Optimization Model for Sustainable Renovations in Buildings

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Abstract

An Optimization Model for Sustainable Renovations in Buildings

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Buildings consume a substantial amount of energy and adversely affect the global climate and environment. According to the US Department of Energy (DOE), buildings account for 39% of total primary energy consumption and 71% of the electricity consumption. The construction and operation phases constitute the largest proportion of the total energy end-use worldwide (Ma et al. 2012).

An innovative and comprehensive set of sustainable materials aiming at the envelope of buildings excluding the roofs is employed to define the renovation alternatives in order to ameliorate the sustainability status of the buildings. The model is comprised of a NSGA-II multi-objective optimization algorithm integrated into a simulation engine. Simulation runs are performed to compute the objective function values and transfer them to the optimization algorithm.

A hybrid fuzzy simulation-based optimization model is developed to select the optimum renovation alternatives. The model simultaneously minimizes annual energy consumption and capital cost of an existing office building based on a multi-objective optimization problem. Fuzzy set theory is assigned to the objective functions to address the uncertainty associated with calculation of energy consumption and capital cost values. Conclusively, the model is implemented on a sample case to substantiate the capabilities of the developed model. The case study is a one-story office building with a double skin facade on the south facing facade in Montreal. The results illustrate nine Pareto optimal points and demonstrate that the generated optimum solutions are capable of causing an average of 35% decrease in the annual energy consumption compared to the conventional building scenario.

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CHAPTER. 1 INTRODUCTION

1.1 Motivation

Energy is consumed in large quantities by households, industries, and business. Energy cost in Canada has been reported as $195 billion in 2013 (Natural Resources Canada, 2013). The energy has been used for heating and cooling purposes in official and residential areas. Additionally, it is used for the operation of appliances, vehicles, machinery and industrial processes. The $195 billion is approximately equivalent to 11% of Canada's gross domestic product (GDP) (Natural Resources Canada, 2013).

Buildings consume a considerable amount of energy and adversely affect the global climate and environment. According to Natural Resource Canada: “residential and commercial/institutional buildings consume about 30 percent of the total secondary energy use”**.** Consequently, they account for almost 29 percent of CO_2 equivalent greenhouse gas emissions. A similar situation is also observed in the United States, where buildings are responsible for 39 percent of the total primary energy consumption and 70 percent of the electricity consumption (US Department of Energy, 2009) About 38 percent of CO_2 emissions, 52 percent of SO_2, and 20 percent of NO_x are produced in the US as a result of energy consumption related to building sector. Apart from the physical need for performing upgrades, the environmental impact of existing building stock creates the need for implementing renovations to enable monitoring energy performance of aging buildings. Green buildings, in particular, have recently become the goal of renovations to prevent resource depletion as well as waste emissions. The goals that shape sustainable refurbishments include conserving resources, waste reduction, minimization of life cycle cost, and ensuring occupants comfort (Woolley et al. 1997).

Like any other construction project that necessitates evaluating the potential designs in the conceptual design phase, in order for the renovation measures to be effective and successful, their impacts must be evaluated in the design phase of renovation strategies. Hence, the impact of each renovation scenario on the finished building can be evaluated. In current renovation practices, designers choose to trust previous experience or building energy simulation programs to determine the suitable quantities of renovation scenarios. However, there are several problems associated with this course of action. Firstly, the previous experience is unable to cover all the feasible circumstances and mirror the complex interactions among different variables. Thus, they might bring about illogical conclusions. Secondly, with regard to the use of comprehensive energy simulation programs such as DOE, EnergyPlus and despite their capability of examining the impact of renovations alternatives on the energy performance of buildings, they are time-consuming. This is because the trial and error process of studying all available options and exploring the best solutions is ineffective. Furthermore, the precision rate would be very low due to the difficulty of exploring a very large search space (Konstantinou 2014).

To address the mentioned problem, this study intends to couple an optimization algorithm to an energy simulation program. This methodology allows finding the optimal or near optimal renovation solutions by exploring through the search space. Owing to the fact that achieving more sustainably developed building stock has become a common goal in the building sector, it drives the improvement of the existing building stock. Different sectors in building stock are perfect candidates for undergoing such transformation. Commercial, and residential buildings, for instance (Konstantinou 2014). Having contemplated the importance of decreasing energy demand of the building sector, the bigger challenge is determining the proper measures to perform the refurbishments in existing buildings.

The importance of considering existing building for performing the refurbishments is due to the fact that the renewal rate of the stock is often very low. Even though it depends on the region, the average rate is 1% per year. On another point, the conditions of existing buildings usually demand recurring restoration. A part of from the fact that existing buildings might suffer from several physical problems, most of them are in low energy and sustainability state. In North America, approximately 70% of the existing buildings are aged over 30 years.

This problem is highlighted by taking into consideration that it was following the energy crisis in the 1970s, that most building regulations were issued mandating thermal insulation of building envelopes (Poel et al. 2007).

The other sensible solution is demolition which is not suitable for aging buildings. With regard to wastes and materials, it is demonstrated by studies that demolition and reconstruction have more devastating impacts to the environment rather than the cycle extension of a building (Thomsen and van Der Flier 2008). Although a considerable amount of energy is consumed during the production and transport process, it is stored in the construction. In contrast, demolition denotes wasting all the energy away. Aside from the embodied energy, buildings are a sort of capital, hence demolition wastes both energy and capital.

For the mentioned reasons, in order to have lower energy consuming buildings with higher comfort standards, the existing buildings ought to undergo refurbishments. They require certain upgrades to have lower operating costs incurred by energy while their comfort, health, and safety is improved. Aside from lower energy and its respective costs, there are the social, and economic aspects of refurbishments. Moreover, technical, structural problems can be resolved as well as improved operational costs and internal conditions.

