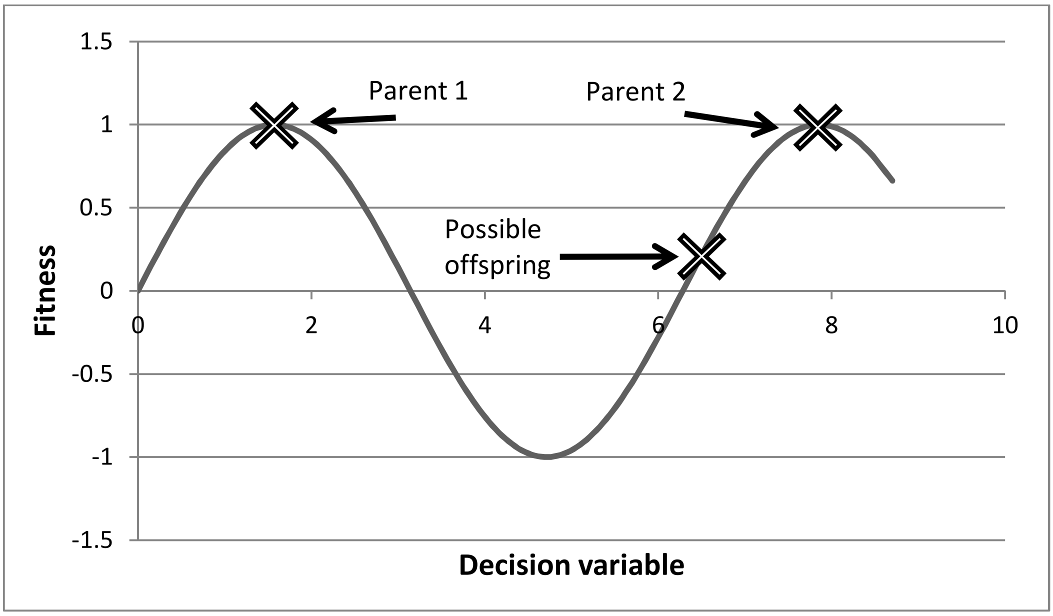

Figure 4.1 - Example of multimodal objective function where an intermediate crossover does not imply an improvement of the fitness.

4.4.4 Selection

The selection operator is the stage of the algorithm in which the best individuals are chosen to survive.

The selection can be done in different ways depending on the operator chosen (Section 2.3.2.5.3). The two main kinds of selection are stochastic and deterministic. In stochastic selection, the probability of an individual to be selected is based on its fitness; in deterministic selection, an individual would be selected or not depending on its fitness.

In this thesis, the implementation of the CEES was done with the idea of rejecting individuals that show a poor fitness for a given value of the environmental parameters because only solutions with high fitness for all values of the environmental parameters are considered ideal. For that, the deterministic selection mechanism was considered more appropriate than the probabilistic selection mechanism.

The deterministic selection mechanism used in the canonical form of ESs is based in ranking the individuals and selecting the best for survival, being the amount of individuals selected a fixed parameter of the optimisation. In this selection mechanism, the difference in fitness between the individuals is not considered as the only factor to be considered is the rank. As an example if we have five individuals (solutions) with consecutives objective values: 2, 5.2, 5.25, 5.3, 12, and the algorithm has to select the best three, the algorithm will not be able to recognise that solution with objective value 5.2 should not be left out as it is (in comparison with the next solution) still attractive.

To make sure that the individuals that have left the area of high fitness are eliminated, the selection mechanism implemented in the CEES was made deterministic, and to make sure that individuals are not eliminated just because the algorithm has to select a fixed number of those in every generation, it was based in a fitness threshold. The individuals belonging to a range of fitness that correspond to the highest fraction of the total range will stay for the next generation despite how many they are. The threshold of fitness is calculated in each generation t with the equation:

$$R(t) = f_{max}(t) - f_{min}(t), \qquad \text{Eq. 4.5}$$

with $f_{max}(t)$ and $f_{min}(t)$ the maximum and minimum value of the objective function in that generation and $R(t)$ the range of fitness. Once the range $R(t)$ is calculated, only the individuals $\boldsymbol{x}$ that satisfy Eq. 4.6 will be selected.

$$f(\boldsymbol{x}, t) > f_{max}(t) - hR(t). \qquad \text{Eq. 4.6}$$

The selection operator described above selects a different number of individuals in each generation, depending on the amount of solutions that get out of the area of high fitness; this is a distinctive characteristic when compared with the deterministic selection operators of the canonical form of ESs.

With this operator, if an individual presents a substantially higher fitness than the rest, almost the whole population will be eliminated. That will create a large number of individuals that will be mutations of this exceptional parent thereby the algorithm will study in detail that area around that possible solution. If this happened at an early stage of the optimisation, the mutation would generate individuals at a large distance of this outstanding parent because the scope of the mutation is controlled. This stops the algorithm getting stuck in small areas of the decision space when a situation such as this one occurs. The differences between a rank based operators and the range based operator is shown in Figure 4.2.

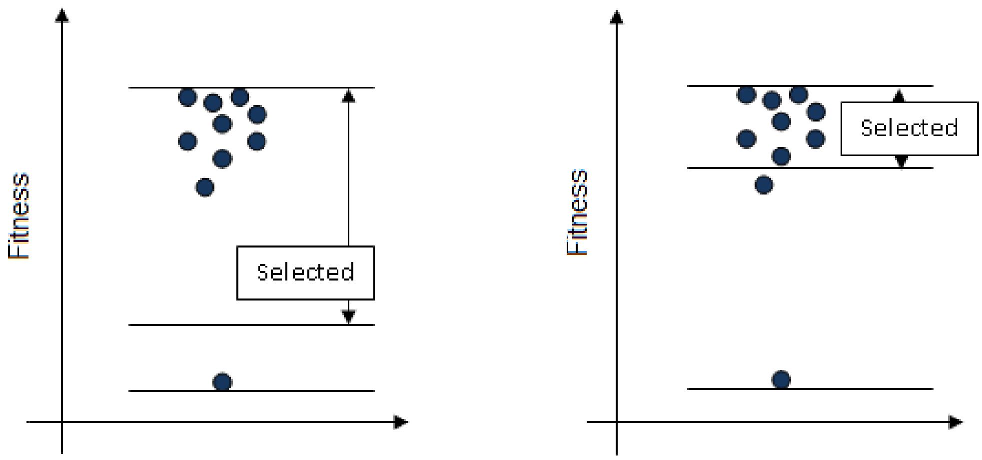

Figure 4.2 - Differences between selecting the members that are into a range of a 75% of the best fitness (left) and selecting the 75% of the individuals with best fitness (right).

4.5 Dealing with constraints in the CEES

There are two types of constraints in the problem at which the CEES was applied i.e. optimisation of low-energy buildings subjected to uncertainties. One is determined by the range of values that the decision variables can take, and the other is the limitation that established the comfort conditions of the building design i.e. some set of values of the decision variables may lead to a building that requires little energy but is not comfortable for the occupants (for example due to overheating).

The exploration of the decision space is done in the CEES through the mutation operator. The way this operator is defined in this algorithm does not allow mutating individuals out of the decision space (Eq. 4.2 Eq. 4.3). As there is no other exploratory operator, this definition of mutation maintains the decision variables within their ranges.

The other type of constraint is the one that is known after the evaluation of the solution. Buildings that do not fulfil the condition of being comfortable have to be considered as not feasible. To deal with these uncertainties a penalty function was used. Solutions that present a good fitness, but are not feasible, will be penalised, this is done by multiplying their fitness with a fixed number. This number and more details about the penalty function will be described in Chapter 9, for more information about penalty functions to deal with constraints see for example (Coley, 1999).

4.6 Code of the algorithm

The resultant algorithm can be read in the Code 4.1.

Code 4.1 - The CEES.

$t \coloneqq 0;$	
$e \coloneqq \ sample\ \alpha$	//picks a random value of the environmental parameter
$initialize\ P(0) \coloneqq \{\boldsymbol{x}_1(0), \dots, \boldsymbol{x}_\mu(0)\}$;	//generates the first generation
$\boldsymbol{while}\ (t \leq T)\ \boldsymbol{do}$	
$e \coloneqq \ sample\ \alpha$	//picks a random variable of the environmental parameter
$evaluate\ \ P(t) : \{f(\boldsymbol{x}_1(t), e), \dots, f(\boldsymbol{x}_\mu(t), e)\}$	//calculates the fitness of the best individuals
$select \quad P'(t) \coloneqq s\Theta_s(P(t))$	//selects the best individuals
$i \ \coloneqq 1$	
$k \ \coloneqq \ 1$	
$\lambda \coloneqq \ size\ of\ P'(t)$	//determines the number of free slots
$\boldsymbol{while}\ (k < \mu - \lambda\ )\ \boldsymbol{do}$	
$mutate \quad \boldsymbol{x}_{\lambda+k}(t) \coloneqq m\Theta_m(\boldsymbol{x}_i(t))$	//fill the slots with mutations of the best individuals
$i \ \coloneqq i + 1$	
$k \ \coloneqq k + 1$	
if (i== λ)	
i = 1	
fi	
$\boldsymbol{od}$	
$t \coloneqq \ t + 1$	
$\boldsymbol{od}$	

4.7 Comparison of the CEES with the Canonical EAs

Table 4.6 shows the differences between the canonical forms of EAs and the CEES.

Table 4.1 - Characteristics of CEES compared with the canonical forms of EAs.

	CEES	ES	EP	GA
Representation	Real-valued	Real-valued	Real-valued	Binary-valued
Fitness is	Objective function value	Objective function value	Scaled objective function value	Scaled objective function value
Self-adaptation	Adaptation by the progress of the run	Standard deviations and rotation angles	None, variances or correlation coefficients	None
Mutation	Flat (Michalewicz)	Gaussian	Gaussian	Bit inversion
Recombination	None	Discrete and intermediate, sexual and panmictic	None	Crossover
Selection	Deterministic, range-based	Deterministic, extinctive or based on preservation	Probabilistic, extinctive	Probabilistic, based on preservation
Constrains	Arbitrary inequality constrains, penalty function	Arbitrary inequality constrains	None	Simple bounds by encoding mechanism

4.8 Application

This section presents the application of the CEES to an optimisation problem of building design subjected to uncertainties. The section also describes the uncertainties that can be found in building design reviewing the works of Hopfe and de Wilde and justifies the reason for selecting occupants' behaviour as the uncertainty of the application.

The validation of the CEES is done with several synthetic functions that change under different environmental parameters to check the efficiency of the algorithm. After this validation, the algorithm is applied to a generic problem of building design consisting of a single dwelling with 4 occupants, the behaviour of the occupants being created with tools that represent those realistically (Richardson *et al.*, 2008).

The results are discussed at the end of the chapter and this is followed by the conclusion and references.

4.8.1 Why occupant behaviour and no other uncertainties?

In Section 2.6.4, the uncertainties found in building energy calculations were described. It has been seen how there are several uncertainties that can influence largely energy calculations. This section justifies why in this thesis only occupants' behaviour was considered as uncertainty.

The previous papers have shown that infiltration levels, U-Values and occupants' related gains are the most significant parameters in the estimation of energy demands.

The results of Hopfe and Hensen (Hopfe and Hensen, 2011) do not agree with the results of de Wilde (de Wilde and Tian, 2009) (Table 4.3).

A short study has been done in this thesis to evaluate the impact of several factors in the energy demand of buildings. The results were compared with de Wilde and Tian; and Hopfe and Hensen findings to verify the validity of the later, as the results of Hopfe and Hensen seem to be not realistic, and the methodology used could be considered inadequate because of the large number of variables compared with the small number of tests.

A simple calculation has been performed to analyse the impact of several uncertainties analytically. For this, a monthly averaged calculation of the energy heating demand has been considered using the following equation:

$$HD = \left(\Delta\overline{T_{\iota-o}}\left(G_{walls} + G_{roof} + G_{win} + G_{inf}\right) + \Delta\,\overline{T_{\iota-g}} * G_{floor} - \alpha * gains\right)\Delta t, \tag{Eq. 4.7}$$

were *HD* is the heating demand for a month [J], $\Delta\overline{T_{\iota-o}}$ is the temperature difference between the monthly averaged outside temperature and the thermostat set point [K], G_{walls} is the total conductance of the walls [W/K], G_{roof} is the conductance of the roof, G_{win} is the conductance of windows, G_{inf} is the conductance due to infiltration, $\Delta\,\overline{T_{\iota-g}}$ is the temperature difference between the averaged ground temperature and the thermostat set point, G_{floor} is the conductance of the floor and Δt is the time period (month) [s]. A factor α has been included to make up for the effect of the non-simultaneity of gains with heating in the daily cycle.

This rather simple equation gives an approximate value of the heating needed to maintain a given building at a given temperature. Because this is an algebraic equation, one can study the dependence of the terms as independent variables. Eq. 4.7 can be extended as follows:

$$HD = \left(\Delta\overline{T_{\iota-o}}\left(A_{walls} * UValue_{walls} + A_{roof} * UValue_{roof} + A_{win} * UValue_{win} + \frac{c_p \rho V}{3600} ach\right) + \Delta\,\overline{T_{\iota-g}} * A_{floor} * UValue_{floor} - \alpha * gains\right)\Delta t, \quad \text{Eq. 4.8}$$

where A_x are the areas of the different surfaces [m^2], $UValue_x$ are the U-Values of those surfaces [W/(m^{2}K)], c_p is the thermal capacity of air [J/(kgK)], ρ is the density of air [kg/m^3], V is the volume of the building [m^3] and *ach* are the air changes per hour [h^{-1}].

Using Eq. 4.8, some of the variables studied by Hopfe and de Wilde can be analysed by derivation of the terms. The variables used by de Wilde that appear in this equation are shown in Table 4.7 (gains divided into *Equipment* and *Lighting*). Some of the variables used by Hopfe and Hensen cannot be found in Eq. 4.8, so they have not been considered in this step. The values of gains are given by a single number in W/m^2 however this has been understood as a nominal power that oscillates during the year simulation.

Table 4.2 - Selected uncertain variables and their ranges from (de Wilde and Tian, 2009) and (Hopfe and Hensen, 2011).

		de Wilde and Tian (for 2020) Uniform probability distribution		**Hopfe and Hensen Normal probability distribution**	
Variable	**Unit**	**Lower B.**	**Upper B.**	**μ**	**σ**
Wall U-Value	W/(m^{2}K)	0.15	0.3	n/a	n/a
Floor U-Value	W/(m^{2}K)	0.1	0.22	n/a	n/a
Roof U-Value	W/(m^{2}K)	0.1	0.22	n/a	n/a
Window U-Value	W/(m^{2}K)	1	2	n/a	n/a
Infiltration rate	ach, h^{-1}	0.1	0.25	0.5	0.17
Equipment heat gains	W/m^2	8	12	20	3.2
Lighting heat gain	W/m^2	6	12	15	2.4

The partial derivatives of Eq. 4.8 show the sensitivity of each of the independent variables in the dependent variable (heating) at the point of analysis (range in Table 4.7) The partial derivatives are:

$$\frac{\partial\, HD}{\partial\, UValue_{walls}} = \Delta\overline{T_{\iota-o}} * \Delta t * A_{walls} \qquad \text{Eq. 4.9}$$

$$\frac{\partial\, HD}{\partial\, UValue_{floor}} = \Delta\,\overline{T_{\iota-g}}\; * \Delta t * A_{floor} \qquad \text{Eq. 4.10}$$

$$\frac{\partial\, HD}{\partial\, UValue_{roof}} = \Delta\overline{T_{\iota-o}} * \Delta t * A_{roof} \qquad \text{Eq. 4.11}$$

$$\frac{\partial\, HD}{\partial\, UValue_{win}} = \Delta\overline{T_{\iota-o}} * \Delta t * A_{win} \qquad \text{Eq. 4.12}$$

$$\frac{\partial\, HD}{\partial\, ach} = \Delta\overline{T_{\iota-o}} * \Delta t * \frac{c_p \rho V}{3600} \qquad \text{Eq. 4.13}$$

$$\frac{\partial\, HD}{\partial\, gains} = -\alpha\Delta t. \qquad \text{Eq. 4.14}$$

Some of those derivatives are functions of the average temperature of each month, to solve this, the derivative was evaluated at the average temperature of the heating season[26], but none of them are dependent on any of the independent variables (i. e. variables in Table 4.7), therefore, it can be said that Eq. 4.8 is linear with respect to every one of those variables.

With this simple way of calculating the heating demand, the effect of each variable in the heating demand can be then calculated in the range of the variables as:

[26] January, February and December.

$$\frac{\partial\, HD}{\partial\, variable} * \frac{Range\ of\ Variable}{Range\ of\ HD} = Normalised\ Sensitivity,$$ Eq. 4.15

or using a more appropriate terminology:

$$\frac{\partial\, HD}{\partial\, variable} * \frac{Range\ of\ Variable}{Range\ of\ HD}$$
$$= Equivalent\ Standarized\ Regression\ Coefficient.$$ Eq. 4.16

To calculate the range of the heating demand, Eq. 4.8 was solved with the extreme values of each variable for each month. Only the positive values were then accepted (negative correspond to cooling), and the negative values were considered as zero (no cooling system). The gains were applied using a fetching factor (α in Eq. 4.8) as it is understood that the gains have a certain lag with the heating (normally happening early in the morning the heating and during the day the gains). This factor was changed by trial and error until the mean obtained was similar to the one obtained by de Wilde (the result was α =0.45). This scaling factor accounts for the lag between gains and heating, and for the solar gains that have not been considered in the steady state at all. As the solar gains would affect all cases and this is a comparative study of the impact of each parameter, this is expected to have no effect in the results.

The SRC obtained with this simple calculation of the variables in Table 4.7 over the ranges selected by de Wilde and Tian, can be seen in Figure 4.3. The results of de Wilde and Tian for the prediction of 2020 are also shown with a scaling factor (as their calculation included future weather data, and two other independent variables were included in the regression).