As the fossil fuel resources are rapidly declining, building industry as a major consumer of this source of energy is in dire need of undergoing radical changes to reduce its usage on fossil fuels. As shown above, concerning existing buildings, the first and foremost course of action to meet this goal is performing refurbishments on aging buildings with undesirable energy performance. To better manage energy demand and avoid depletion of resources there has been an inclination towards utilizing renewables sources of energy in the building industry in the past few years. Moreover, the escalation in Green House Gas (GHG) emissions has been another motive towards utilization of renewable energy technologies (Arndt, Baringer, and Johnson 2010) (Parry et al. 2007). In this study, the target of renovations is the building envelope as it constitutes the main portion of energy consumption. Two performance criteria are examined in this thesis: 1. Annual energy consumption and 2. The capital cost of renovation scenarios. Aside from renewable technologies such as PV panels, the integration of innovative materials and strategies in the envelope are studied.

1.2 Problem Statement

As mentioned in the motivation section above, the building sector constitutes a considerable proportion of primary energy consumed in many developed countries. According to the US Department of Energy (DOE) buildings are responsible for 39 percent of the total primary energy consumption and 70 percent of the electricity consumption (US Department of Energy 2009). Apart from the resource depletion, this unrestrained utilization of energy sources adversely impacts the environment. Since buildings are a major consumer of energy, they produce a sizeable proportion of Green House Gas (GHG) emissions, air pollutants, and solid wastes. For instance, in 2002, buildings in the US were accountable for nearly 38% of CO_2. With regard to existing buildings, most of them are in low energy and sustainability state. In North America, approximately 70% of the existing buildings are aged over 30 years.

When addressing the requirement of energy reduction in existing buildings by means of renovations, the common methodology is mostly using guidelines identified as general recommendations regardless of the unique features of each project. The protocols and regulations provide benchmarks for energy consumption behavior but fail to address information on requirements of their implementation in the design phase. In reality, however, every single project has to have access to detailed measures, and elaborately explained procedures as the location, project specifications, available budget and clients' preferences are different (Nemry et al. 2010). Another problem with using predefined guidelines instead of whole building energy analysis in the conceptual design phase is that the energy performance is an evaluation of energy performance takes place after determining renovation measures (Konstantinou 2014).

In case of using building performance assessment tools instead of guidelines, the decision-making process will occur based on mere energy performance. However, the cost factor is also a prohibitive factor in implementing renovation measures. Thus, for the successful implementation of sustainable renovations, all performance criteria must be taken into consideration. The process of finding the optimum solutions in terms of energy and cost form the fundamental problem this thesis is aiming to address. More specifically, discovering the optimum renovation alternatives while simultaneously minimizing annual energy consumption and capital costs defines the problem statement in this study.

1.3 Scope and Objectives

The overall goal of this thesis is to reduce annual energy consumption in existing buildings through sustainable envelope renovations. More elaborate objectives with their respective sub-objectives are as follow:

1. To reduce annual energy consumption in office buildings.
    1.1 Perform whole building performance assessment.
    1.2 Evaluate the renovation alternatives in the conceptual design phase.
    1.3 Define pertinent performance criteria to evaluate the proposed renovation alternatives.

2. To identify the optimum renovation alternatives.
    2.1 Perform optimization on proposed renovation alternatives to find the optimum solutions which are the trade-offs between the performance criteria (energy consumption and cost).
    2.2 Use of Building Performance Simulation (BPS) integrated into the optimization algorithm to reduce the computational time of the investigation.

3. Address the uncertainty associated with the performance criteria used in the optimization.
    3.1 Defining fuzzy set theory to address the uncertainty pertaining cost and energy consumption objective functions.
    3.2 Defining fuzzy membership functions of the unit cost for all renovation alternatives.
    3.3 Defining fuzzy membership functions of the u-value for all renovation alternatives.

A renewal project has various stages starting from project kick-off to the very last steps, such as operation and future maintenance. However, the scope of this research is limited to the renovation of the design process. This research aims at studying the renovations on an office building. It evaluates the proposed scenarios by assessing the two criteria- energy performance and capital costs- to identify the trade-off between these conflicting objectives. As mentioned earlier, the renovations are intended to cover the envelope of the building. Renovation scenarios consist of innovative material and strategies in the envelopes; to name a few, double façades, Building Integrated Photovoltaic panels (BIPV), PCM materials and so on. A large number of these scenarios rely on renewable energies, solar in this study. Wind energy is not considered since wind the access is restricted in urban environments as well as the lower geostrophic wind speeds and thereby lower generation capacity in comparison with rural areas.

1.4 Research Methodology

In this thesis to perform sustainable renovations in existing buildings, the alternatives for renovations addressing the envelope are defined. A building model is created in DesignBuilder, and the required input data for the simulation are added based on the ASHRAE standard. The objective functions of the consideration of uncertainty are defined. The fuzzy set theory is used to address the uncertainty involved in the cost and energy functions. The simulation engine, EnergyPlus, is integrated into the optimization algorithm, NSGA-II, in the DesignBuilder software. As for the optimization, the design variables which were previously defined are inputted. The objective functions are also defined in the optimization algorithm. As the optimization is initialized, the simulation engine calculates the amount of energy and cost functions for each set of variables and transfers the respective values to the optimization module simultaneously. Once the termination criteria of the optimization are met, the optimum solutions are displayed by a Pareto front. The Pareto front consists of several optimum scenarios each including the defined renovation alternatives.

1.5 Thesis Outline

This thesis is composed of 6 chapters. The next chapter will present a literature review on sustainable renovations, followed by energy and cost assessment tools, and finally by optimization algorithms. The third chapter describes the proposed model, and the fourth expands on energy and cost calculation performed by the simulation engine followed by the optimization algorithm. The fifth chapter presents the model implantation and results. Conclusively, the last chapter summarizes the entire study.

CHAPTER. 2 LITERATURE REVIEW

2.1 Energy Consumption in Building Sector

According to natural resources in Canada, there are two general types of energy use: primary and secondary. Primary energy use includes the total requirements for all users of energy. This also includes secondary energy use. Additionally, primary energy use refers to the energy required to transform one form of energy into another (e.g., coal to electricity). It also includes the energy used to bring energy supplies to the consumer (e.g., pipeline). Furthermore, it entails the energy used to feed industrial production processes (e.g., the natural gas used as feedstock by the chemical industries). In 2013, the total amount of primary energy consumed in Canada was estimated at 12,681 PJ (One petajoule is approximately equal to the energy used by more than 9,000 households in one year) (Natural Resources Canada, 2013).

With regard to Secondary energy use, natural resources Canada defines it as the energy used by final consumers in various sectors of the economy. Secondary energy use also includes the energy required to heat and cool homes or businesses in the residential and commercial/ institutional sectors. Secondary energy use accounted for about 70 percent of the primary energy use in 2013. (Natural Resources Canada, 2013).

During the operation phase of a building, there are two sources of secondary energy that are responsible for energy consumption: electricity and natural gas. In this study, the secondary energy is studied, and the source in question is electricity. According to the US Department of Energy, buildings account for 39% of total primary energy consumption and 71% of the electricity consumption. Among all phases in the life cycle of a building, the construction and operation phase constitutes a large proportion of total energy end-use worldwide (Ma et al. 2012). In the building sector, the larger proportion of energy is consumed by existing buildings (Konstantinou 2014).

Owing to the fact that the rate of replacement of existing buildings by the new buildings is 1-3% per year, an improvement of energy efficiency in existing buildings is of paramount importance for a reduction in global energy use, as well as environmental sustainability (Roberts 2008). A substantial amount of research has been conducted to explore energy efficiency opportunities with the goal of enhancing energy performance in existing buildings (Ardente et al. 2011). These studies reveal that the energy consumption in existing buildings can be significantly decreased through appropriate refurbishments (Xing, Hewitt, and Griffiths 2011). To account for resource depletion and energy waste, the philosophy of Green building design and Sustainability have been developed and practiced. (Woolley et al. 1997).

2.2 Innovative Sustainable Envelope

2.2.1 General

As mentioned before, renovating existing buildings with energy efficient component and strategy could significantly reduce the energy consumption of buildings. In this respect, several materials/ strategies used in the envelope which make contributions to energy saving are introduced.

High rise buildings usually have high energy consumption, caused by high heat losses during the heating season and high solar gains during the cooling season. Renewable energies and innovative material and strategies have recently been more focused on to reduce the energy consumption of high rise buildings, commercial and institutional in particular (Ioannidis 2016).

An effective means to the energy reduction is the development of low-cost photovoltaic panels that can be integrated into the building envelope. More precisely solar facades, opaque or transparent solar facades that can incorporate some of these technologies capable of producing thermal and electrical energy on site; such as building integrated photovoltaics (BIPV) and building integrated photovoltaics/thermal (BIPV/T) systems. Another type of technologies is the semi-transparent photovoltaics (STPV) windows that can allow partial passage of solar radiation through them and generate electricity simultaneously.

An example of a transparent solar façade is Double Skin Facade (DSF) that combine the active and passive features. According to Saelens et al., a DSF, as shown in the Figure 1 normally consists of an external and an internal skin separated by a cavity that is used as an air channel (Saelens et al. 2003). DSFs can give support to the reduction of the energy consumption of buildings by interacting with the adjacent zones and the environment (Ioannidis 2016).

Figure 1. An example of DFS in a new office building in the Netherlands [https://facadeworld.com/2014/03/15/solarlux-nijverdal/]

2.2.2 Double Skin Façades

According to Safer et al. a double skin façade (DSF) can be defined as a " special type of envelope, where a second skin, usually transparent glazing is placed in front of a regular building façade" (Safer, Woloszyn, and Roux 2005). The cavity between the two facade or skins is known as a 'channel'. To avoid overheating in cooling season and improve energy saving in cooling season, this channel is normally ventilated either naturally or mechanically and even by means of a hybrid system including both types (Omrany et al. 2016). The concept of a double skin facade was originally presented in the early 1900s. However, further progress made by the end of the 1900s was inconsequential. It has been in recent years that utilizing DSFs has become more prevalent in building envelope. The channel or cavity between the two skins can be airtight or ventilated (Chan et al. 2009). The ventilation could be forced or natural. The exterior skin is normally a toughened single glazed panel and may be fully glazed. The interior skin is commonly not forcibly fully glazed, however, double glazing with insulation. According to literature the optimum width of the gap between the two skins can vary between 200 mm to 2m and beyond (Chan et al. 2009). The principal advantage of an airtight DSF is increasing the building thermal insulation and reducing heat loss in winter. There are further benefits to DSFs as presented below (Shameri et al. 2011; Barbosa and Ip 2014; Ghaffarianhoseini et al. 2016).