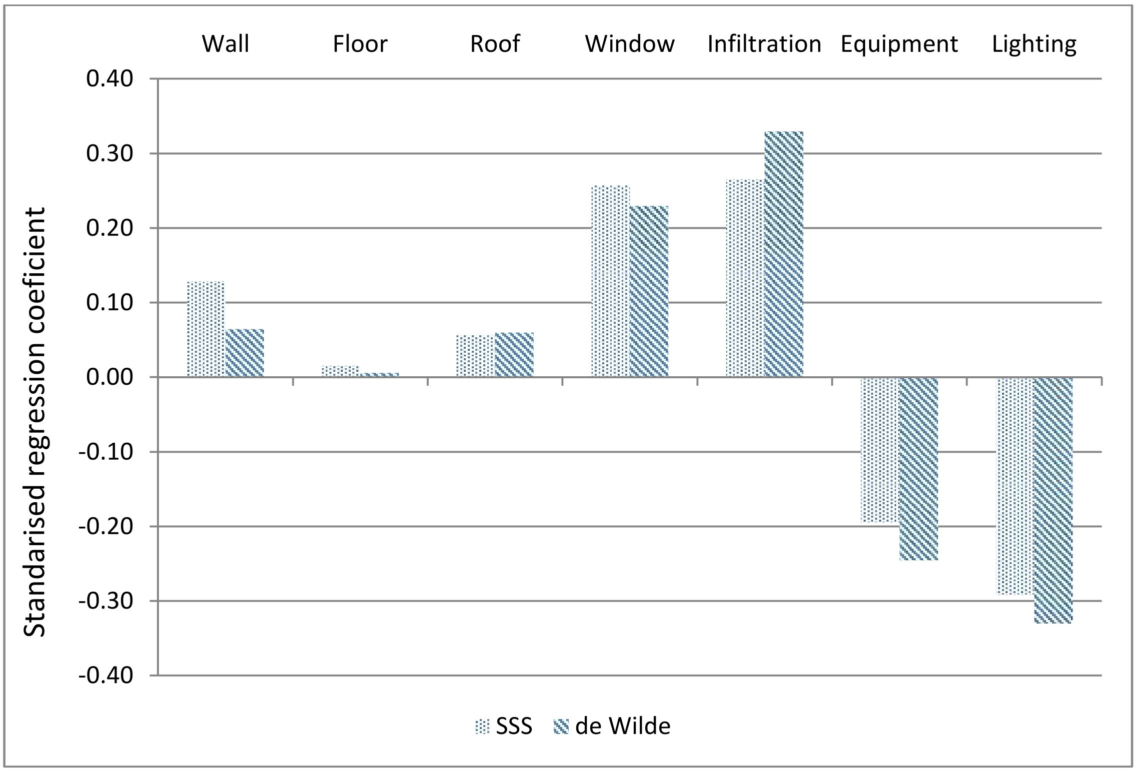

Figure 4.3 - Equivalent Standardised Regression Coefficients, obtained by the analysis of a simple steady-state (SSS) formula and from de Wilde and Tian 2009 with an scaling factor.

It can be seen in Figure 4.3 that the parameters with the higher impact are the gains and the infiltration followed closely by the U-Value of windows and the U-Value of walls. The results obtained with the simple steady-state calculation are similar to the ones obtained by de Wilde and Tian and justify the importance of two parameters that are highly related with the occupants: gains due to equipment, and gains due to lighting. Having found, that the application of this simple calculation provided relatively accurate estimation of the impacts of each variable in the energy demand, the same was done to evaluate the results of Hopfe and Hensen.

Hopfe and Hensen performed a similar sensitivity analysis of the factors that affect energy calculations in buildings in (Hopfe and Hensen, 2011). Hopfe used a large number of independent variables (63) that correlated using a set of 200 samples. The results show that infiltration is the independent variable with the biggest impact on the energy calculation. However, this large difference between the impact of the infiltration and the impact of the other parameters might be the consequence of a base model with high levels of infiltration that mask the rest of the parameters, or to a rather small number of samples that provide, in general, misleading results. The latter is believed to be the most important weakness of this research. For two points in each of the decision variables, one would need $9x10^{18}$ points; however 200 are used in Hopfe's research.

In their work, Hopfe and Hensen uses the thickness, conductivity, density and thermal capacity of each material as independent variables, and cooling and heating demand as dependent variable, only heating was considered in this thesis. If Eq. 4.8 is used to analyse the impact of those in the heating demand, density and thermal capacity are not in the equation (as it is a steady-state formulation). However, conductivity and thickness can be included by making:

$$U - Value = \left(\sum_i \frac{t_i}{k_i}\right)^{-1}, \qquad \text{Eq. 4.17}$$

if one does not consider the convective resistances that will be constant for all the walls. Above, t_i and k_i are the thickness [m] and conductivity [W/(mK)] respectively of each layer of material in the construction. Substituting Eq. 4.17 in Eq. 4.8 , the derivatives with respect to thickness and conductivity are:

$$\frac{\partial\, HD}{\partial\, t_i} = \Delta\overline{T_{\iota-o}} * \Delta t * A_{surface} * \left(\sum_j \frac{t_j}{k_j}\right)^{-2} * \frac{1}{k_i} \qquad \text{Eq. 4.18}$$

$$\frac{\partial\, HD}{\partial\, k_i} = \Delta\overline{T_{\iota-o}} * \Delta t * A_{surface} * \left(\sum_j \frac{t_j}{k_j}\right)^{-2} * \frac{t_i}{{k_i}^2} \qquad \text{Eq. 4.19}$$

where $A_{surface}$ is the area of the surface (wall, roof or floor).

In this case, the derivatives depend on the variables t_i and k_i themselves so the relationship between the heating demand and those variables is not linear. To obtain the sensitivity with heating demand of each one of the independent variables, the regression will approximate to a linear relationship depending on the range of the variables. In the simple calculation, the central point of the range of the variables was used to calculate the value of Eq. 4.18, and Eq. 4.19 for each parameter. The rest of the derivatives were constant and calculated as in the previous example.

Again, the equivalent SRCs were calculated in a simplified manner and compared with the results of the paper of Hopfe and Hensen. This can be seen in Table 4.3.

The parameters obtained as most influential using the simplified steady-state formulation seems to be less unexpected when they are examined critically, than those obtained in the work of Hopfe and Hensen.

The fact that the analysis of Hopfe and Hensen pointed out parameters that do not greatly influence the energy demand calculations, might be caused by poor sensitivity analysis due to the small number of samples (200) used for such a large number of parameters (63): Swiler and Giunta recommended at least as many samples as ten times the number of parameters (Swiler and Giunta, 2007).

Table 4.3 – The most influential parameters when calculating energy demand according to (Hopfe and Hensen, 2011) and obtained by a simple steady-state calculation.

Variable	from Hopfe rank	Variable	Steady-State Calculation. rank	Equivalent SRC
Infiltration rate	1	Gains	1	-8.64
Outside emissivity roof	2	Conductivity of Insulation of walls	2	6.47
Conductivity of brickwork of floor	3	Infiltration rate	3	3.10
Thickness of felt layer of roof	4	Thickness of insulation of walls	4	-0.809
Heat capacity of felt layer of roof	5	Conductivity of insulation of floor	5	0.408
Thickness of ceiling tiles of roof	6	Thickness of insulation of roof	6	-0.396
Density of clay of floor	7	Thickness of insulation of floor	7	-0.161
Thickness of stone chippings of roof	8	Conductivity of insulation of roof	8	0.123
Density of brickwork of floor	9	Conductivity of clay of floor	9	0.0859
U-Value of glass	10	Conductivity of tiles of the roof	10	0.0675

The reason of performing this simple analysis in this thesis was to justify why the following application was carried out using occupants' behaviour as the only uncertainty. The two works found in the literature that study the impact of uncertainties in the calculation of energy demands in buildings (de Wilde and Tian and Hopfe) give different parameters as the most influential. With this simple exercise, it was proven that the parameters obtained by de Wilde and Tian are more likely to be correct than those from Hopfe and Hensen, and therefore the selection of the most influential uncertainties were those suggested by de Wilde and Tian i.e. parameters that depend on occupants' behaviour[27].

Also, it has been seen from previous experimentation, that when performing optimisation to reduce energy demands in buildings, the final results are similar to buildings designed under the *Passivhaus* standard. In those buildings, occupants' behaviour has a great impact on the energy demand (as was seen in (Schnieders and Hermelink, 2006). They saw this impact by studying the equation for steady-state heating demand of a building analytically. In buildings design under the *Passivhaus* standard the independent variables studied before have to take the values shown in Table 4.4. When the same analysis of sensitivity is performed with the simple method shown above but using these ranges, the equivalent SRSs are those shown in the last column of this table. The sensitivity of heating demand to internal gains is clearly the highest among the other variables.

Table 4.4 -Lower and upper bounds of the independent variables chosen by de Wilde in (de Wilde and Tian, 2009) required for the *Passivhaus* standard and the SRC equivalent for those ranges.

Variable	**Units**	**Lower bound**	**Upper bound**	**SRC Equivalent**
Wall U-Value	$W/(m^2K)$	0.080	0.10	0.0043
Roof U-Value	$W/(m^2K)$	0.080	0.10	0.0028
Win. U-Value	$W/(m^2K)$	0.75	0.85	0.0065
Infiltration	ach, h^{-1}	0.02	0.03	0.0022
Gains	W/m^2	2.4	10.7	-0.147

The same methodology that shown to be qualitatively valid before (i.e. able to replicate roughly the results of de Wilde and Tian) seems to highlight the gains as the parameter with the highest impact on calculated energy demands for buildings designed under the *Passivhaus* standard.

[27] Considering the results of de Wilde and Tian resulting the weather forecast of 2020

It is believed in this thesis that this standard is going to gain popularity in the future, and buildings will be designed with high levels of insulation and low levels of infiltration and windows and other components will be pushed to higher standards. At that point, and after seeing the results shown in Table 4.4 and other works such as (Schnieders and Hermelink, 2006), occupants' behaviour seems will most likely be the most important factor influencing energy demands on buildings. In the case of refurbishment, the measures will also lead to higher efficiency and therefore the impact of the factors previously calculated will also apply. In this case, the number of decision variables will be less than in new build, as the project is more constrained, apart from that, the method shown in this chapter could be applied equally to those problems.

4.8.2 Preliminary validation of CEES with synthetic functions

Building energy performance evaluation is a computationally expensive exercise that normally takes longer than 30 seconds per annum simulation. Although this might seem a small amount of time, it becomes substantial in an optimisation method where many (thousands in most cases) evaluations need to be performed, resulting in long computational times for the full run. For that reason, several synthetic objective functions were created to validate the CEES, before this is applied to the optimisation at hand.

4.8.2.1 The synthetic functions

The functions have been used to evaluate the performance of the potential algorithm. The objective functions are as shown in Table 4.5, and will be further explained in this section.

Table 4.5 - Test functions to evaluate the efficiency of the CEES under uncertain environments.

Test function name	Expression	Domain	Identifier
Test function 1	$f(x,\alpha) = 10(1\text{-}2\alpha)\cos(0.2x)$	$x \in \mathbb{R} \mid -10 \le x \le 10$	Eq. 10.20
Test function 2	$f(x,\alpha) = x^2+10(1\text{-}2\alpha)\sin(x)$	$x \in \mathbb{R} \mid -10 \le x \le 10$	Eq. 10.21
Test function 3	$f(x,\alpha) = 0$ $f(x,\alpha) = 5\alpha(1+\cos(x))$ $f(x,\alpha) = 0$	$x \in \mathbb{R} \mid -10 \le x < -3.14$ $x \in \mathbb{R} \mid -3.14 \le x \le 3.14$ $x \in \mathbb{R} \mid 3.14 < x \le 10$	Eq. 10.22
Test function 4	$f(x,\alpha) = 0$ $f(x,\alpha) = -5\alpha(1+\cos(x))$ $f(x,\alpha) = 0$	$x \in \mathbb{R} \mid -10 \le x < -3.14$ $x \in \mathbb{R} \mid -3.14 \le x \le 3.14$ $x \in \mathbb{R} \mid 3.14 < x \le 10$	Eq. 10.23
Test function 5	$f(x,\alpha) = -\ (1-(x+1)^2)$ $f(x,\alpha) = (-\alpha-0.6)\ 2^{(-8.0\lvert x-1\rvert)}$	$x \in \mathbb{R} \mid -2 \le x < 0$ $x \in \mathbb{R} \mid 0 \le x \le 2$	Eq. 10.24

The functions in Table 4.5 include a parameter α that represents the environmental parameter; this parameter was considered as a random real number with a flat probability distribution that takes values in the interval (0, 1). The functions defined in Table 4.5 present different optimal points depending on the value of the environmental parameter. The aim of this research was to find a method that is capable to finding the points that are close to optimal for any environment. Therefore, the optimal points are those that secure a minimal value of the objective function i.e. those that do not get worst with changes in the environmental parameter.

Each function has several features that help in the evaluation of the optimisation algorithm. All of them have been used for a minimisation problem.

Test function 1 has the highest variability with respect to the environmental parameter. The two functions which originate when taking the extremes values of the environmental parameter (0 and 1) can be seen in Figure 4.4. Although an objective function similar to this test function is unlikely to happen when optimising building parameters, this test function has been introduced to check the validity of the algorithm when the convexity of the function changes completely from one scenario to another. The most desirable output in this case is locating the solutions at the points where the two extreme curves cross. These two points represent the most conservative results when carrying out optimisation as any other point that can achieve lower values of the objective will only do it for some environments.

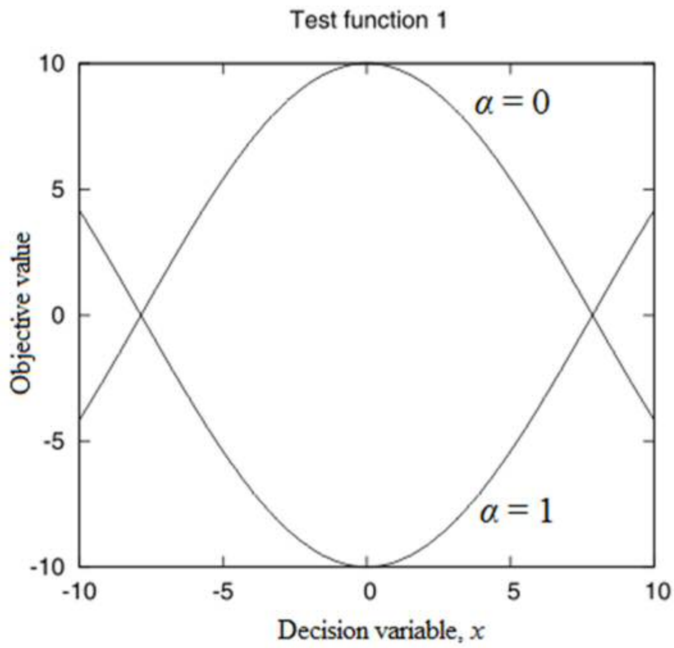

Figure 4.4 - Test function 1 for the extreme values $\alpha = 0$ and $\alpha = 1$.

Test function 2 shows a clearer tendency in terms of convexity, and the closer one is to the solution the clearer is the variations in the objective function due to the uncertain parameter. The function can be seen in Figure 4.5. The optimal robust solution is in this case at $x = 0$.

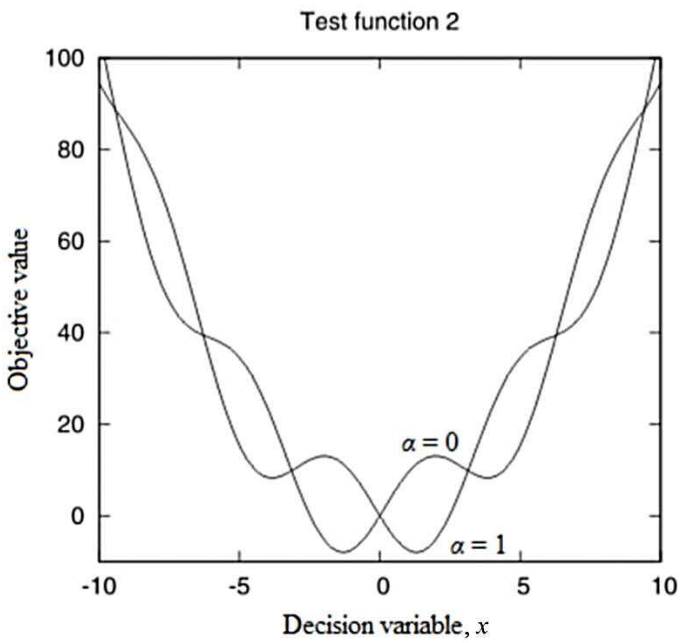

Figure 4.5 - Test function 2 for the extreme values $\alpha = 0$ and $\alpha = 1$.

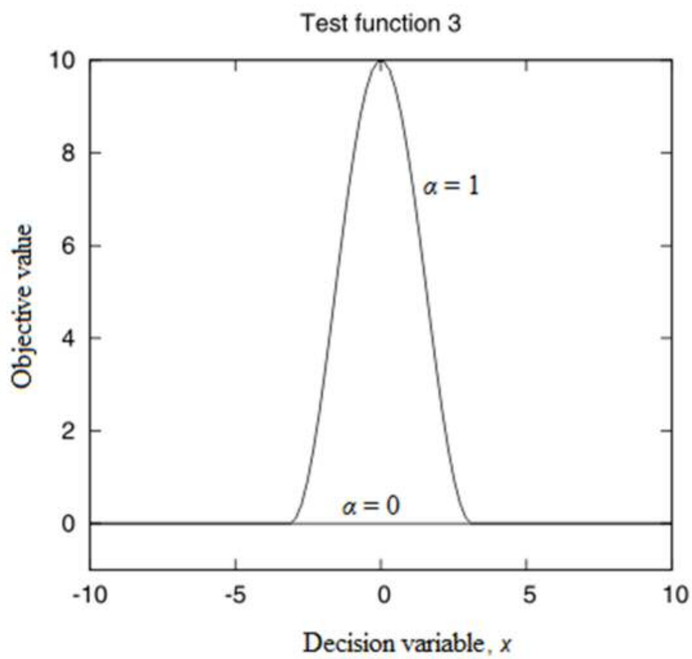

Figure 4.6 - Test function 3 for the extreme values $\alpha = 0$ and $\alpha = 1$.