- As the outer skin is generally fully glazed, this system offers an adequate visual connection with the outside environment.
- DSFs facilitate daylighting, as a large volume of daylight can enter the building without causing excessive glare.
- DSFs contribute to the aesthetic qualities of buildings.
- DFSs enhance indoor air quality through natural ventilation along with improved thermal comfort without any further electricity requirement.

Despite various benefits of DSFs, there are a few drawbacks to them as well, which are as follow:

- DSFs incur higher costs of design, construction, and maintenance in comparison with the conventional single facade.
- The application of DSFs entail higher weight o building’s structure
- DSFs though benefit from transparent qualities, they might cause overheating on sunny days since a higher cooling demand is brought about.
- The design process of DSFs can be a challenging task as several factors are to be taken into consideration, such as geometric parameters, glass selection, ventilation strategy, shading, daylighting, esthetics, wind loads, maintenance and cleaning cost expectations

2.2.3 Building Integrated Photovoltaics (BIPV, BIPV/T)

BIPV

Either for the purpose of being integrated into the building envelope or towards achieving net zero or near net-zero buildings, there has been a surge in the utilization of BIPVs in the building envelope in recent years. The BIPVs become part of the envelope by replacing parts of the conventional building envelope. These photovoltaics become the active part of the envelope, essentially by being mounted on facades or roofs (Jelle and Breivik 2012). Figure 2 depicts four types of BIPVs namely BIPV foil products, BIPV tile products, BIPV module products, and Solar cell glazing products.

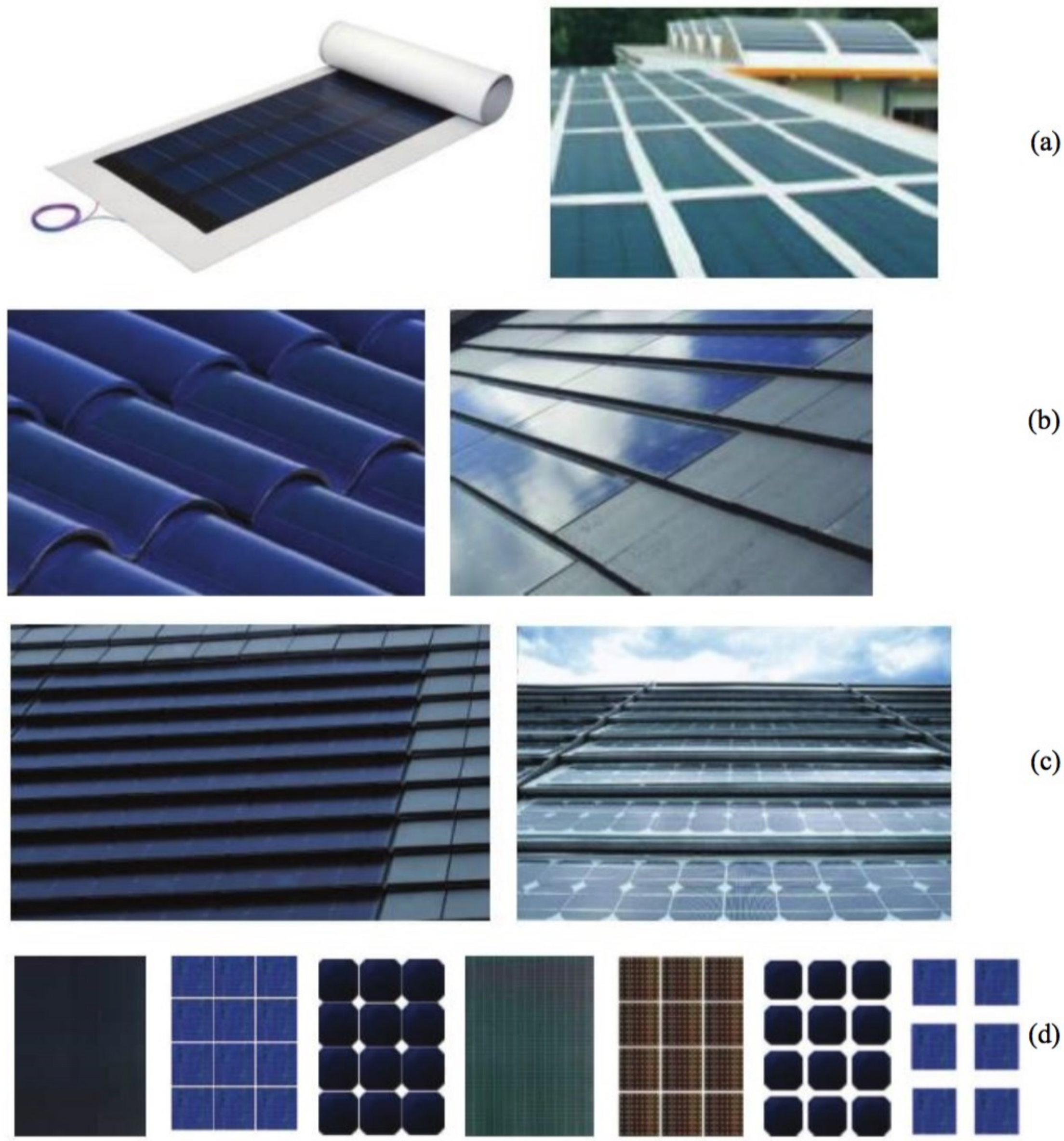


Figure 2. Four types of BIPVs. (a)Foil products, (b) BIPV tile products, (c) BIPV module products, (d) Solar cell glazing products (Jelle and Breivik 2012)

BIPV/T

Building Integrated Photovoltaic/ Thermal (BIPV/T) is a developing technology, combining electricity production, heat production and the integration of photovoltaics on the structure of the envelope of the building.