Test function 3 introduces an interesting characteristic for the analysis of population based optimisation algorithms: The optimum is not a single point but a sub-space of points in the decision space (from -10 to -3.14 and from 3.14 to 10). This test function represents the scenario in which an environmental parameter may render some of the solutions suboptimal for a given environmental parameter. Any point within the intervals [-10, -3.14] and [3.14, 10] is optimal for this objective function, the points in the interval (-3.14, 2.14) are not optimal as a change in the environment makes them worse.

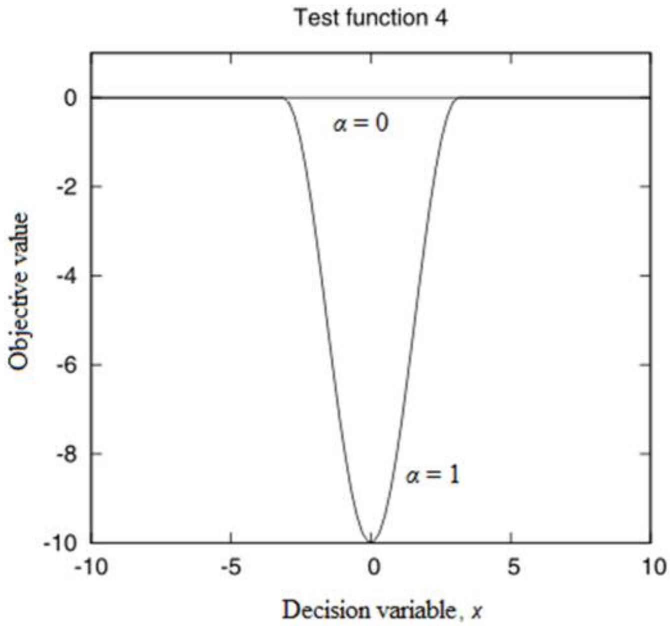

Figure 4.7 - Test function 4 for the extreme values $\alpha = 0$ and $\alpha = 1$.

The opposite case is found in Test function 4. For this test function, all solutions present the same optimality for $\alpha = 0$, but for $\alpha = 1$, the solutions from an area of the decision space improves. The optimum of this objective function is found at the point where $x = 0$. An interesting characteristic of this objective function is that some robust optimisation methods are not able to consider the point $x = 0$ as optimal (see Section 2.4.3). This is the case when the optimisation method uses re-evaluation of each solution for a set of values of the environmental parameter and later calculates the extreme of all the evaluations (maximum in the case of performing minimisation), in that case, the objective value of all solutions would be zero. For this function, the algorithm will find that the point at $x = 0$, is as good as any other point in the decision space, and therefore the solutions given by the algorithm would be placed at any point of the decision space. This could be an argument for dismissing the use of robust optimisation algorithms that create robust counterparts that only take into account extreme values of the set of objective values obtained with re-evaluation of the objective function.

Finally, Test function 5 is a modified version of one of the test functions used in (Branke, 1998). This function studies the possibility of having two local optima, one being better than the other only for some values of the environmental parameter.

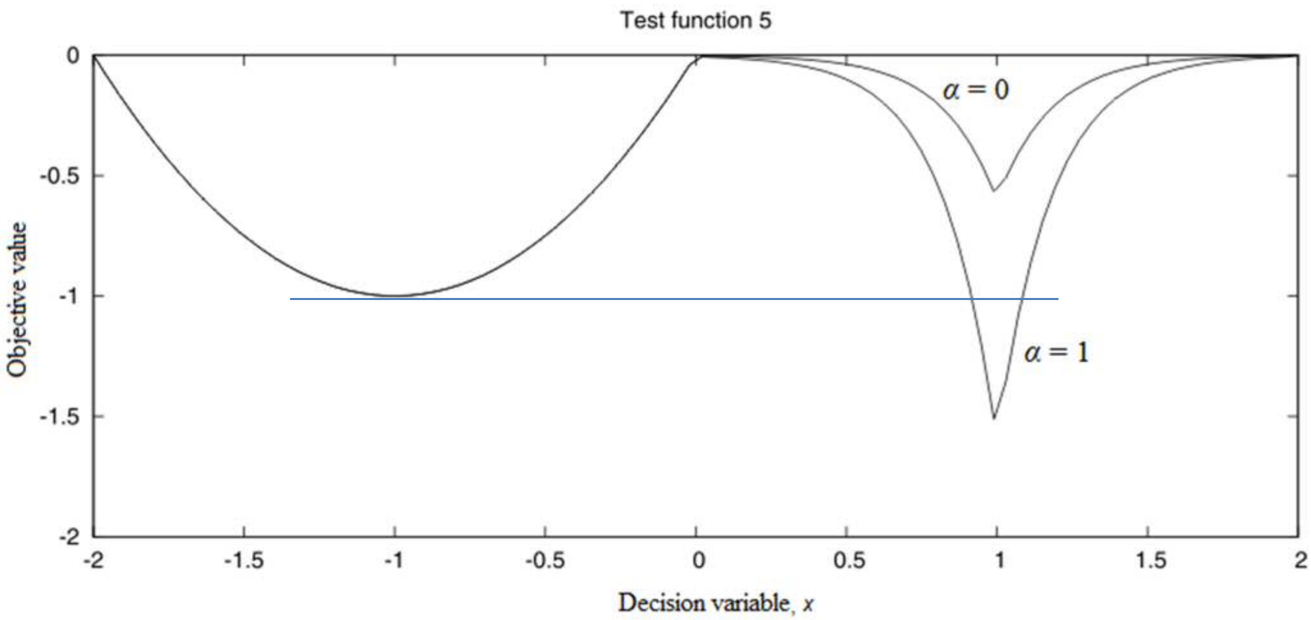

Figure 4.8 - Test function 5 for the extreme values $\alpha = 0$ and $\alpha = 1$.

Branke proved that EAs "prefer" smooth peaks (Figure 4.8 left) over sharp peaks (Figure 4.8 right) as the smoothness represent robustness for uncertainties of type B: a change of the decision variable does not modify the value of the objective functions if the peak is smooth.

4.8.2.2 Results and discussion of the CEES applied to synthetic functions

The CEES was tested with these synthetic objective functions and the results are shown in the following.

To verify the validity of the results, the algorithm was run 500 times for each one of the objective functions, each of the times with different starting points and a different sequence of random numbers[28]. An example of one of the runs for a test function similar to Test function 2 can be seen in Figure 4.9. The results with all the runs are shown as histograms. The results are shown and discussed in the following paragraphs.

[28] Random numbers are not easily generated in digital computers. In my case, the series of random numbers was seeded with a different seed for every run, which ensures different random numbers.

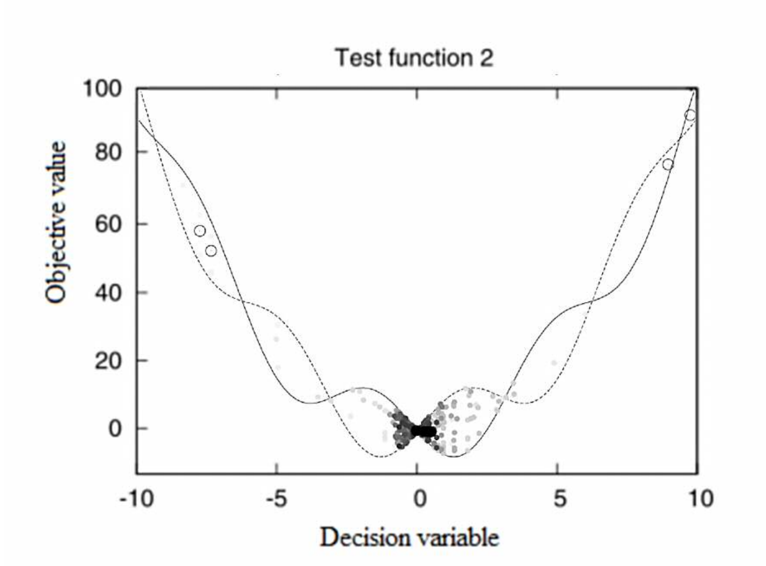

Figure 4.9 - Example of one run of the CEES in Test function 2. The hollow circles represent the first generation, the rest indicates the generation on a grey scale: the darker the colour the more advanced the generation, with the black circles the final solutions.

The results of the algorithm when solving Test function 1 can be seen in the histogram shown in Figure 4.10. It can be seen in this figure that the algorithm did not perform well for Test Function 1. This function seems to be too sensitive to the environmental uncertainty for the algorithm to find the robust optima. Although, the solutions offered by the algorithm are acceptable as they are mostly within the intervals (-10, -3) and (3, 10), intervals where the function has the least variation. The CEES did not perform well in the search of the robust optima for this function; however, it is unlikely that the objective function of the problem at hand (minimisation of energy demand subjected to uncertainties) would have such a substantial sensitivity to the environmental parameter (occupants).

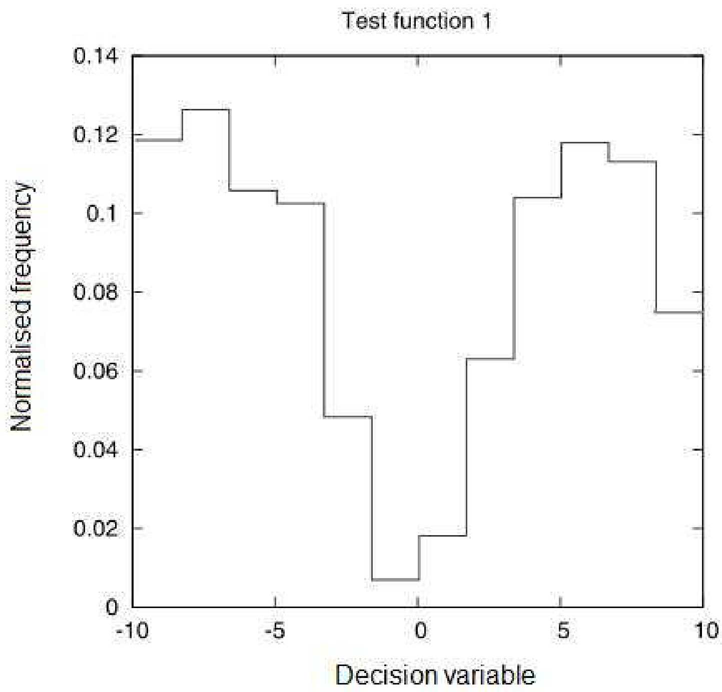

Figure 4.10 - Histogram showing the frequency of the solutions given by the CEES with Test function 1.

The next function to be evaluated was Test function 2; the results are shown in Figure 4.11. This figure shows that the CEES performed well in this case. For this function, 72.2% of the solutions fold into the interval (-0.4, 1), including the optimal robust value at x = 0: the solution that occurs with the highest frequency (32.6%).

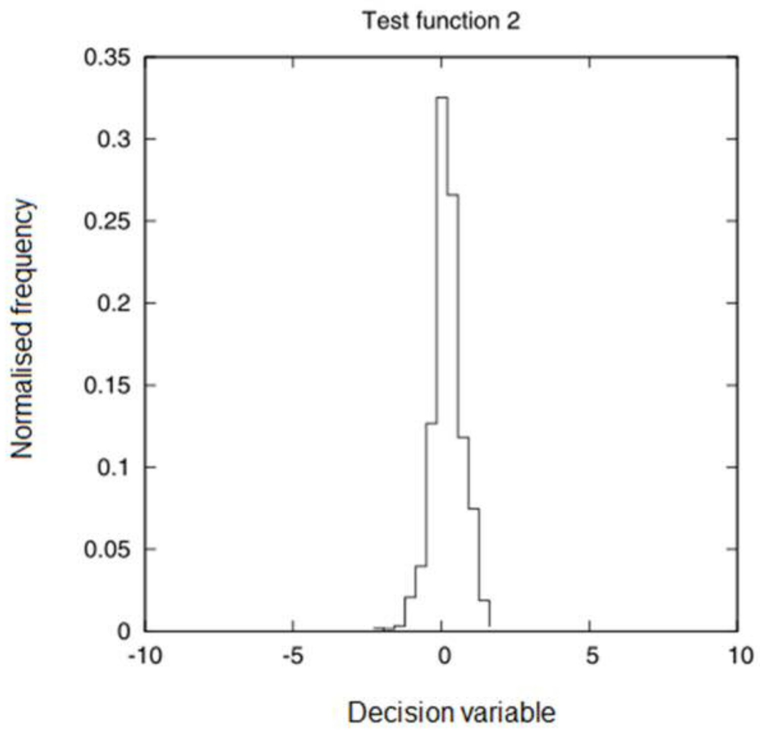

Figure 4.11 - Histogram showing the frequency of the solutions given by the CEES with Test function 2.

Test Function 3 presents the extra difficulty for having an infinite number of optima. The population is formed by a limited number of individuals, and therefore they cannot cover the whole subspace of solutions. The solutions are shown in Figure 4.12. In this case, the CEES selected mainly the solutions from the intervals (-10, -3.33) and (3.33, 10) with the percentage of solutions in these ranges of 96.6%, this is a good result because the real robust optima are located in the intervals: (-10, -3.14) and (3.14, 10). The relatively high frequency of solutions in the range (0, 3.33) shows that the algorithm might give the wrong answer in some of the runs; however, it should be noted that the number of solutions showing up in that range is only 2.8% i.e. relatively small.

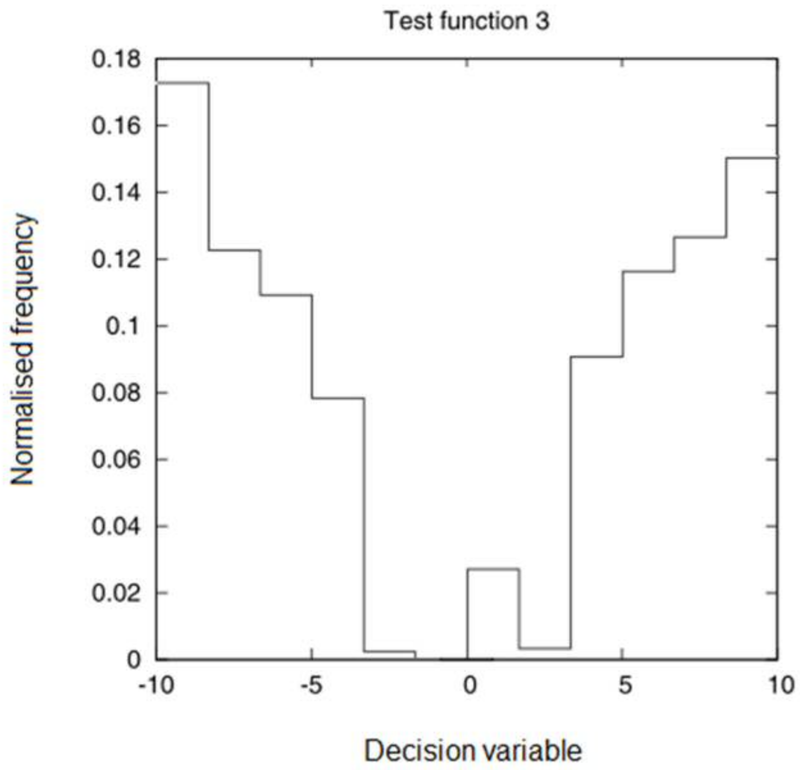

Figure 4.12 - Histogram showing the frequency of the solutions given by the CEES with Test function 3

The solutions of the run using Test function 4 are shown in Figure 4.13. The histogram of the results for this test is self-explanatory. For this case, all solutions are found within the range (-0.52, 0.52). This narrow range shows the success of the CEES with this test function. It should be noted that applying an optimisation algorithm that pre-process the objective to obtain a robust counterpart would give as robust solutions any of the points of the decision variables. Therefore it would not be able to "notice" that the points close to $x = 0$ improve for certain environments.

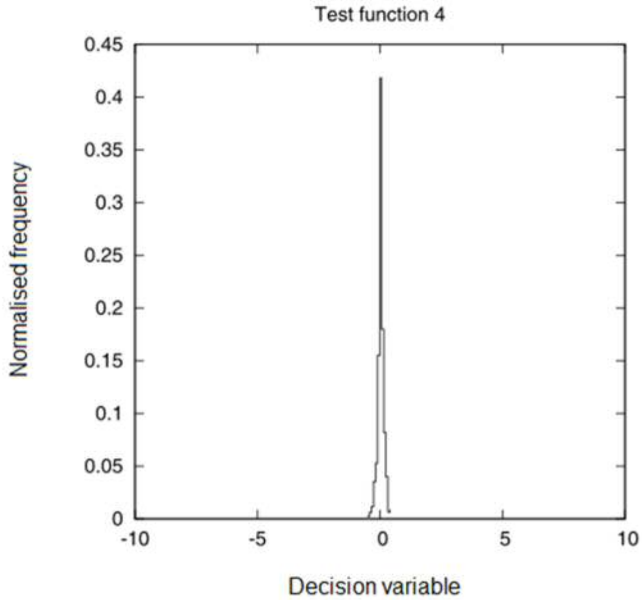

Figure 4.13 - Histogram showing the frequency of the solutions given by the CEES with Test function 4.

The results of testing the CEES with Test function 5 can be seen in Figure 4.14. Similar results are found with this function to the ones found for Test function 4. All solutions belong in this case to the range (-1.031, -0.974) a narrow range of only 0.057 units. The CEES is capable of distinguishing in this case the robust peak and the non-robust peak.