The structure of a BIPV/T involves a photovoltaic panel integrated at the exterior of the building envelope which forms a small cavity between the photovoltaic and the envelope of the building. Through this way, the air flowing inside the cavity eliminates heat from the photovoltaic, causing it to cool down. This procedure aids the system in two ways:

1. Increasing the efficiency of the photovoltaics, as they are sensitive to the increase of their temperature.
2. By Preheating the air that can be led into the HVAC system, hence reducing the energy consumption of the building.

An example of a BIPV/T is represented in Figure 3

Figure 3. BIPV/T demonstration project in a Concordia University building in Montreal. (Athienitis et al. 2011)

2.2.4 Switchable /Dynamic, Reflective Glazing

Switchable reflective glazing is essentially an adjustable tint glazing and is typically appropriate for cooling load dominant buildings with significant solar gain (Sullivan et al. 1995). In some kinds of switchable reflective glazing, the optical properties change as a function of the incident solar radiation, either by employing a low DC voltage (electrochromics (EC)) or by using hydrogen (gasochromics) to change from bleached to a colored state. In other kinds, light-based elements such as switchable reflective light shelves reflect solar radiation (Bahaj, James, and Jentsch 2008). A life-cycle energy analysis of 25 years was conducted on Electrochromic windows in Greece, which showed an energy reduction of 54%, compared to a standard window (Papaefthimiou, Syrrakou, and Yianoulis 2006). The payback period was found to be about 9 years, and the total energy cost savings ranged from 228 to 569 D/m^2 for 10 and 25 years of EC window operation. Innovation in window technology is dynamic, or switchable glass. Two control versions of electrochromic windows are currently available: 1. Electrochromic windows controlling solar gain by means of a transparent conductor placed between the glass panes that can be progressively darkened or lightened using an electric current. 2. The glass not allowing heat gain, however, remaining transparent. The window can be manually tinted or controlled by a mechanized procedure. It should be born in mind that there is a distinction between these windows and privacy glass, which uses liquid crystal technology to switch from clear to opaque, and has no capability of energy-saving (proremodeler.com).

2.2.5 Thermochromic Windows

Thermochromic windows are installed in many commercial, retail and residential buildings throughout the world. The thermochromic glass uses the heat from direct sunlight to tint the windows when required. As the sunlight becomes more direct and intense, the glass becomes darker. This function allows the windows to significantly reduce the heat load coming into the building and since the glass transmission adapts continuously over a range of temperatures, a natural balance and maximum use of daylighting is achieved. The aim of thermochromic windows is to help reduce glare, fading, noise, and to increase safety.

Thermochromic windows include a safety interlayer, built from extruded thermochromic materials into polyvinyl butyral (PVB). The layers were laminated between two pieces of tempered glass and mounted on an insulated glass element through a low emissivity coating. Because of the laminated design, this group of windows can be used as a building block to satisfy most of the building codes and design requirements. The interlayer can be laminated to nearly any tint or thickness of glass and used with high-performance Low-E coatings and specialty glass (www.commercialwindows.org).

2.2.6 Application of Phase Change Materials (PCMs) in wall systems

With their ability to materialize the goal of heating control, PCM materials have drawn attention in the last decade. The mechanism through which they function is absorbing the surplus energy and releasing it when there is an energy deficit. Accurate application of PCM materials in the building envelope makes contributions to the reduction of energy consumption together with retaining the comfort levels of the indoor environment in the conditions of minor temperature fluctuations. The most widespread use of PCM materials in buildings is in the installation of wallboards close to the interior side of the building envelope (Omrany et al. 2016). When these impregnated wallboards are placed inwards, PCM materials with their high thermal storage capacity can absorb and release the heat in the building for a major part of the day. The application of these wallboards in lightweight building structures that normally have low thermal inertia is favorable due to their adequate thermal storage capacity. PCMs can be classified into two broad categories of organic and inorganic (Xu, Li, and Chan 2015; Pielichowska and Pielichowski 2014). According to Xu, B., P. Li, and C. Chan organic compounds used for PCM include paraffin waxes, esters, acids, and alcohols; inorganic materials include salt hydrates, eutectics of inorganic salts, and metals and their eutectics (Xu, Li, and Chan 2015). PCMs made from organic mixtures generally have low melting points, and can merely be used for room-heating thermal storage. Inorganic compounds, on the other hand, are suitable for applications of high-temperature thermal storage (Bradshaw, Cordaro, and Siegel 2009). Several investigations have been conducted with the goal of discovering the effects of PCMs-based materials used in the building envelope on the overall indoor temperature and energy consumption.

Lee et al. (Lee et al. 2015) studied the thermal performance of south and west facing walls (in the northern hemisphere) equipped with a thin layer of PCM. 'PCM thermal shield (PCMTS)' was included into the wall through a thermal shield, using which the PCM was included in thin sealed polymer pouches, formed in sheets laminated with aluminum foil on both sides. The PCMTSs were installed at five locations, one at a time, at various depths inside the wall cavities of the south and west facing walls. Two identical test cases were utilized to experimentally assess the thermal performance of south and west facing walls with and without PCMTS. According to Lee et al. results suggested that at the optimal location of PCMTS, the peak heat flux reductions were 51.3% and 29.7% for the south and the west walls, respectively (Lee et al. 2015).

Mandilaras et al. examined a typical double-story residential located in Greece. The Walls comprised of multiple layers of insulation materials and gypsum plasterboard panels including PCMs (BASF – MicronalR PCM melting point of 23 °C) for the goals of thermal energy storage (Mandilaras et al 2013). Sensors were installed in different locations of all external walls so that detailed temperature measurements could be provided. To only focus on thermal characterization of the walling system, the building was left closed, unoccupied, without any energy systems installed. It is demonstrated that within the predicated conditions, the thermal mass of the walling system was enhanced during late spring, early summer and fall, due to the PCM implementation, also leading to a decrease of the decrement factor by a further 30–40% and an increase in the time lag of approximately 100 mins.

2. 3 Challenges in Sustainable Renovations

Renovation of existing building may be a desirable solution to energy waste. However, it has numerous challenges. Aside from uncertainties such as climate change, services change, human behavior change, government policy change, etc.; the subsystems in buildings have high interactions. Different renovation scenarios may exert different impacts on building subsystems caused by the mentioned interactions. Hence, the selection of renovation actions become very complex. Handling these interactions is a significant challenge in the practice of performing renovations. Furthermore, a decision made at the conceptual design phase by evaluating various design alternatives have major effects on the building performance, energy performance in particular.

Among other obstacles in conducting green renovations, is the budget limitations. The inclination of owners to burden costly retrofits merely to achieve energy efficient buildings is another setback in this respect. In addition to interactions of sub-systems in a building, the interrelationships among various design parameters, a multitude of performance criteria, and the existence of different life cycle stages render the renovations in existing buildings a complex and elaborate task.

2.4 Building Performance Simulations (BPS) and Optimization in Renovations

Owing to the fact that the goal of energy assessments and analyzing building performance is achieving energy-efficient buildings, the methods through which enhancement options are evaluated ought to be taken into close consideration. Generically dividing these methods, they are either parametric simulations or iterative ones. The former approach alternates each variable input while the rest are remained constant to monitor the results of objective functions. Subsequently, this procedure is repeated for all other variables. A major drawback of this approach is being time-consuming as well as delivering only partial improvements. The reason for this partiality is complex and non-linear nature of interactions among design variables. The latter approach, iterative methods, are used as a solution to this problem. These methods can deliver optimal or near-optimal solutions to a problem using less time and effort. In this category, improved approximations to a solution are infinitely generated by the points in the search space meeting all optimality criteria. Since the nature of these practices is iterative, computer programming is regularly used to facilitate the process. In whole, the above-mentioned methods are recognized as "simulation based-optimization" or "numerical optimization" (Nguyen, Reiter, and Rigo 2014).

Consequently, a computer-based tool or methodology which is capable of assisting designers in the conceptual phase of green building design is required to enhance the performance of existing buildings through sustainable renovations (US Department of Energy, 2009). Simulation programs which include whole building assessment ensure that all interactions among systems and components in a building are considered in addition to taking into account the interrelations among various renovation alternatives. A further advantage of simulation programs is their ability to address performance criteria such as cost goals. In other words, simulation programs pave the way for proper evaluation of the renovation alternatives. Despite the availability of simulations assessing building retrofit technologies, the selection of such renovation alternatives is another problem to resolve. This decision to select which set of renovation measures should be used for a specific case is a multi-objective optimization problem. This optimization problem could be subject to many constraints and limitations, and energy saving is not the only criterion. The optimum solution is a trade-off among different objectives such as economic and energy-related objectives. Furthermore, the text-based format of inputs and outputs in simulations simplifies their integration with optimization.

There have been several studies investigating the implementation of renovations through building simulation programs and optimization. Some of the simulation programs include EnergyPlus, TRNSYS, DOE-2, ESP-r, EQUEST, ECOTECT, DeST, Energy-10, IDE-ICE, Bsim, IES-VE, PowerDomus, HEED, Ener-Win, SUNREL, and Energy Express (Crawley et al. 2008).

The result of an interview of 28 building optimization experts (Attia 2012) showed that GenOpt (Wetter 2003) and MatLab environment (Beale, Hagan, and Demuth 1992) is most commonly used in building optimization. GenOpt is a free generic optimization tool designed to apply to build optimization problems (BOPs). Thus it is suitable for many purposes in BPS with acceptable complexity. A constraint of the current GenOpt versions is that it does not involve any multi-objective optimization algorithm. As with Matlab optimization toolboxes and Dakota (Adams et al. 2009), since they are not specifically designed for building simulation-optimization; they necessitate more complex skills to use. The Neural Network toolbox in Matlab and the surrogate functions in Dakota enable utilization of a surrogate model. However, in the case of integration with the optimization module, using the surrogate models introduce fitting error which is the product of variation of the surrogate model from actual simulations and can dramatically undermine the accuracy of the method. For this reason, in this study simulation engines are utilized to calculate the objective function values and simultaneously transfer them to the optimization platform.