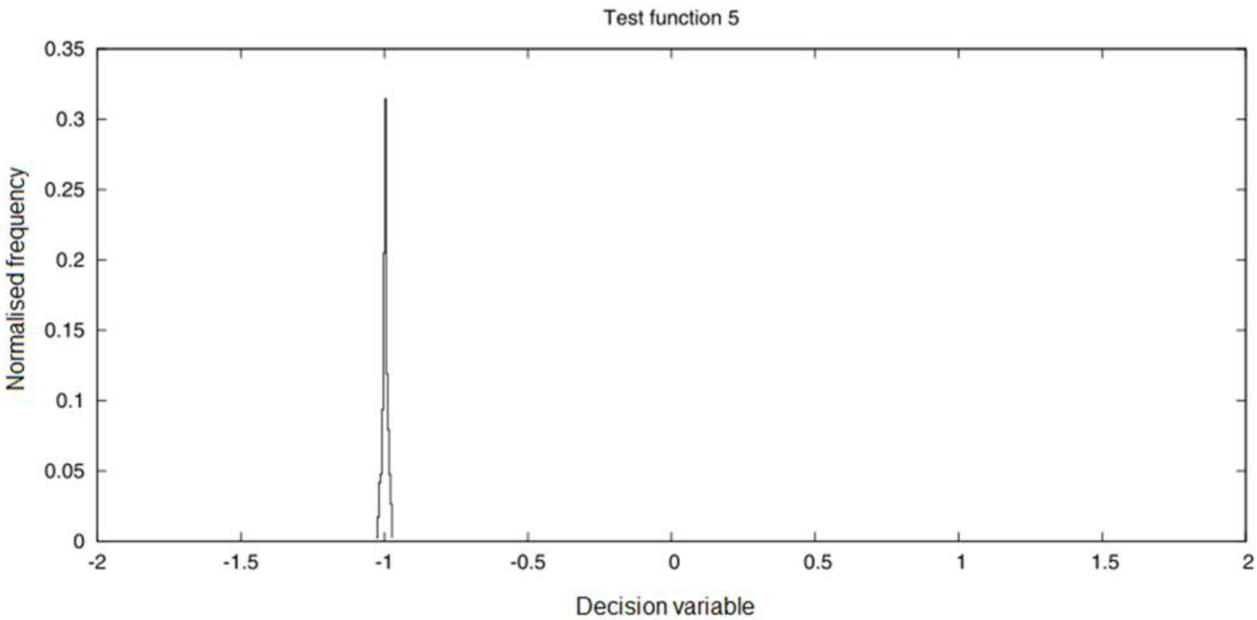

Figure 4.14 - Histogram showing the frequency of the solutions given by the CEES with Test function 5.

4.8.2.3 Conclusions of the test with synthetic functions

The CEES has been seen to provide robust solutions in most of the tests. The results with Test function 1 are the worst in this set. However, because of the peculiar nature of the function one could assume that it is very unlikely that the objective function of any problem at hand would have that kind of sensitivity to the environmental parameter.

The CEES has been shown to be effective with the rest of the functions, it should be noted the outstanding efficiency of finding the robust optima in Test functions 4 and 5. Although the results for Test functions 2 and 3 are not perfect, they are better than those that one could find performing the optimisation for a single value of the environmental parameter.

4.8.3 Real world application

4.8.3.1 Problem definition

Optimisation of a building model can be used to calculate the best architectural/constructional parameters that optimise a given objective function such as heating, emissions or comfort levels.

Optimisation can also be used for more specific problems when the design is in a more developed stage and the variables are more specific (for example studying only window shape and size to optimise lighting as in (Suga *et al.*, 2010)).

As previously mentioned, occupants' behaviour can have substantial impact on building's performance. If a building design is optimised with the aim of targeting low-energy consumption under single specific conditions of use, the solution could be misleading, as different occupants may render the solutions sub-optimal, or non-acceptable. One example being a dwelling with a specific, targeted, thermal mass that relies on the thermal capacity of partitions to store precisely the heat that is generated from electric appliances and metabolic gains during the day.

The occupants' behaviour is considered as the uncertainty in this work, with the behaviour considered as a set of environmental parameters i.e. uncertainties of *type A* under the Beyer and Sendhoff classification (Beyer and Sendhoff, 2007). This work allowed the evaluation of the differences between two optimal buildings obtained with two different methodologies:

1. Traditional optimisations: the optimisation is done for a single given statement of occupant behaviour.

2. Optimisation with the CEES: the algorithm will consider solutions that are near-optimal for a wide range of occupant behaviours (environmental parameter).

The CEES was applied to a building design problem to obtain robust solutions and a traditional EA to obtain optimal solutions for a single behavioural pattern (where an averaged family behaviour was used). The aim of this work is to compare the impact of considering only a single behavioural pattern and considering several runs of the CEES.

The methodology could be used for more specific problems in which the building is at a later stage of design. However, in this application the building is only constrained to maintain floor area and height (but not aspect ratio); apart from those restrictions, all variables may change via the decision space described in Table 4.6.

The optimisation generates solutions that provide general architectural rules for designing low-energy buildings that are robust against changes to occupant behaviour. The approach can therefore be seen as an attempt to reduce risk. As cast, it is aimed at optimising the early-stage design where few decisions have been made, and flexibility still exists. Due to the limitations of the thermal model, the variability on the occupant behaviour is the level of use of electric appliances, and the timing of them and the level of occupancy and its timing.

The building was modelled with a single thermal zone, implying that the air is fully mixed in the building. This makes no difference in the energy demand for different layouts, which is not totally accurate. If the CEES is applied with a single thermal zone (as done here) then the user has to assume that the calculations are approximate and variations may arise once the simulations are done considering a multi-zone model. If in the other hand the optimisation is done with multi-zoned models, the results will be more accurate but much more information will be needed about occupants' habits (such as door openings) to have an accurate guess of the internal heat flows. Fail to do this; the consideration of a multi-zone model will only come with a larger computational time and not necessarily a higher accuracy.

The conductivity and capacity of the internal partitions of the building have been included in the problem as these parameters are understood to have an important role in low-energy buildings. The variables can take any value in the interval defined by the lower bound and the upper bound (real encoding, see Section 4.4.1). The construction of the wall can only be A, B, C or D from Table 4.7.

The value of infiltration is considered as the infiltration through cracks and openings that cannot be closed. As the house is considered rectangular, aspect ratio is the ratio between the length of the North and South façade and the West and East façade. Fenestration is the proportion of the area of each façade that is covered with window(s). For the thermal model having one window or two makes no difference Although the ventilation would be different, the fenestration area has been considered as a single window to reduce the number of decision variables. The Wall type is detailed in Table 4.6, and the internal partitions are modelled as if they were built with a single material characterised by two decision variables.

Table 4.6 - Variables that form the search space. IP: Internal partitions.

Variable	Type	Lower bound	Upper bound	Unit
Infiltration	Real	0.03	0.6	*ach*
Aspect Ratio	Real	0.3	3	*m/m*
Fenestration, North	Real	0.05	0.8	m^2/m^2([29])
Fenestration, South	Real	0.05	0.8	m^2/m^2
Fenestration, East	Real	0.05	0.8	m^2/m^2
Fenestration, West	Real	0.05	0.8	m^2/m^2
Wall Type	Symbolic	A	D	
Insulation[30]	Real	100	500 (U-Value=0.1)	*mm*
Conductivity of IP	Real	0.2	2.3	$W/(mK)$
Capacity of IP	Real	200	3000	$J/(kgK)$
Max. Heating Pow.	Real	200	20000	*W*

Table 4.7 - Construction types.

Construction	Outside Layer	Intermediate	Inside Layer
A	200mm concrete	Insulation (100-500mm)	25mm stucco
B	200mm ”	” (100-500mm)	200mm concrete
C	25mm stucco	” (100-500mm)	200mm ”
D	25mm ”	” (100-500mm)	25mm stucco

EnergyPlus was used to evaluate the different solutions. The base model is a two storey dwelling located in London that has been modelled as a single zone. An ideal heating system with a set-point of 23˚C was used. Ventilation occurred when the house reached a temperature in excess of 27˚C and the occupants were present, thus simulating the opening of windows by the tenants (this, like the set point, is itself

[29] Area of fenestration per area of façade in the four instances.
[30] The insulation used has a thermal conductivity of 0.05 W/(mK).

a behaviour and could have been included within the changing environment; however there was limited data on this behaviour in the literature so it was fixed). To simulate ventilation, the equations from section 16 of (ASHRAE, 2009) were used; these equations take into account the air flow driven by wind and by thermal forces due to the stack effect. The effective opening area was related to the size of the windows selected in each solution.

Ventilation motivated to improve air quality (such as opening windows in the morning) has not been separately modelled. This ventilation is hard to model as it is highly dependent on the habits of tenants, and little data exist. More complete modelling of this kind of ventilation is suggested for further work by including it as another environmental parameters (see (Rijal *et al.*, 2007) or (Yun *et al.*, 2009) for an elaborated model of windows opening).

The number of non-comfortable hours that a building design will have during its operation is a crucial factor for its success. Buildings that overheat, or operate at a range of temperatures that the occupants find unpleasant will be considered as failure in design; and will worsen the image of the designer and of low-energy design architecture. Designers have to make sure that a building design will perform well in any scenario.

To evaluate comfort, the ASHRAE *Standard 55* (ASHRAE, 2009) was used, with the building simulator reporting the number of non-comfortable hours that have been experienced in each solution when the building was occupied. *Standard 55* could be considered too strict for domestic dwellings, so a solution is allowed to have up to ten per cent of all hours in the year (i.e. 876) reaching non-comfortable conditions before it is considered non-viable (to see the definition of comfortable hours under *Standard 55* see (ASHRAE, 2009)). The calculation of non-comfortable hours is calculated internally in EnergyPlus, for this, temperature and humidity is used. In this work, I have considered that a non-comfortable hour is reported if it is non-comfortable with winter clothes or summer clothes. Interventions of the occupants to improve thermal comfort further than opening windows to enhance natural ventilation have not been implemented in this study.

The objective function to be minimised is the heating demand over a year in kWh/m^2 (no cooling has been considered as natural ventilation is allowed). When a solution presents more than 876 non-comfortable hours the solution is considered non-comfortable and therefore not acceptable. To discard solutions that are considered non-comfortable, the heating demand is multiplied by a penalty factor of a hundred. That way, the objective function of a non-comfortable low-heating solution will always be worse than comfortable solution with average heating demand. A penalty factor of a hundred is sufficient to make the objective value of a non-valid solution larger than any other valid solution in the search space. If the heating demand turns out to be zero for one solution, and this solution is non-comfortable, the solution will be assign an objective value of 100. With such a penalty factor, the solutions that violate the condition of non-comfortable hours are unlikely to be preserved in the next generation.

4.8.3.2 Modelling the occupants

As previously discussed, the results obtained from single runs of typical building models potentially contain unexamined uncertainties due to only considering one representation of occupant behaviour. Here, the optimisation allows for multiple representations of occupants including changes to occupancy and incidental gains from electrical items. These incidental gains are substantial when compared to the annual space conditioning gains required by low-energy buildings and therefore need to be accurately accounted for.

Occupancy and appliance-use profiles were generated for this work by a third-party tool (Richardson *et al.*, 2008), which uses a first-order Markov-Chain technique, and details of occupancy and energy use at a ten-minute resolution (ONS, 2000). The Markov-Chain technique is an established stochastic method for generating data (Gilks *et al.*, 1996). A first-order Markov-chain means that the state of the system during the next period is dependent only on the current state, not on any preceding states. For example, the probability of whether an occupant is in the building is correlated only with whether they were present during the last ten minutes, not whether they were present during the ten minutes before that.

The representation of occupancy in the model provides the primary method for creating synthetic occupancy and electricity demand data with appropriate aggregate daily profiles. As an example, from Table 4.8 we see that if a two-person dwelling is unoccupied (the number of active occupants = 0) at 21:00 then there is an 89.2% chance the house will still be unoccupied at 21:10.

Table 4.8 - Example transition probability matrix for a two-person household on weekdays, including activity probability. Data from Richardson et al. (2009).

		Next state (at 21:10) Number of active occupants		
Current state (at 21:00)	Number of active occupants	0	1	2
	0	0.892	0.082	0.025
	1	0.038	0.878	0.084
	2	0.003	0.043	0.954

To create the high-resolution appliance-use profiles Richardson *et al*. use the household journal data to define 'activity profiles', where a particular listed activity has associated appliances with a certain chance of a switch-on event occurring. Combined with details of the mean power use and cycle lengths for each appliance (from various sources, see (Richardson and Thomson, 2010)), load profiles are thereby stochastically generated. An example electric load and occupancy profile can be seen in Figure 4.15; these profiles are useful since they have been shown (Richardson *et al.*, 2008) to display similar statistical characteristics to the measured UK appliance-use and occupancy patterns used to create them, and hence they can be used to represent a large range of likely UK behaviours.

With this tool, 100 profiles were generated representing different occupants' behavioural patterns. These 100 profiles were then adjusted to the data used by (Richardson and Thomson, 2010) to make sure that the variability of the profiles was realistic with the possible building uses that can be found in the real world. Once the profiles were adjusted, they were compared with the real data used by Richardson. The correlation can be seen in Figure 4.16. The profiles were scaled to represent realistically the problem at hand, which has a different floor area to the data shown by Richardson's et al.

After doing this and to improve the algorithm in terms of delivering robust solutions, 44 profiles were selected out of the 100 that are equidistant considering the x axis of Figure 4.16.

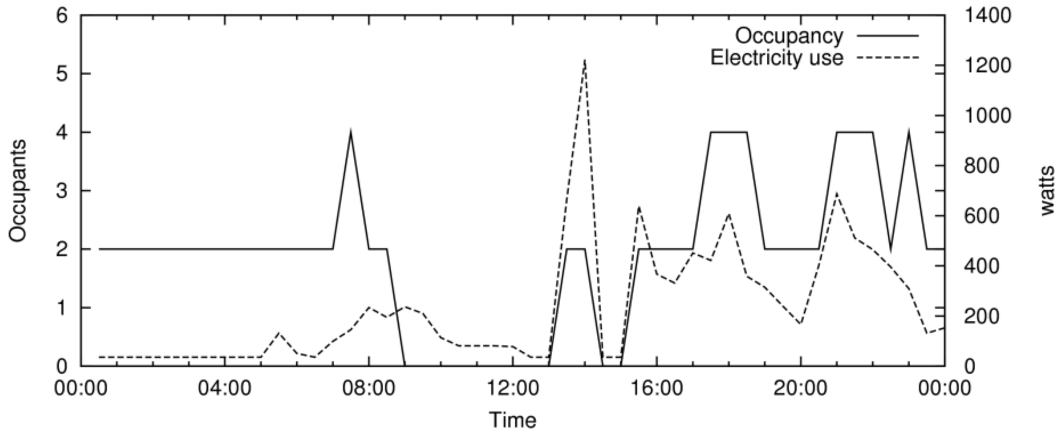

Figure 4.15 - Example electricity (watts) and occupancy (number of people) gain profiles as generated by third-party software (Richardson and Thomson, 2010).

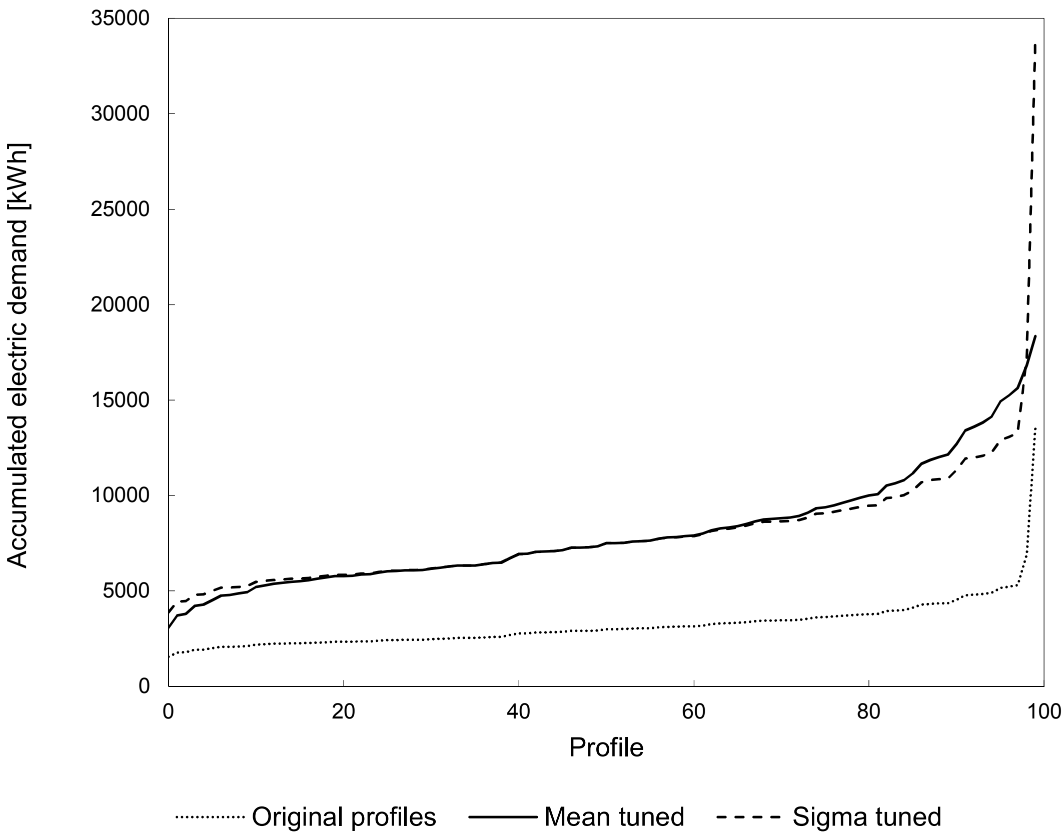

Figure 4.16 - Accumulated electric demand per annum of the 100 different profiles. Generated with Richardson's tool (dotted), and adjusted to represent a realistic demand for the problem at hand in mean (dashed) and in standard deviation (solid).

The profiles generated for this study represent the use of electrical appliances and the occupancy on the building. The rest of events and conditions that are related to occupancy (such as thermostat set-point) were fixed, but the addition of these factors is suggested for further work.

4.8.3.3 Results and discussion

The optimisation took 24 hours to run when using a population of 100 individuals and 200 generations (Intel core 2 duo at 2.93 GHz, single threaded code). This should be compared to 12 hours if only a single occupant behaviour was considered. The differences in time is because in the CEES, the solutions that survive from one generation to the next still need to be evaluated, in opposition to the "static" algorithm.

Both optimisations were run for 200 generations and each converged to a different single solution: The two final solutions obtained can be seen in Table 4.9.

Table 4.9 - Final solutions obtained with single occupant behaviour and with CEES. IP: Internal partitions.