In the field of assessing renovations in buildings, Ascione, Bianco et al. performed a GA optimization on the thermal comfort and annual primary energy demands for the space heating and cooling. They studied several variables with regard to the HVAC and ventilation systems as well as insulation levels. Even though they defined several budget scenarios, they did not directly include a cost objective in the optimization process. Furthermore, the range of variables indicating energy efficiency measures does not encompass a wide range of innovative sustainable materials or strategies. Lastly, the concept of uncertainty was not taken into account for any parameters (Ascione et al. 2015). Abdallah, El-Rayes et al. investigated green building upgrade measures with the aim of reducing Carbon emissions and energy consumption through a GA optimization. The upgrade measures mainly covered HVAC systems, water heaters, lighting and did not concentrate on the envelope. Moreover, the cost limit was defined as fixed budget scenarios rather than an objective function in the optimization. Moreover, the uncertainty issue was not discussed (Abdallah, El-Rayes, and Clevenger 2015). A study on Energy consumption optimization in schools sector in Jordan by Ali Al-Arja and Awadallah in 2016 discovered optimum renovation solutions addressing energy consumption and thermal comfort, leaving out a cost objective. Several limitations are associated with this research; first and foremost alternatives are evaluated through a parametric study rather than a multi-objective optimization. Secondly, a lack of a wide range of renovation alternatives is evident. Furthermore, the cost criterion is not studied in the evaluation. Finally, no uncertainty analysis is performed, (Ali Al-Arja and Awadallah 2016). Sharif and Hammad investigated a simulation-based optimization of building's renovations considering an extensive range of alternatives including both envelope and HVAC and ventilation systems. However, they did not address uncertainty with either cost or energy objective (Sharif and Hammad). Marzouk and Abdelkader assessed minimizing construction emissions using building information modeling and decision-making techniques without taking into consideration the uncertainty involved in the calculation of energy consumption (Marzouk and Abdelkader 2017). Conclusively, for most of the mentioned studies, the energy consumption comprised of heating and cooling demand. However, this research considers the consumed energy with respect to lighting, plug loads, etc. in addition to the heating and cooling demand.

2.5 Uncertainty Involving Cost and Energy Consumption

In a construction project the cost, duration, energy consumption of buildings and several other variables are subject to change due to several parameters such as weather, resource availability, etc. (Zahraie and Tavakolan 2009). Hence, performing risk analysis in construction is very common. Conventionally, probability theory has been applied in handling uncertainty with respect to simulation model inputs (Sadeghi, Fayek, and Pedrycz 2010). A limitation regarding probability theory, restricting its use is the case where the number of experiments is not sufficiently large. Moreover, the requirement of the human experts, with subjective and linguistically expressed data necessitates other approaches rather than probability theory as they are not appropriate for objective scientific conclusions due to their subjectivity and ambiguity (Sadeghi, Fayek, and Pedrycz 2010). In contrast, Fuzzy set theory introduced by Zadeh offers a methodical approach for handling subjective and linguistically parameters for expressing uncertainty in the absence of precise and complete information (Zadeh 1975). A fuzzy set *A* on the universal set *X* is defined by its membership function μ(*x*) and represents the degree that *x* belongs to the fuzzy set. In probability theory, however, a probability density function (PDF) is defined on continuous variables. The area under the curve of a PDF can be used to discover the probability that a random variable falls into a particular interval (Sadeghi, Fayek, and Pedrycz 2010) (Pedrycz and Gomide 2007). Figure 4 introduces a PDF and a fuzzy membership function. In fuzzy set theory, in lieu of representing the probability value, the degree to which the objects belong to the properties of the fuzzy set is represented (Pedrycz and Gomide 2007). Consequently, despite the ability of probability theory to manage the information gained from historical data, fuzzy set theory is able to represent the imprecise information of experts' judgments.

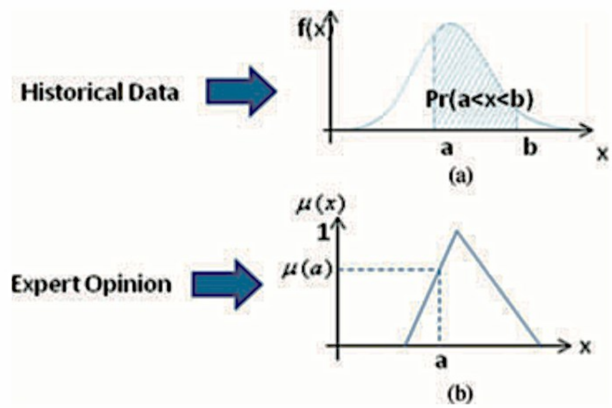


Figure 4. (a) A Probability Density Function (PDF), developed based on historical data. (b)A fuzzy set developed based on experts' judgment (Sadeghi, Fayek, and Pedrycz 2010)

2.6 Optimization

Optimization is the procedure of finding the minimum or maximum value of a function by choosing a number of variables subject to a number of constraints. The optimization function is called cost or fitness or objective function and is usually calculated using simulation tools. Because of code features, the results may be non-linear and have discontinuities, making necessary the use of special optimization methods that don't require the computation of the derivatives of the function. Optimization methods can be applied to several different building design problems such as massing, orientation, façade design, thermal comfort, daylighting, life cycle analysis, structural design analysis, energy and of course cost. The structural design (i.e., selection of beam/columns cross-section) and building controls (operation/scheduling) optimization are not part of the present review. However, in some of the reviewed cases optimization of both building design and setpoint scheduling or more advanced multi-disciplinary optimization was applied (Machairas, Tsangrassoulis, and Axarli 2014).

Optimization investigates the types of problems which involve the minimization or maximization of one or multiple objectives that are functions of several variables. This procedure is performed systematically by selecting proper values of real or integer variables in an acceptable set.
Multi-objective optimization handles simultaneously two or more contradictory objectives within a certain set of constraints (Bandyopadhyay and Saha 2012).

2.6.1 Optimization Techniques

According to Goldberg (Holland and Goldberg 1989), Optimization techniques can be categorized into three groups: enumerative methods, calculus-based methods, and guided random search techniques. All of which are discussed below.

2.6.1.1 Enumerative Methods

In these methods, the algorithm sequentially evaluates the objective function within a finite search space, or a discretized infinite search space, at every point in the space. However, methods of this type lack real-world applicability. Even though they propose an improvement on basic trial-and-error heuristics, they are unable to assess the whole search spaces, especially in the field of building design as they are often too large. For this reason, this technique cannot be a practical proposition (Bandyopadhyay and Saha 2012).