Variable	Type	Traditional	CEES	Unit
Infiltration	Real	0.030	0.030	*ach*
Aspect Ratio	Real	0.67	0.47	*m/m*
Fenestration, North	Real	0.0500	0.0500	m^2/m^2
Fenestration, South	Real	0.0582	0.0575	m^2/m^2
Fenestration, East	Real	0.0500	0.0500	m^2/m^2
Fenestration, West	Real	0.0500	0.0500	m^2/m^2
Wall Type	Symbol	A	C	
Insulation	Real	499.6	482.6	*mm*
Conductivity of IP	Real	0.20	1.04	$W/(mK)$
Capacity of IP	Real	2649	2047	$J/(kgK)$
Max. Heating Pow.	Real	200.0	1497	*W*

It can be seen how, as expected, the characteristics of this building are very close to the requirements asked under *Passivhaus* standards. And therefore, the assumption of considering the occupants as the key uncertainty in the optimisation is justified (see Table 4.4). The infiltration value is very small; therefore, there is effectively no air exchange with the outside. This implies that a mechanical ventilation system has to be put in place to maintain healthy levels of ventilation. This does not imply a substantial increase of the heating demand, when this is done using a heat exchanger with high efficiency (as it is the common practice for *Passivhaus*); however, the cost of this equipment has to be taken into consideration.

It should be noted that several variables are chosen at the boundaries of the decision space. This is a valid solution in optimisation problems. Furthermore, in linear problem solutions are always found in boundaries. In the case that the operator does not want to get boundary layers, penalty functions can be added to the objective value that tend to infinity as the solution approach to the boundaries of the problem.

We can see how a few decision variables have been assigned different values depending on the method. The solution obtained with the CEES is in general a more heavy-weight solution, as it has the layer of concrete in the inner part of the wall, also. The internal partitions have been given more conductivity to absorb and release heat more rapidly.

The fenestration areas are very small. This could be because of the way the building has been modelled. No lighting has been considered and therefore, the availability of day lighting does not imply a better solution. This is mistaken in principle, but lighting was not included in the evaluation of the objective function due to the difficulty of quantifying this parameter with a single number in EnergyPlus.

The way ventilation was modelled has also affected the selection of the fenestration areas. The model has a single thermal zone, and therefore two windows opened in opposite facades create a stream of air that goes across the building with no difficulties. Most windows cannot be opened completely in real buildings, and therefore, the model was created with a discharge coefficient in buildings of 0.1. This represents a window that can only be opened 1/6th of its area.

In real life the layout of the building will determine the position of the rooms and doors, and to produce cross ventilation, all the doors between one window and the other are open. Apart from that, discharge coefficients (that are modelled in the windows) will also apply to doors and geometrical features that make the air turn (such as corridors or corners in the interior of the building). As a result and considering that the optimisation did not consider day lighting both optimisations have suggested solutions with small windows.

The aspect ratio is slightly different in both solutions; this difference could be due to a small sensitivity of the objective function to aspect ratio in that point of the decision space. Also, the insulation in the solution obtained with the CEES is slightly smaller than that obtained with the traditional method. This could be due to the effect of having the concrete as a heat buffer before the insulation.

The maximum heating power is much larger in the solution obtained by the CEES, but this is due to the way the heating system was modelled and the heavier construction in this solution. In reality, it is likely that a heavy weight building and a real heating system will lead to a larger number of non-comfortable hours due to the lag between the trigger of the thermostat and the actual rise of the internal temperature in the building. Still, the heating energy demanded in the solution obtained by the CEES is feasible, and probably suggest having a high power instant heating system such as electric air heaters more than traditional boiler-radiators system.

To evaluate the solutions, the profiles where sorted by accumulated electricity used, under the assumption that the probability of overheating increases with this value. The two solutions were tested (simulated) using 44 different profiles that spanned the environmental parameter spectrum (44 different families). Each solution was simulated to obtain the heating demand and the number of non-comfortable hours per year. This simulation was performed using the occupancy profiles that can be found in a 2σ interval of the normal distribution (this interval represents 68% of the possible occupancy profiles i.e. 30 profiles). The profiles used are equidistant when being sorted by accumulated energy use (see Figure 4.16). Extreme profiles outside this range are less likely to happen, and robust designs that perform well under those are difficult to find with any method that does not include exhaustive reiteration of all options, therefore, they were excluded.

The results of these simulations are shown in Figure 4.17. It can be seen that when considering the profiles within the 2σ range, the design of the building obtained with “traditional” optimisation can become non-comfortable for more than one third of the behavioural patterns used. This represents a great risk for the design team.

Solutions (buildings) with very low heating demand were obtained with both algorithms (see Figure 4.17 top), the best one approaching the energy performance of *Passivhaus* (15kWh/m^2). This means that accounting for occupancy changes does not automatically imply the generation of low-efficiency buildings.

There are several points that can be extracted from Table 4.9. In both cases very large windows are undesirable; although they provide “free heating” through solar gains, much of this does not occur when needed; instead, it is likely that the solar gains arise when other gains (e.g. electrical gains) are also contributing to a potentially uncomfortable temperature. To release the excess of heat from the coincidental gains, solar gains will eventually trigger ventilation, and the free heat is lost through openings. This makes windows more an architectural requirement for the acceptability of living spaces than a building element to improve energy savings. It should be noted, that in this thesis, windows were considered to have no effect over the savings in lighting. In this work, the electricity use for lighting was fixed for all the behavioural patterns, after choosing an average value. However, it is acknowledged that windows could influence the use of electricity for lighting and ultimately the total internal gains. Making the electrical use for lighting dependant on the illuminance received due to windows is suggested for further work.

The CEES was able to adjust the conductivity and the thermal capacity of the partitions to make the best use of free gains. Although the CEES's final solution has less insulation than the solution obtained with a single statement of occupancy, the greater thermal mass in conjunction with the higher thermal conductivity of partitions makes up for this and provides a design with low heating demand. The solution obtained with the CEES makes a better use of the gains, but, designers that want to produce designs robust to different occupants will need to consider that they come at the expense of increasing the heating demand by around a 25% over that possible when design for a single occupants' profile. In gross terms, this increment is small due to the low demands achieved by the designs (~10kWh/m^2). This is however of potential importance if multiple profiles were used with the framework of meeting a building code or the *Passivhaus* standard.

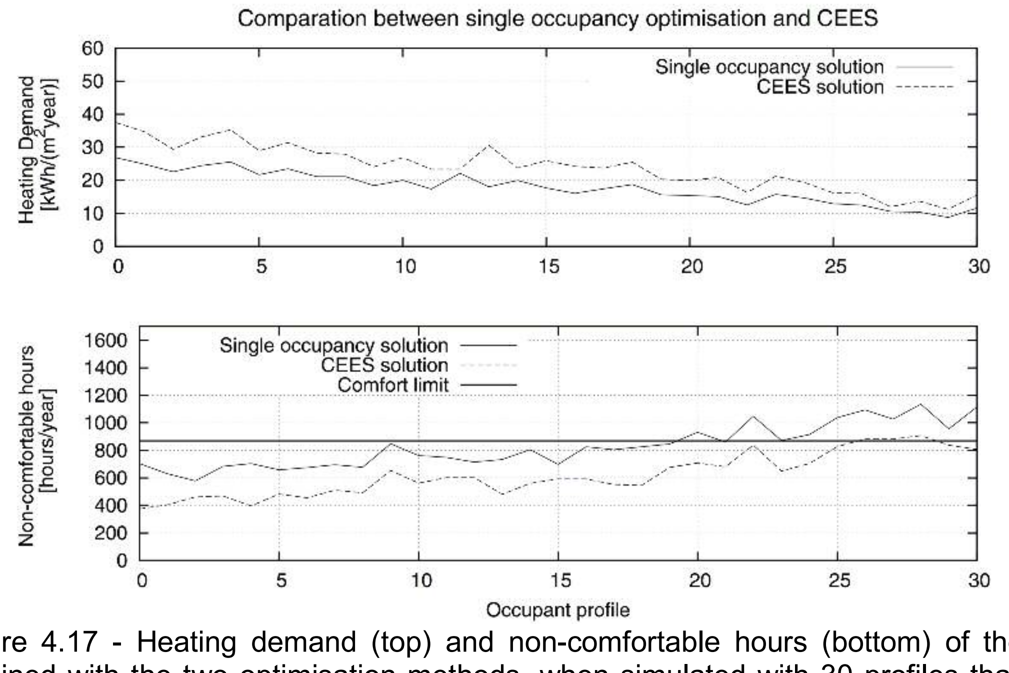

Figure 4.17 - Heating demand (top) and non-comfortable hours (bottom) of the solutions obtained with the two optimisation methods, when simulated with 30 profiles that belong to the 2σ interval of the distribution of profiles. (Occupant profiles have been ordered by accumulated electricity use).

The improvement given by the CEES is clear when the number of non-comfortable hours is examined (Figure 4.17 bottom). The building obtained with the CEES is found to always outperform the one produced with only a single pattern of occupancy, and only violates the condition of comfort, very slightly, for three profiles (profiles 26, 27 and 28; over by 3, 3 and 38 hours respectively).

4.9 Conclusions

The methodology presented here is a first step to more elaborate optimisation mechanisms that will provide building designers with solutions robust against the many parameters which are in truth unknown or ill-defined during the design stage, may vary during value engineering or construction, or dependent on the behaviour of occupants over the many decades a building may last, without the need to simulate each possible combination of parameters.

It should be noted that this optimisation was possible because there are enough number of profiles in existence to understand the probability of the uncertainties due to the occupants. When the CEES is used including other uncertainties certain information about their probability will be needed to make sure that the uncertainties are propagated during the search.

As this optimisation technique requires only a relatively small increase in computational time, and produces more robust solutions than those obtained using ordinary optimisation methods, its use may be of interest not just to building scientists, but by practising engineers. It is recommended that in future all such optimisation runs are made using a realistic spectrum of behaviours (including set-points), and that the approach is expanded to include other elements of design that might show variance during construction, for example, U-values and air tightness. This it is hoped will reduce some of the risks associated with the designing and occupation of very low energy buildings.

The buildings that were design with the CEES show less risk of being uncomfortable. However, it should be mentioned that those created with this method consume on average a 25% more energy for heating. That should be taken into account when designing this kind of building.

As the CEES is a stochastic optimisation method, and does not sample all the solutions for all the possible behaviour profiles, it is expected that the solutions will be more robust than those obtained with traditional methods, but will not be 100%

robust. The computational cost of finding these perfectly robust solutions will be too high. The CEES produced quasi-robust solutions at very low computational times.

The CEES has been applied to a single-objective optimisation problem; however, more objectives could be added to the optimisation using Pareto optimality (Section 2.3.1.2). Other factors such as measurements from lifecycle analysis or capital investment could be option of additional objective to be optimised.

5 Sequential Optimisation for Building Design

Contents

Nomenclature

$f(\boldsymbol{x},t)$ – Objective function.

$\boldsymbol{x}$ - Solution.

t – Time [s].

Ω – Subspace of feasible solutions.

σ – Step size of the CMA-ES.

EA – Evolutionary Algorithm.

ES – Evolutionary Strategy.

CMA-ES – Covariance Matrix Adaptation Evolutionary Strategy.

DOP – Dynamic Optimisation Problem.

CM – Covariance Matrix.

GA – Genetic Algorithm.

5.1 Introduction

This chapter presents a methodology that uses a self-adaptive optimisation method to perform optimisation of building designs, based on models of different complexities.

The literature review in Section 2.6 showed that one of the problems of performing optimisation for building design is the long computational time. Although in a research environment supercomputers or cloud computing might be a solution to this technical barrier, in professional practise, this is a barrier difficult to overcome, and can slow down the deployment of these methods.

The decision space is the space of possible solutions in an optimisation problem; however, not all areas of the decision space are worth being investigated with the same levels of accuracy. The methodology introduced in this chapter would use different assessment methods depending on the stage of the optimisation as a way of economising the computational time spent in the assessment of solutions.

For the method presented here, a self-adaptive algorithm able to notice changes in the way of calculating the objective function was used. The review of Evolutionary Algorithms (EAs) (Chapter 4) showed that Evolutionary Strategies (ESs) and more specifically the Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) is able to analyse the decision space and move the population of solutions in an appropriate direction. This “intelligent” evolution towards the areas with high fitness is achieved through self-adaptation (Bäck, 1996).

This chapter aims to outline the methodology created for this thesis of using self-adaptive optimisation methods with sequential assessment of the solutions using three models with different physical fidelity to perform efficient optimisation of buildings. The method will be applied in Section 5.5 to an optimisation of a low-energy building.

5.2 Aim and hypothesis

After the review of the literature in optimisation methods, and optimisation methods applied to building design, it was seen that new optimisation methods might be developed to aid building design. Those methods could use surrogate models to assist the optimisation. Those models sounded especially suitable for this research as the number of decision variables in building design optimisation is large and because simplified models of buildings were developed previously in this research (Chapter 3).

The aim of this work was to develop an optimisation method that would use simple models to achieve a more efficient search. It was seen in this thesis that there exist simple models of buildings that represent their thermo dynamic behaviour, and can be created with trivial computational time. Those are the Lumped Parameter Models (LPMs) based in RC-networks. The method developed in this thesis would use these dynamic models as simpler models.

The hypothesis was that using simple models, with the methodology shown in Chapter 3, would be an efficient way of performing optimisation for building design. This was assumed because in the creation of these simplified models the most relevant decision variables are the only ones being considered. The creation of the model itself is capable of focusing on the most important parameters, leaving secondary decision variables for the later stages of the optimisation where the more complex simulator is used.

With this method, a new approach was taken that does not need to perform a computationally expensive assessment of solutions until the optimisation is close to the optimum/a. The models were different ways of assessing the solutions going from simple hand calculation methodologies to RC-network based models, and to complex benchmark simulators: the latter being considered as representing the “true” objective function[31].

Changing the assessment tool at certain stages of the optimisation makes the problem an optimisation in dynamic environments (with only two changes in our case). The following section is a description of these problems and settles the bases of the selection of the CMA-ES as the function optimiser chosen in this thesis.

[31] EnergyPlus is one of the most complex simulators available for building design Crawley, D.B., Hand, J.W., Kurnmert, M. & Griffith, B.T., 2008. Contrasting the capabilities of building energy performance simulation programs. *Building and Environment,* 43, pp.661-673. However, its fidelity to reality is not guaranteed.

5.3 Dynamic optimisation problems

The objective function in some optimisation problems is not constant in time, but instead, changes during the optimisation. The algorithm must track the optimum as it moves through the objective landscape to make sure the best option is always chosen. Such problems are called Dynamic Optimisation Problems (DOPs), and solving them has gained considerable popularity in the last few decades (Cruz *et al.*, 2011). Examples are complex control in robotics or network management.

The formulation of a DOP is:

$$\text{optimise } f(\boldsymbol{x},t), \qquad \text{Eq. 5.1}$$
$$\text{subjected to } \boldsymbol{x} \in \Omega.$$

where f is the objective function, $\boldsymbol{x}$ is the set of decision variables, t is the time at which the objective function is evaluated and Ω is the set of viable options (the decision space). If one compares the formulation of Eq. 5.1 to that of a traditional optimisation problem (Eq. 2.1), the time parameter is the only difference. In DOPs, the objective function (or objective landscape for a more graphical understanding) changes as the optimisation is performed. This generates a landscape with one or more moving peaks.

The review by Cruz et al. (Cruz *et al.*, 2011) outlines the features that an optimisation algorithm should have in order to be efficient in tracking a movable optimum in a DOP. In most DOPs, the objective landscape does not change continuously in time. Instead, the optimisation algorithm is capable of performing i iterations with a static objective landscape before the next change occurs. During the i iterations, the algorithm has to look for the location of the peak. However, it is not intended that the algorithm will converge completely in that single point, as the algorithm should be able to move to other areas of the landscape efficiently if the objective landscape changes (similarly to the football players that have to maintain their position and no go all for the ball, as the position of the game might suddenly change on the pitch).

Population-based algorithms have proven to be a good way of maximising exploration of the decision space, and thus being able to recognize changes in the objective space (Goldberg, 1989). Algorithms that use a set of solutions (populations), instead of a single one, are able to evaluate several points of the decision space in each iteration. If the spread of these points is maintained, the algorithm will always have some notion of the shape of the objective landscape. This spread of solutions is called diversity (following the evolutionary jargon).

Branke detailed the features that make an algorithm suitable for solving DOPs (Branke, 2001). These are:

1. Increasing diversity after a change,
2. Maintaining diversity throughout the run,
3. Use of memory, and
4. Multiple populations.

The review by Cruz et al. (Cruz *et al.*, 2011) pointed out that Evolutionary Algorithms (EAs) are one of the most popular and efficient ways of solving DOPs. EAs are population-based algorithms that have been used to solve optimisation problems for almost four decades now (see Chapter 4). They have proven effective in several synthetic objective functions and real-world problems, and have produced satisfactory results (see (Coley, 1999), (Beyer and Schwefel, 2002) , (Bäck and Schwefel, 1993), (Deb, 2001) for general texts on EAs). These algorithms use crossover, mutation and selection to find the best individuals (solutions) when a population (set of solutions) evolves (converge) over generations (iterations). Cruz et al. described EAs and, in particular, Evolutionary Strategies, as the most popular type of algorithm found in the literature for solving DOPs.

The review by Cruz et al. and the one by Branke (Branke, 2001), describe how increasing diversity, following a change in the environment, or maintaining that diversity are ways of adapting a traditional EA to make it capable of solving a DOP. In this work, a specific EA has been selected that is able to enhance diversity intrinsically when needed. This algorithm is the Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) developed by Hansen et al. (Hansen *et al.*, 2003). The algorithm evaluates the necessary exploration of the decision space by calculating the Covariance Matrix (CM) of the solutions of each generation. These calculations allow the algorithm to recognize internally the changes that might have happened in the decision space. The algorithm is described in more detail in the following section.

5.3.1 The algorithm: CMA-ES

The Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) is a modification form of EAs. The CMA-ES was created by Hansen et al. (Hansen *et al.*, 2003) with the aim of reducing the stochastic nature of ESs by using the Covariance Matrix (CM) in each population of solutions. The CM provides information about the shape of the decision space to the algorithm.

The CMA-ES has been proven to be an efficient method for optimisation in building design (Kampf and Robinson, 2009), its main strength is that the algorithm is able to recognise changes in the objective landscape through the CM, and adapt to those new scenarios. Although the calculation of the CM could be considered as a computationally expensive calculation, if the time needed to calculate this matrix is compared with the time needed to perform an annual simulation of a building using a complex simulator (EnergyPlus in our case), the time taken to perform this calculation is trivial (three order of magnitude smaller), especially using small population sizes (12 individuals in this work).

The algorithm has been used in this research in the form of the code provided by (Hansen, 2012).

The following sub-section describes the assessment methods that were used in the application of this method.

5.3.2 Building assessment tools

Following the description of assessment tools in Section 2.2, three ways of evaluating the objective function were chosen in this work:

1. Simple calculation methodologies: sets of algebraic equations or graphical tools that allow the calculation of energy demands for a given building.

2. RC-networks based simulators: simulators which use an RC-network to represent the thermo-dynamic response of the building.

3. Benchmark simulators: tools more commonly used by architects and building scientists, benchmark simulators are comprehensive simulator suites that consider a multitude of phenomena that occur in the building. Examples of these are IES - <VE> or EnergyPlus.

This separation into three groups is mainly based in complexity of each method. However, there is an assumption here that computational time is proportional to final accuracy, but this is not proven[32]. In Figure 2.7, the different kinds of calculations are compared qualitatively, against computational time and model fidelity; Figure 5. is shown to relate these assessment tools with the differences of making an FEM simulation with different number of cells (different accuracy). These two figures have been shown to illustrate the similarities between different ways of assessing the objective function in building energy assessment and solving a mechanical problem with different accuracies.

[32] The higher complexity of a building model is due to a larger number of phenomena being represented by the code. However, simulating a larger number of phenomena does not imply having a better accuracy. The more phenomena represented the larger the number of inputs that are asked to the modeller. Even if those inputs are chosen under a fair judgment, they will be uncertainty. Examples of this is a weather file for a location that might come from observed data, but it is unlikely to happened again, or the consideration of solar gains, but considering an ideal horizon/sky. In opposition to this detailed simulators, simpler calculations are normally used with values that come from empirical correlations which can make the overall calculation more accurate than in the case than a complex simulation with the wrong inputs.

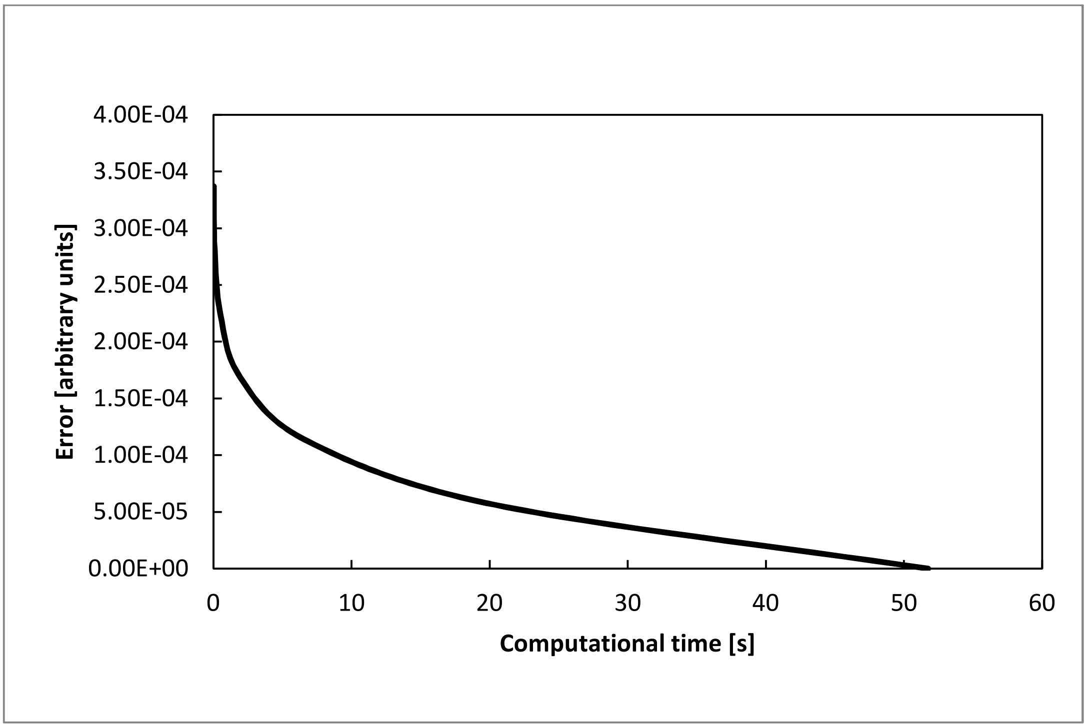

Figure 5.1 - Improvement of accuracy at the cost of longer computational times when the number of cells is increased in an FEM problem (the Boussinesq problem).

In this thesis a procedure is suggested whereby multiple building assessment tools are used at different stages of the optimisation. Starting with those with the less model fidelity, the process will follow up towards the models with larger model fidelity. This is expected to be a more efficient way of using computational resources than maintaining the same levels of accuracy along the run as done in traditional optimisation. The algorithm has to be such that is able to update the search when a more complex simulator is used, so the variables that were left behind in the previous iterations get evaluated and optimised when they are needed.

For this research, three stages using three different assessment tools are used. Although the selection of the number of stages is rather trivial, it is sufficient to use the main three building assessment tools represented in the previous classification from the review in Section 2.2.

One tool was selected for each of the stages listed previously. These tools are: the LT-method as the simple calculation methodology; an LPM simulator as the RC-Network simulator; and EnergyPlus for the benchmark simulator. Although there exist some weaknesses in some of these assessment methods, these tools were chosen to check the validity of the methodology, the reason for this will be explained in the application.

5.4 Implementation

The methodology developed in this research uses building assessment tools with different computational times at different stages of the optimisation for reducing computational times. The simpler calculation methods are considered simpler models, and the benchmark simulator the closest computational assessment tool used to the real objective function.

Changing the assessment tool during the optimisation run will imply a change in the objective function; therefore will make the problem a dynamic optimization problem (DOP).

The review of Cruz (Cruz *et al.*, 2011), shows that when an optimisation algorithm has to optimise an objective function that changes during the run (a DOP), some iterations are needed for the algorithm to recognise and eventually adapt to the change. That means that too many changes in the landscape can have a negative effect because the continuous variability of the landscape would not allow the algorithm time to adapt to the changes.

The method developed in this thesis is a cross-over between optimisation using different models and optimisation in dynamic environments. In this case, the change in the landscape is triggered by the algorithm itself once it has been seen that the run is reaching a termination criteria, with the changes being the selection of the next assessment method.

To implement the sequential optimisation algorithm, which has been called here CMA-ES with Sequential Assessment (CMA-ES-SA), the CMA-ES has been used with the default parameters suggested by the author in (Hansen, 2012). The algorithm is started with the simplest assessment tool, and it is run until the termination criteria are reached. These termination criteria will be further explained in the application but can be summarised as:

1. The scope of the search has become smaller than a given value; therefore the assessment method has to change to maintain diversity.

2. The algorithm gets stagnated: More than *N* generations without reaching Condition 1 (the algorithm is not converging)

When the algorithm reaches one of the termination criteria, the code changes to the next assessment tool and modifies the parameters of the algorithm to ensure the exploration of the new objective function. This is repeated for the third assessment tool (EnergyPlus in our application) and when the algorithm reaches a termination criteria exclusive for this stage the run is finished.

One of the mechanisms that can be read in (Cruz *et al.*, 2011) to improve the efficiency of algorithms in dynamic environments is to maintain diversity. In the methodology shown here, to achieve this, the algorithm will change to the next assessment method before the population has converged completely.

The CMA-ES recognise changes in the objective landscape through the CM, if the change on the assessment tool generates a substantial change in the objective landscape; it is expect that the algorithm would change the parameters of its operators to adapt to this change.

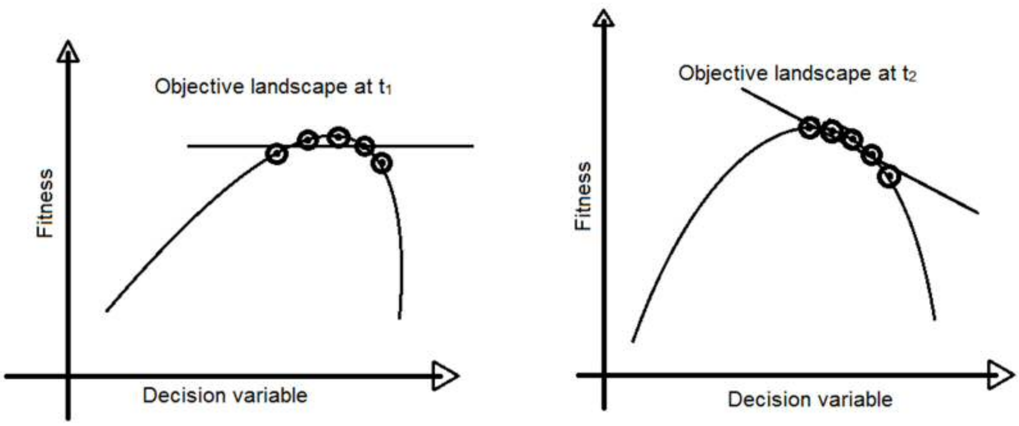

Figure 5.2 - Interpretation of the recognition of the landscape by the CM in one dimension: The straight line shows a linear regression of the solutions (circles). The same population that shows a linear regression with slope close to zero in the left, shows a linear regression with negative slope after a change in the objective landscape.

The mutation operator in the CMA-ES is self-adaptive; this means that the algorithm evaluates how much the scope of the mutation should be dependent on the population and in which direction the population should move. This is equivalent to calculating the gradient in continuous derivable functions, but CMA-ES calculates this on a discrete way (through the CM). As the variability of the objective function changes less with variations of the decision variables (equivalent to a gradient of zero) the algorithm makes the scope of the mutation smaller, this is equivalent to focusing on a smaller area. If the members of a population are over a peak in the objective function, the algorithm will see no substantial modification of the objective function with the covariance matrix of the individuals, if the landscape changes and they appear in the next iteration in an area with a substantial slope, the algorithm would detect that a movement needs to be done to the population and therefore will modify the scope of the mutation to make that happened. The CMA-ES, also internally modifies the probability of direction of the mutation to aim for the areas of the landscape likely to give high fitness individuals (illustrated in Figure 5.2).

Hansen et al. used the CMA-ES on the presence of uncertainties before in: (Hansen *et al.*, 2009). However this was not a dynamic optimisation problem or optimisation with different models.

5.5 Application

To evaluate the strengths and weaknesses of the method that was described in this chapter, its application to a building design problem was performed.

This application tests the capability of an evolutionary optimisation algorithm (CMA-ES) to solve an optimisation problem in which the objective landscape varies due to changes in the technique for calculation of the objective function. The optimisation algorithm selected is the CMA-ES, and the three techniques for calculating the objective function are: an LT-calculation, an LPM simulation and EnergyPlus. The use of the CMA-ES with sequential assessment has been called CMA-ES-SA.

The problem was defined to emulate real optimisation problems that can be found in architecture. The optimisation was single objective, but the method can be easily adapted to run multi-objective. The objective was the energy demand (heating and cooling) as this thesis has been highly motivated by the current need of reducing energy use in buildings.

The building is an office that is constrained to have 70 m^2 that is part of a larger office block. The gains have been extracted from (CIBSE, 2006) and represent the benchmark values Table 5.1. The decision variables include the properties of the fabrics of the envelope, the material properties of the internal partitions, the fenestration, and overhangs for windows in the South, East and West façade. Also, the aspect ratio and the infiltration levels were considered as decision variables. All the variables can be found in Table 5.2.

Table 5.1 - Benchmark values for internal heat gains for offices.

Density of occupation [person/m^2]	Heat gain [W/m^2]		
	People	Lighting	Equipment
1/8	10	12	20

Many decision variables have been selected in this problem because this methodology is trying to offer an alternative to optimisation methods that use meta-models with large computational time needed upfront to build the surrogates. With this application, it will be tested if the methodology presented performs well with large decision spaces.

The decision variables included in the problem control almost all thermally relevant elements of the building (see Table 5.2). Some of the elements are more relevant to the overall energy demand than others (insulation compared with width of overhang), these decision variables have been chosen on propose, to verify the capabilities of the algorithm to focus in the variables that are more significant than others along the optimisation.

Table 5.2 - Variables forming the decision space. IP are internal partitions.

	Variable	Type	Lower bound	Upper	Unit
	Infiltration	Real	0.021	0.6	*ach*
	Aspect Ratio	Real	0.3	3	*m/m*
	Fenestration,	Real	12	80	*%*
	Fenestration,	Real	12	80	*%*
	Fenestration, East	Real	12	80	*%*
	Fenestration, West	Real	12	80	*%*
	Wall Type	Symbol.	Construction A	Construction D	*n/a*
	Insulation	Real	100	500 (U-	*mm*
	Conductivity of IP	Real	0.2	2.3	*W/(mK)*
	Capacity of IP	Real	200	3000	*J/(kgK)*
South Overhang	Depth	Real	0.0	2.0	*m*
	Left extension	Real	0.0	5.0	*m*
	Right extension	Real	0.0	5.0	*m*
East Overhang	Depth	Real	0.0	2.0	*m*
	Left extension	Real	0.0	5.0	*m*
	Right extension	Real	0.0	5.0	*m*
West Overhang	Depth	Real	0.0	2.0	*m*
	Left extension	Real	0.0	5.0	*m*
	Right extension	Real	0.0	5.0	*m*

Table 5.3 - Possible constructions of solutions.

Construction	Outside Layer	Intermediate	Inside Layer
A	200mm	Insulation	25mm stucco
B	200mm ”	”	200mm concrete
C	25mm stucco	”	200mm ”
D	25mm ”	”	25mm stucco

5.5.1 The algorithms

Two algorithms have been used in this application, the one created in this thesis: the CMA-ES using sequential assessment (CMA-ES-SA) and a canonical form of GA. GAs are popular optimisation methods broadly used in the literature of building design and therefore, they seem as an adequate algorithm to take as the baseline. Several works can be found in the literature were GAs were used, examples in building design are: (Coley and Schukat, 2002; Ooka and Komamura, 2009; Kayo and Ooka, 2010; Tuhus-Dubrow and Krarti, 2010; Caldas and Norford, 2002; Suga *et al.*, 2010; Wright *et al.*, 2002; Magnier and Haghighat, 2010; Wang *et al.*, 2005; Caldas and Norford, 2003; Chantrelle *et al.*, 2011; Juan *et al.*, 2009).

Both optimisation algorithms have been implemented in Octave (similar to Matlab) to facilitate their comparison. The genetic algorithm has been given the values recommended by Schaffer in (Schaffer *et al.*, 1989) for crossover probability and mutation probability (Table 5.4), the algorithm has been run with 100 individuals, and uses the stochastic universal sampling as selection mechanism (Baker, 1987). The CMA-ES has been given the default parameters provided in the code by the author (Table 5.5) (Hansen, 2012).

The decision variables have been normalised into the interval [0, 10] as recommended by Hansen (Hansen, 2012) in the CMA-ES-SA. However, to have the same accuracy in both algorithms, the same has been done in the genetic algorithm. For both algorithms the decision variables will take values between 0 and 10.

Table 5.4 - Default parameters of the GA, from (Schaffer *et al.*, 1989).

Parameter	**Value**
Population size	100 individuals
Selection mechanism	Stochastic universal sampling
Crossover probability	0.75 crossovers per couple
Mutation probability	0.005 mutations per bit

Table 5.5 - Default parameters of the CMA-ES, from (Hansen, 2012).

Parameter	**Value**
Population size	12 = (4+3*ln(dimensions))
Number of parents	6 = (population size / 2)

The algorithms have been provided with specific features to make sure that the optimisation is performed adequately. In the case of the CMA-ES-SA, the algorithm is able to detect that the population is converging into a few points (losing diversity) by checking the value of the time-step of mutation (called sigma ‘σ’ but not representing the standard deviation). When the step size is smaller than a given value, the algorithm changes automatically the assessment method or terminates the run depending on the current stage. The actions are shown in Table 5.6.

Table 5.6 - Initial, final and intermediate steps of the CAM-ES-SA.

Assessment method	Action at the start of using the method	Termination/Change of assessment method
LT-Method	Initialisation of the algorithm	$\sigma < 0.5$ or simulations > 500
LPM	Nothing	$\sigma < 0.1$ & simulations > 1000
EnergyPlus	Nothing	$\sigma < 0.09$ or stagnation

When using the GA the decision space has to be discretised for every decision variable, in this problem, the decision space has been discretised in 50 values per variable. This means that, for the GA, the decision variables will have a precision of 10/50=0.2 units. This accuracy is translated differently in the physical values depending on the range of each one. This encoding represents 9.54×10^{33} possible solutions in the decision space.

Evolutionary Strategies (ESs) do not need discretization of the decision space as the variables are kept in real format. However, to make sure that advantage is not given to any of the methods, the CMA-ES-SA is allowed to evolve only until it reaches the same levels of accuracy of the discretised space of the GA. The GA can be run for as many generations as the operator decides, but the ES is self-stopped by definition when certain accuracy is reached. To make sure that the judgment of the computational times is fair, the GA has been stopped when the solution is similar to that obtained by the CMA-ES-SA. The details of discretisation and termination are summarised in Table 5.7.

Table 5.7 - Parameters of the optimisation algorithms.

	Precision of variables	Termination
GA	0.2 units (=10/50)	objective < solution of CMA-ES-SA
CMA-ES-SA	No predefined limit	$\sigma < 0.09$ (Table 5.6)

The CMA-ES-SA has its most substantial strength on using different models to analyse the solutions along the optimisation. These models are different methods of calculating the heating and cooling demands. The following section shows how the building was modelled for each of these assessment methods.

5.5.2 The assessment methods

This section shows the way the building was modelled in each of the assessment tools.

5.5.2.1 Model for the LT-Method

The office modelled for this work, is located in London, therefore being mid European coastal, it is considered to have each of the façades orientated to each of the cardinal points. The fenestration percentage of each façade is an independent decision variable and it is considered that these windows are not affected by casted shadows from surrounding obstacles. The LT-Method suggests separating passive areas to non-passive areas and so was done for this application. The passive areas are delimited by external walls and the imaginary surface parallel to them 6 meters into the zone, this multi-zone configuration was used for the EnergyPlus model too (Section 5.5.2.3).

Although this method is obsolete and poor in respect to the number of variables used, this method has been used to proof that the Sequential Optimisation method is robust and delivers good results even with poor starting points. In the application of this method in further problems a monthly average calculation could be a good option as the first assessment tool.

5.5.2.2 Model for the LPM

The building created with the characteristics defined by the decision variables was created for each solution, and then the equivalent RC-network was obtained. The RC-network representing all the elements of the building was then reduced to a LPM with the methodology shown in Chapter 3 (Ramallo-González *et al.*, 2013). The office is modelled as a single zone, to make possible its representation by the LPM. The model does not include ceiling and floor, as these surfaces are considered adiabatic because the office above and below the one studied were considered at the same temperature. The computational time needed to run a yearly simulation with this model was 0.29 seconds

To perform the simulation, the model shown in Figure 3.13 has been equipped with an ideal heating and cooling system, but also with natural ventilation.

To do that, the software calculates the cooling load for each time step and it checks if that demand can be covered with natural ventilation by window opening (the software recognise how much air can be moved depending on the windows size that is a decision variable), if this load can be totally covered by natural ventilation, the windows will open the appropriate fraction to provide the adequate cooling. In the case that this is not enough, ventilation will happen first, and the cooling load will be calculated on top. With this the model is trying to mimic the capability of the more complex system used in EnergyPlus that is able to adjust the airflow taken from the outside to cool down the inside of the office.

The solar gains are calculated in a basic way for this simulator. The solar radiation per square meter in each time-step was calculated and reported for each of the surfaces of the building (North, South, East and West) using EnergyPlus, before performing the optimisation, and stored in a data base. These solar gains consider no overhangs. For each solution, the fenestration area of each façade will be multiplied in each time-step by the area of the window in each façade and the summation of those will give the total solar gain for each time-step. The gains due to metabolic, light and electric appliances were the same as in the run with EnergyPlus.

To simulate the buildings, this model has been solved using state-space equations, and boundary conditions read from a weather data file of London ((DoE, 2011)). The integration time-step of the equations was of 0.1 hours (6 minutes).

5.5.2.3 Model for EnergyPlus

The simulation in EnergyPlus is the most complex of all three. The way the building was modelled in this simulator is as follows.

The office is modelled in EnergyPlus as a single story office in a multi-storey block, with no exchange of heat through floor and ceiling (adiabatic).

The conditioning equipment is an air-based system that uses an electric chiller and a gas furnace to deliver cold and warm water respectively that circulates through coils on the outlets of the air ducts for each area. The conditioning system is able to use un-conditioned outside air to cool down the office, which is equivalent to the natural ventilation modelled in the LPM simulator.

The model is multi-zone as the one described for the LT method with the addition of a plenum zone that gathers the air flow from the zones and returns it to the conditioning system. The geometry of the office with an aspect ratio of 1.0 and with arbitrary windows and overhangs can be seen in Figure 5.3.

The office has been surrounded by four surfaces with the same height of its walls but located at 30 meters away of each façade, with this; the shadow of potential buildings is represented.

The objective function is calculated after summing up the heating demand and the cooling demand multiplied by a constant factor. This factor accounts for the different price of primary energy use for the chiller (electricity) compare with the furnace (gas). The factor was the same in the three assessment methods.

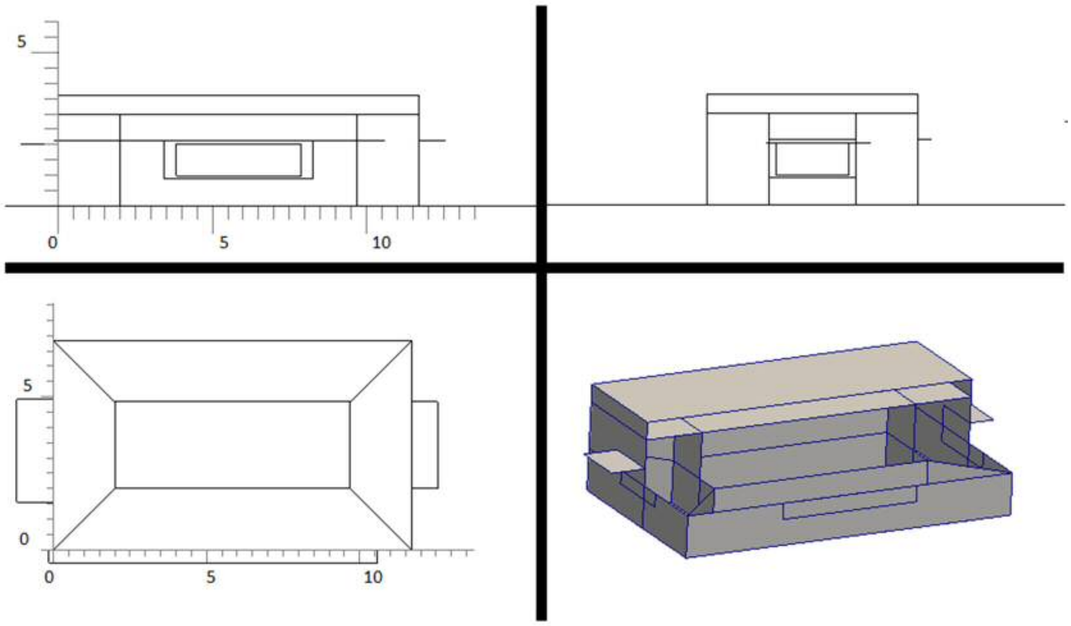

Figure 5.3 – Example of the 3D geometrical model of the office used for this work, the overhangs, windows and aspect ratio vary. The units are metres.

The next section shows the results of using the CMA-ES-SA to minimise the annual energy demand (heating and cooling) for the application described.

5.6 Results and discussion

The sequential optimisation methodology CAM-ES-SA was applied to the problem described before: an office in a block located in London with 70 m^2 floor area and with the decision variables as shown in Table 5.2. In order to study the benefits of the approach, the same optimisation problem was solved using a traditional GA and the CMA-ES-SA. To verify the solutions that can be obtained using only the simpler models, two more runs were performed using GA and the LT-method and the GA and the LPM simulator solely.

To evaluate properly the accuracy of the method, the two approaches, the GA and the CMA-ES-SA have been applied several times and the results of these runs studied.

Firstly, 20 runs were done using the CMA-ES-SA. The solutions of this set are represented in Figure 5.4b.

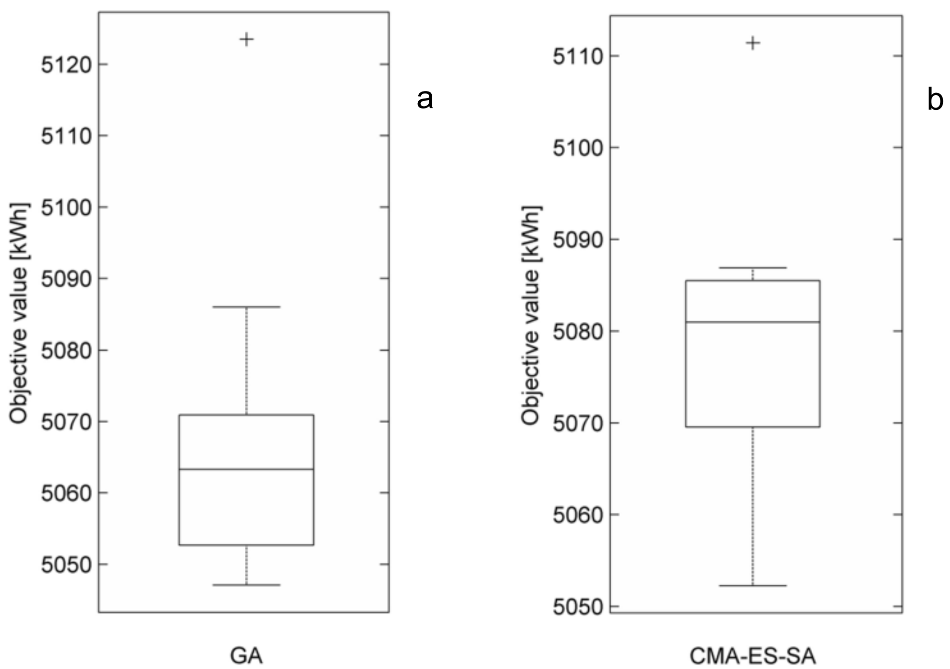

Figure 5.4 - Boxplot of the results obtained with the traditional GA (a) and the CMA-ES-SA (b). The single point represent an outliner in both cases: Points are drawn as outliers if they are larger than q3 + w (q3 – q1) or smaller than q1 – w(q3 – q1), where q1 and q3 are the 25th and 75th percentiles, respectively.

The same optimisation problem was solved using the GA; in this case, 9 runs were performed. The parameters needed to achieve solutions of the order of those that were obtained with the CMA-ES-SA were investigated. A population size of 100 individuals and a number of generations of 140 came out as the most efficient combination; the results of the nine runs using the GA are shown in Figure 5.4a.

It can be seen that the variability of the solutions obtained with the CMA-ES is of 30.40 kWh, around 0.6% of the average value of the objective function. This variation between solutions, although substantial in numerical algorithms theory, it is negligible in building energy calculations[33]. It was shown that the energy calculations have a much larger variability due to other uncertainties in Section 2.6.4.

This shows that the two optimisation methods were run until reaching solutions with similar values of the objective function as imposed by the termination criteria. After seeing that both algorithms were run in a way in which they delivered the same accuracy in the solution, the computational times were studied. The result is shown in Figure 5.5.

[33] The difference between using a desktop computer, with a nominal power of 100W, and using a laptop with a nominal power of 50W, 8 hours a day 5 days a week, sums up a total difference in energy demand of 104 kWh over the year.

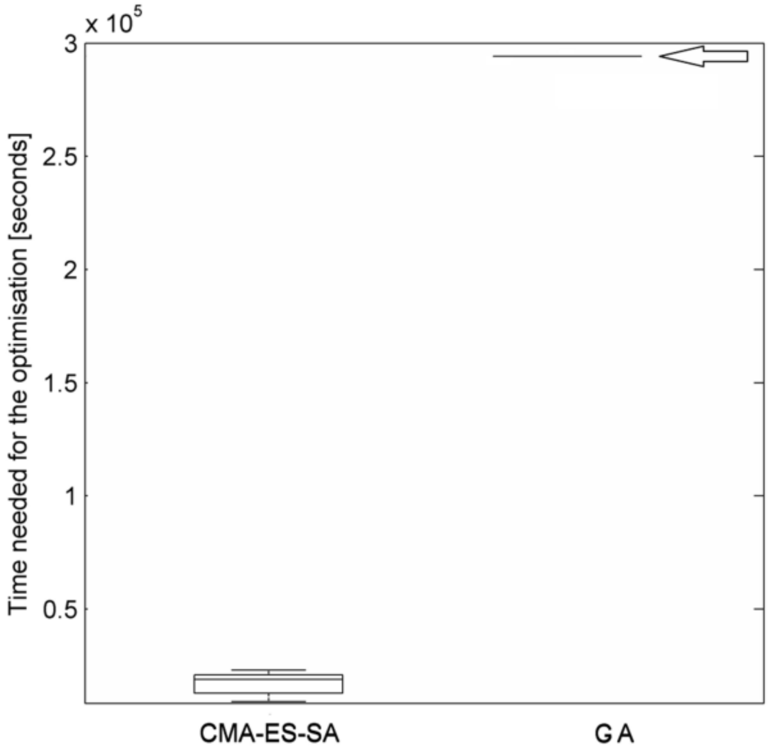

Figure 5.5 - Time differences in running the two optimisation methods. The time for the GA is always the same as the generations and population size has been fixed to achieve the same accuracy as the CMA-ES-SA (see previous figures), the time of the CMA-ES-SA varies.

The CMA-ES-SA used different times for every run, as the algorithm is stochastic and this makes the times at which the assessment methods are changed different, also the speed of converging in each of the steps is different. In opposition, the GA was always run with 100 individuals and 140 generations, and therefore makes always 14000 evaluations of the objective functions. It was found that when the GA is run for 140 generations, the solutions are similar to those given by the CMA-ES-SA, but the times needed to run the CMA-ES-SA are a fraction of the time needed for the GA.

Figure 5.5 shows that the differences on times are substantial, even in the worst case scenario the CMA-ES-SA is much faster than the GA.

To understand better the optimisation problem in both cases, one solution from each of the set of the runs was studied in more detail.

One of the results from the optimisation using the CMA-ES-SA gave an objective value of 5080.97 kWh, the solution with the GA gave an objective value of 5086.00 kWh. The value of the decision variables for both of these solutions are shown in Table 5.8

Table 5.8 - Results of the optimisation runs using specific assessment tools, and sequential optimisation.

				Genetic Algorithm			CMA-ES-SA
		Variables	**Units**	**LT**	**LPM**	**e+**	**Sequential**
	1	Infiltration	ach	n/a	0.021	0.021	0.021
	2	Aspect ratio	m/m	0.374	1.098	1.326	1.673
	3	U-Value wind.	W/(mK)	n/a	1.966	1.890	1.921
	4	North Window	%	12.7	22.1	12.01	12.56
	5	South Window	%	14.0	12.1	33.78	23.31
	6	East Window	%	21.9	12.0	12.10	12.60
	7	West Window	%	47.0	12.0	12.05	12.18
	8	Wall Type	symbolic	n/a	C	C	C
	9	Insulation	mm	n/a	499	499.7	500.0
	10	*k* - partitions	W/(mK)	n/a	1.85	2.39	2.398
	11	c_p – partitions	J/(kgK)	n/a	2976	2999	2989
South Overhang	12	Depth	m	n/a	n/a	1.050	0.774
	13	Left extension	m	n/a	n/a	1.614	2.485
	14	Right extension	m	n/a	n/a	1.549	2.060
East Overhang	15	Depth	m	n/a	n/a	0.665	0.742
	16	Left extension	m	n/a	n/a	0.172	3.660
	17	Right extension	m	n/a	n/a	0.935	4.740
West Overhang	18	Depth	m	n/a	n/a	1.828	0.610
	19	Left extension	m	n/a	n/a	1.433	4.435
	20	Right extension	m	n/a	n/a	0.026	2.790
Best objective			kWh	28014	5197	5086.00	5080.97
Evaluat’s				7000	14000	14000	1009+ 1716+ 1356
Time per simulation			s	0.001	0.29	16.70	0.001, 0.29, 16.7
Total time			s	7	40600	**238,000**	**23,551**

Two other runs using the GA and only the LT-method and only the LPMs have been also included in Table 5.8 for illustrative proposes.

Table 5.8 shows the values of the decision variables together with other parameters of the optimisation. The first set of decision variables (from 1 to 11), are the ones able to interpret by the method that uses LPMs, and are supposed to be the most influential in the energy demand of the building. Most of the values for these variables are very similar using the GA and the CMA-ES-SA, and the ones that are not similar, show an interesting fact: the aspect ratio and the windows size lead to similar sizes of windows. It can be seen that the aspect ratio in the solutions from the GA and the CMA-ES-SA are different, this ratio, is going to have an impact in window size, as the last one is defined as a percentage of the area of the façade. If one observes the aspect ratio and the size of the window in the south façade, one can see that although the window in the solution of the CMA-ES-SA is smaller, the aspect ratio is larger, and therefore, the effect of both decision variables together make the solution more similar to the solution in the GA.

Another interesting thing to note from Table 5.8 is the failure of implementing the overhangs properly in the optimisation. For the assessment tool, an overhang that extents 4 meters over the window is as valid as one that extends 0.5 meters, no penalisation was put in place for solutions that have overhangs that are too large. Also, if an overhang needs to be at least let it be said 1 meter, and the simulator recognise that having an overhang of 5 meters is as good in the energy demands, then any value between 1 and 5 will be chosen by the algorithm and therefore, the user will not be able to know what is best, as he/she would not be able to recognise from the solutions the "at least x meters" condition. Including this type of decision variables in the algorithms in the future can be challenging and would need to be done properly.

It can be seen in the number of function evaluations, that the CMA-ES-SA need less than the GA even without differentiating between the stages with different assessment tools. The GA needed 14,000 function evaluations, and the CMA-ES-SA needed 4,081 in this example. This could be because using models with different physical fidelity allows the algorithm to concentrate in the variables that mater the in each stage; because the efficiency of the CMA-ES itself is higher than the efficiency of the GA or because a combination of the two. Observing the comparisons done in (Bäck, 1996) one could assume that CMA-ES would always be more efficient.

The number of function evaluations that were needed using the computationally expensive simulator (EnergyPlus) are few when using the sequential optimisation (CMA-ES-SA). This will have the greatest impact on the total computational time. Only 33.23% of the function evaluations are carried out with EnergyPlus, the rest, 66.77% of the function evaluations, are done with the other two assessment tools, although this is a large percentage of the evaluations, it only accounts for 2.15% of the total computational time of the optimisation as these are assessments that are “cheap” to run. The benefits of using this pre-processing in the optimisation using the simpler models are clearly shown in this case; the extra computational time of this pre-processing with these models is negligible (~8 minutes) compared with the savings in computational time that produced when compared with a traditional GA (~two and a half days, or 214450 seconds). A representation of how the computational time is spread in the optimisation using the CMA-ES-SA can be seen in Figure 5.6.

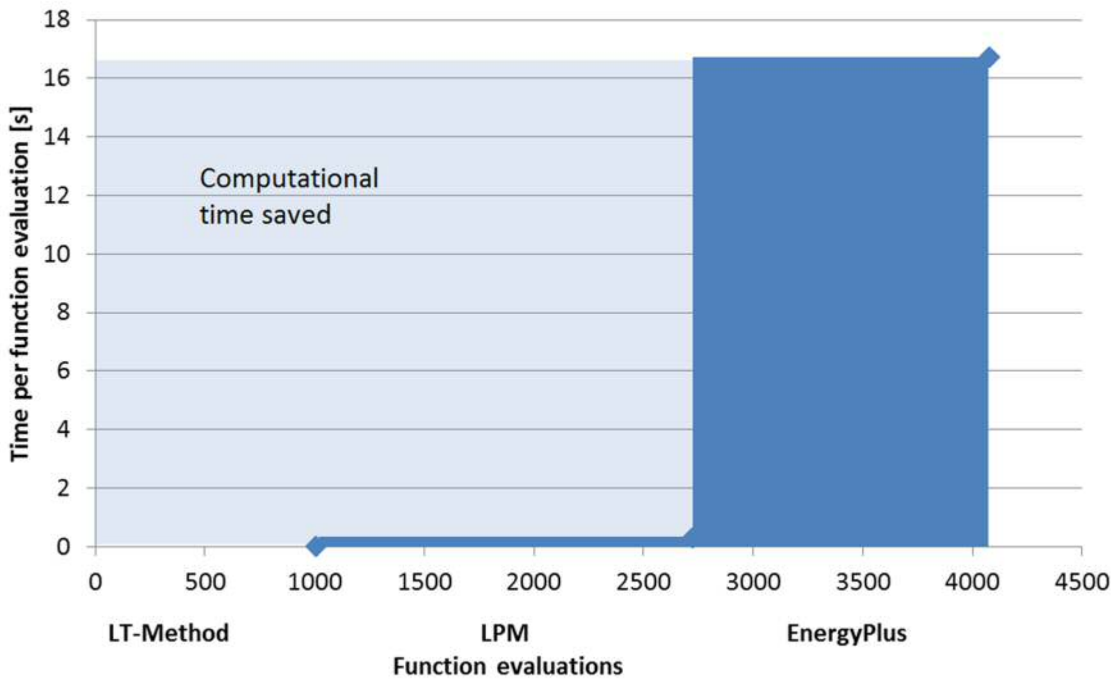

Figure 5.6 - Graphic showing the time spent in each stage of the optimisation using the CMA-ES-SA for the case shown in Table 5.8. Time is represented by areas in this graphs and measured in seconds. The computational time saved has been shown as the light blue area.

If one observes the results of the optimisations performed by using only one of the simpler models (either the LT-method or the LPMs) in Table 5.8, one can see that the runs carried out using the LT-method as the assessment tool, although much faster, could not reach a low-energy design. This was expected as the LT method is a very basic tool that does not even interpret the majority of the variables. In the case of the solution found using only LPMs, the optimum found is close to the minimum found when using GA and EnergyPlus (around 2%). This justifies the selection of these simulators for optimisation problems as was done by (Coley and Schukat, 2002) (Kampf and Robinson, 2009) and (Wright *et al.*, 2002). One could think after seeing this result that one should go straight to the use of LPMs for optimisation; however, it should be noted that the problem at hand here is rather simplistic. There is no detailed study of the air flows, illumination or other components. In other cases, where real buildings are being created, a much higher level of model fidelity would be needed. It is believed that the CMA-ES-SA has a great potential for those problems. Also, it has been seen that the optimisation suits are being implemented in complex software such as IES-VE and EnergyPlus, with the CMA-ES-SA this software tools could improve efficiency in their search.

Figure 5.8 and Figure 5.7 show the evolution of the optimisation using the GA and the CMA-ES-SA respectively for the examples shown in Table 5.8.

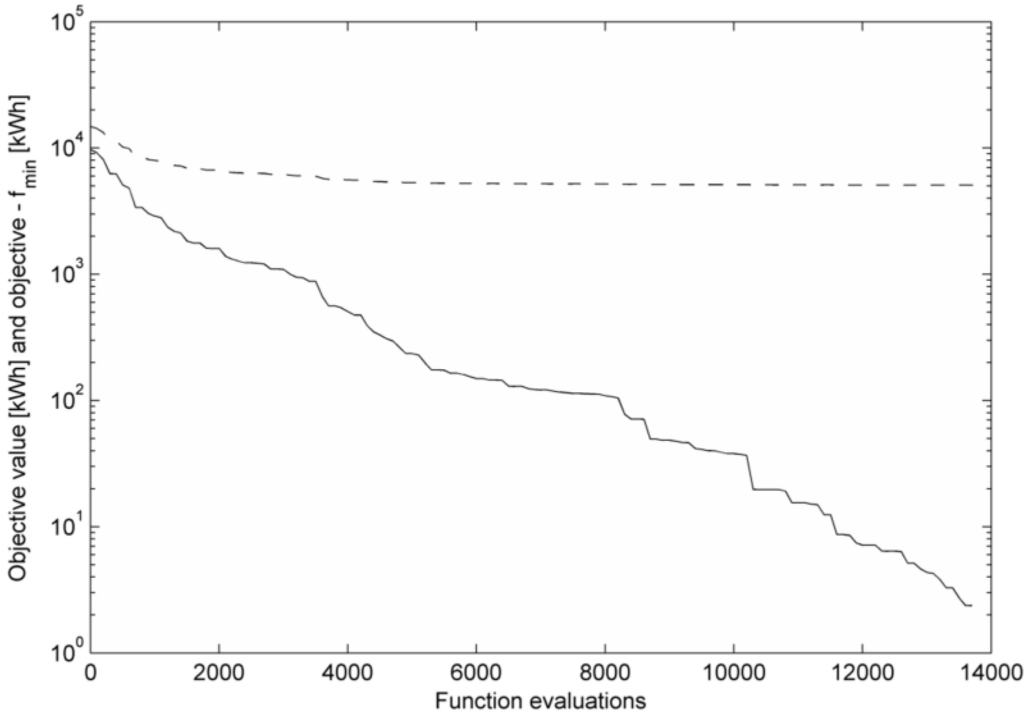

Figure 5.7 - Evolution of the GA using EnergyPlus. Minimum value of the objective function found (dashed line). Relative improvement of the objective value found until then (solid).

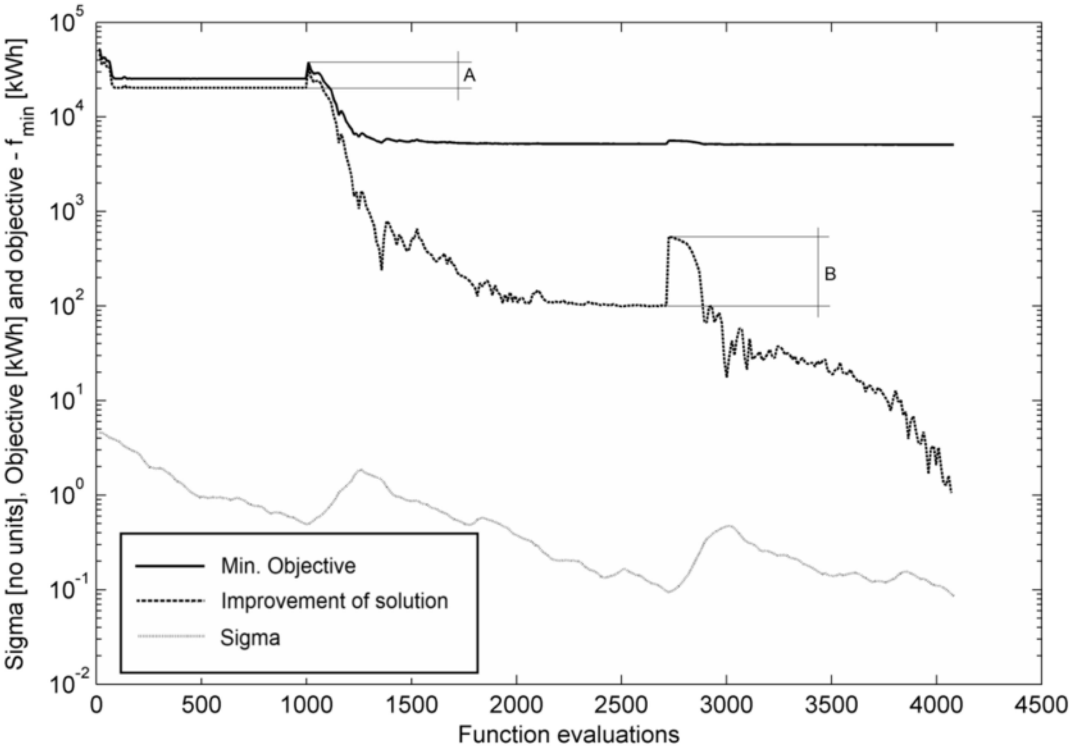

Figure 5.8 - Evolution of the CMA-ES-SA. “A” shows the differences between the objective values of the best solution at the moment of changing the assessment tool from the LT-Method to the LPM. “B” shows the differences between the objective value of the best solutions at the moment of changing the assessment tool from the LPM to EnergyPlus.

Figure 5.7 shows that, in the GA, the solution get improved with a relative change of 10 ^{4} at the beginning, and refines to a relative improvements of the order of 2 kWh after 14000 function evaluations. In the case of the CMA-ES-SA, the improvement on the objective value of the solutions is steeper. It can be seen that in the stage of the optimisation where LPMs are used (from the point at the optimisation where “A” is marked to the point where “B” is marked) the accuracy of the search grows rapidly getting an improvement of the solution of the order of 100kWh in about two thousand function evaluations. This can also be seen in the stage where EnergyPlus is used, in which the improvement of the solutions goes from around 500 kWh to 1 kWh in around 1300 evaluations.

This rapid convergency of the method explains the higher efficiency of the CMA-ES-SA, it can be seen that the GA gives a constant logarithmic improvement of the solution. However the CMA-ES-SA shows that at the beginning of each change of the assessment tool, the algorithm improves the solution rapidly, and making the assessment sequential provides 3 such stages.

Finally it should be said that two of the 20 optimisations done with CMA-ES-SA failed as they converged immediately after changing to EnergyPlus. The similarities in the objective landscape when the assessment tool was the LPM and then the assessment tool was EnergyPlus, make the algorithm unable to recognise the change and therefore diversity was not augmented. The termination criteria (σ <0.09) was reached before the CMA-ES-SA was able to explore the new landscape provided by EnergyPlus. This problem is easily solvable by imposing a minimum number of function evaluations for EnergyPlus. In this case a minimum of 100 function evaluations would be enough, as this would allow the algorithm to increase the step-size and eliminate the potential premature convergency.

The CMA-ES is effective in adapting the parameters of the optimisation to new landscapes, and therefore in solving this kind of optimisation problem. If one observes the step-size (sigma) of the CMA-ES-SA in Figure 5.8, one can see that at the points where “A” and “B” are located (i.e. where the assessment tool changes), sigma starts getting larger. This is because the algorithm is able to recognise the changes in the landscape, and starts increasing the step-size to make sure that the new landscape is explored properly. However, it would appear that the algorithm should be forced to run a minimum of function evaluations at each stage to ensure that the internal mechanisms of the algorithm are able to recognise the new objective landscape. The premature convergency is likely to happen when the sigma required to change the assessment tool is similar to the sigma required to terminate the optimisation, as happened in this case.

The algorithm was able to cope well with the symbolic variable, providing the same results in the CAM-ES-SA run and the GA run.

5.7 Conclusions

The methodology suggested in this thesis has been seen to need less computational time for solving the problem shown in this chapter than a GA that uses only one assessment tool.

It is seen that the optimum found using the LPM simulator is similar to that found using EnergyPlus. This justifies the use of this kind of model in previous publications (Coley and Schukat, 2002) or (Wright *et al.*, 2002).

Several software developers, such as IES-<VE>, and EnergyPlus are integrating optimisation modules into their packages see Section 2.6.2.1. These new modules can have long computational times if the objective functions are always evaluated using the whole comprehensive dynamic simulator; this thesis shows that there are more efficient ways of searching for optimal solutions in building design and those are using self-adaptive optimisation methods and models with lower model fidelity. This method is similar to the natural method of building design, where simplified tools are used in the early stages when many variables have to be determined, and only at later stages more complex tools are used. There are also clear analogies to product development or scientific thought, where a series of ever more complex models are created with piece meal optimisation in between.

The results of this work are in general satisfactory. However, improvements are possible; for example, choosing a different number of building assessment tools, or changing the criteria that make the algorithm jump from one assessment tool to the next, would increase efficiency further. It is though that in the case of running an optimisation, where the maximum level of accuracy requires running simulations that take the order of hours, the CMA-ES-SA could show a much better reduction in the computational times compared with the traditional method.

If one considers that the user is able to find assessment methods that require a computational time that is one order of magnitude smaller than the previous, then the reduction could be even larger. If the most accurate assessment tool used a long computational time (for example10 hours), the operator could find assessment tools which computational times are different by an order of magnitude, then one could speculate that the time needed to run the CMA-ES-SA might be as shown in Table 5.9. In this table 1500 evaluations have been chosen.

The total value in this hypothetical case would be $6x10^7$ seconds, or 7 months: an impracticable time in reality. However if one calculates the time that would be needed when using a GA and only the most accurate assessment tool, with 3 times the number of function evaluations needed (as in the application above) that makes 13500 function evaluations. Those evaluations performed with an assessment tool that takes 10 hours, results in 15.5 years, and that time, really is unfeasible. This comparison gives numbers that are out of the scope of any building professional; however, it has been done to illustrate that the CMA-ES-SA has potential, and that potential increases with the complexity of the problem and the complexity of the simulation package.

Table 5.9 - Hypothetical time share when running the CMA-ES-SA on a problem where the most accurate assessment tool takes 10 hours to run.

	Time	**Time in seconds**	**Function evaluations**	**Time**
Assessment tool 1 (Most accurate)	10 hours	36000	1500	54000000
Assessment tool 2	1 hours	3600	1500	5400000
Assessment tool 3	6 minutes	360	1500	540000
Assessment tool 4	36 seconds	36	1500	54000
Assessment tool 5	3.6 seconds	3.6	1500	5400
Assessment tool 6	0.36 seconds	0.36	1500	540
Assessment tool 7	0.036 seconds	0.036	1500	54
Assessment tool 8	0.0036 seconds	0.0036	1500	5.4
Assessment tool 9	0.00036 seconds	0.00036	1500	0.54
Total				**6.00E+07**

6 Closure

Contents

6.1 Summary

The research presented in this thesis is an attempt to increase the number of methodologies for modelling buildings and optimising their design. The motivation of doing so was found in the need for the building sector to produce low-energy buildings that would help tackling climate change by reducing emissions.

The simple, but yet accurate, dynamic simulators are easy to understand, require little computational time, and make the user aware of the physics of the problem. It is believed that if adopted these would help professionals who do not have the resources to employ a building physicist or purchase and learn to use expensive software packages.

Automatic optimisation of building design is a powerful tool, and can lead architects and engineers to low-energy designs; however, perspective should never be lost, and the professionals performing these optimisations should have always in mind what they are optimising and for what proposes.

The importance of uncertainties in building design motivated the learning and understanding about design under uncertainties. This thesis includes a new methodology that performs optimisation subjected to uncertainties for building design.

Also, the use of optimisation can have an important technical barrier that makes it unfeasible for most professionals namely long computational time. This thesis presents a method that uses models with different physical fidelity to accelerate the optimisation, making it more accessible to architects and engineers, even if they have not access to powerful computational resources.

The key outputs have been:

- An improved methodology to create Lumped Parameter Models of buildings that is more accurate and efficient than the alternatives in the literature
- An optimisation method capable of taking into account the occupants and with that produces building designs that are less likely to fail during their life span.
- An optimisation method that uses models with different complexity and self-adaptive optimisation to reduce computational times.

6.2 Conclusions

Several conclusions can be drawn from this research.

The methods shown in this thesis for the creation of simple dynamic models seems to be more accurate than the alternatives found in the literature; also, it has been seen that those models, can have very similar accuracy to the models used in more complex simulators such as EnergyPlus.

It has been seen that uncertainties have a substantial effect on the energy use calculated for design, and accordingly they have a substantial impact on the results of optimisation runs. The method shown in this thesis that performs optimisation taking into account the uncertainties (Chapter 4) is able to uncover solutions that would not be chosen by traditional optimisation. The building designs chosen with a traditional method might be uncomfortable for 11 out of 30 families; the design selected by the method created for this thesis does not fail substantially in any of the 30 test families used. It is true that the definition of the non-comfortable hours is a stochastic method, therefore the fact that a given number of families found the building uncomfortable is not deterministic; however, the solutions obtained with the method in this thesis will always have a superior acceptance than those obtained with optimisation with a single behavioural pattern.

The optimisation method presented in Chapter 5 introduces the use of several assessment methods using models with different physic fidelity in building design. This method is inspired by the resolution of problems in other disciplines, what means that there is a large literature. When the method was applied, the simple models developed in Chapter 3 were used this helped with the implementation of the methodology and made it even more effective. The use of sequential optimisation as shown in Chapter 5 can reduce computational times by more than 90%. This optimisation method replicates the natural design process where the assessment tools get more complicated as the project evolves and more variables have to be determined.

In general, it seems that to achieve low-energy buildings, it will be needed to treat design in a more technological way. The example of the *Passivhaus* shows standards with very strict requirements, and it has been seen that those buildings are successful in achieving low demands. After the research carried in this thesis, it could be said that the way we see buildings has to become more precise, if buildings are to be built with the energy demands that have been established by policy makers. It also appears that this new way of designing buildings, under much tighter standards, could borrow methods and techniques used previously in other disciplines in which the design and production has been highly controlled in the past (such as mechanical and aerospace engineering).

6.3 Further work

This thesis presents three new methods for building design. Although the methods have been validated in the application section, the author is aware that more examination of the methods would be needed before they can be deployed; however, the limitation in time and resources of this research did not allow a more thorough validation of the methods.

In the case that more research were done along the lines presented in this thesis, several things should be investigated.

The method shown here in Chapter 3 for the reduction of building models to LPM needs a comprehensive validation of the hypothesis taken in the method. Most authors use the first order model for the representation of a single slab of material; however, some of the publications found in the literature point in a different direction and suggest that this simplification is insufficient in accuracy. The validity of using the first order approximation instead of a second order should be tested.

The optimisation method that creates robust solutions has been applied on a “real-world” problem. The results of this application were satisfactory; however, more validation has to be done. The method needs to be tested on different problems, and also by increasing the number of uncertainties, for example varying the thermostat set point for each family or the way windows are opened.

The sequential optimisation method shown in Chapter 5 has been proven to work well. This methodology has been applied to a specific optimisation problem, and the optimisation was performed a number of times to ensure that the results were consistent. However, as in the previous methodology, it would be good to test the method for other applications and using different assessment tools.

6.4 Acknowledgments

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