2.6.1.2 Calculus-Based/Numerical Methods

Numerical methods, also called calculus-based methods, are sometimes considered ‘‘systematic” (Nielsen 2002) and rely on the mathematical expression of objectives, or their gradients. Their goal is to meet a set of necessary and sufficient conditions that must be satisfied by the solution of the optimization problem (Bourazza 2006) (Goldberg and Holland 1988).

Numerical methods can be further divided into two categories, namely direct and indirect methods. Direct search methods perform moving in the function space by moving in a direction related to the local gradient. In indirect methods, the solution is obtained by solving a set of equations resulting from setting the gradient of the objective functions equal to zero. The calculus-based methods are local in scope and also presume the derivatives exist (Bandyopadhyay and Saha 2012).

Several researchers have used this method in the field of building design. Bolattürk (Bolattürk 2006) optimized the thickness of insulation layers by this method in which a mathematical expression of the life-cycle cost was produced, the derivative was calculated, and the optimum value is the one for which the derivative is zero. The ‘‘simplex” method and its variants, such as the Hooke-Jeeves method, were used by Peippo et al. (Peippo, Lund, and Vartiainen 1999) to optimize the design of solar low-energy buildings, using the objective function of capital and energy costs. Bouchlaghem and Letherman (Bouchlaghem and Letherman 1990) investigated the building envelope and used analytical and graphical methods to optimize its thermal performance.

The main disadvantage of these methods is that the possibility of convergence relies on the regularity of the objective functions, which, as a result, must have an explicit expression, or permit derivatives. For this reason, their application is mainly restricted for many practical problems, although they can be very efficient in a small class of unimodal problems.

2.6.1.3 Guided Random Search Methods

These methods are based on enumerative methods. However, they benefit from additional information concerning the search space to guide the search to potentially acceptable regions of the search space (Bandyopadhyay and Pal 2007), (Holland and Goldberg 1989). These methods can be further subdivided into two classifications, namely single-point search and multiple-point search, dependent on whether it is searching just at one point or with several points at a time. Simulated annealing is a popular example of a single-point search technique that uses thermodynamic evolution to search for the minimum-energy states. Evolutionary algorithms such as genetic algorithms are well-known examples of multiple-point search, where according to Bandyopadhyey et al (Bandyopadhyay and Pal

2007) “random choice is used as a tool to guide a highly explorative search through coding of the parameter space.” The guided random search methods are practical in tackling problems where the search space is large, multimodal, and discontinuous, and where a near- optimal solution is acceptable, rather than a true optimal.

2.6.2 Multi-Objective Optimization

Definition

The stochastic search technique usually used for multi-objective optimization is divided into single point search and multiple point search. Moreover, the multiple point search includes Evolutionary Algorithms. Several algorithms form this category namely GAs (Genetic Algorithms), Particle swarm optimization, Simulation annealing (SA), Ant Colony, and Harmony Search Algorithm.

2.6.2.1 Genetic Algorithms

A genetic algorithm is a commonly used an evolutionary algorithm that takes advantage of the principle of natural selection to evolve a set of solutions towards an optimum solution (Holland and Goldberg 1989). Genetic algorithms (GA) are population-based algorithms, and they can efficiently handle non-linear problems with discontinuities and many local minima; for this reason, they are broadly used in the field of building optimization. Wright and Farmani (Wright and Farmani 2001) used GA for simultaneous optimization of the fabric construction, HVAC system size and the control strategy. Coley and Schukat (Coley and Schukat 2002)used GA to minimize annual energy use while Znouda et al. (Znouda, Ghrab-Morcos, and Hadj-Alouane 2007) optimize the design of Mediterranean buildings. Oliveira Panão et al. (Panão, Gonçalves, and Ferrão 2008) used GA for the optimization of the urban building efficiency potential and Rakha and Nassar (Rakha and Nassar 2011) to optimize the ceiling form to achieve predefined daylight uniformity. Pernodet et al.

Genetic algorithms have various variations, some of which are Pareto and some non-Pareto which will be discussed as follow.

2.6.2.1.1 VEGA (Vector Evaluated Genetic Algorithm)

This population-based non-Pareto algorithm includes a special selection operator in which several subpopulations are generated by employing proportional selection according to each objective function. VEGA was the first multi-objective genetic algorithm devised for tackling multi-objective problems (Schaffer 1985).

2.6.2.1.2 MOGA (multi-objective genetic algorithm)

In this Pareto based, non-elitist approach, an individual is assigned a rank associated with the number of all individuals in the current population that has dominated the individual and is summed with1. Also, a niche method is used to distribute the population over the Pareto optimal area. The drawback of this method is the very low convergence rate as well as problems with niche size parameters (Erickson, Mayer, and Horn 2002).

2.6.2.1.3 Niched Pareto GA (NPGA) To select the winner between the two candidate solutions, a Pareto dominance-based tournament selection with a sample of the population is used. IF the tournament has same results for both candidates, the outcome is decided through fitness sharing. The drawback, again, is selecting an appropriate value of the niche size parameter (Erickson, Mayer, and Horn 2002).

2.6.2.1.4 Non-Dominated Sorting GA (NSGA)

In this approach to select the non-dominated solutions. All non-dominated individuals are classified into one category, with a dummy fitness value proportional to the population size. This group is then eliminated, and the remaining population is classified again. This process is reiterated until all the individuals in the entire population are classified. The selection operator is stochastic remainder proportionate. Even though the method has a very high convergence rate, it suffers from problems related to the niche size parameter, similar to previous approaches (Srinivas and Deb 1994).

2.6.2.1.5 NSGA-II (Elitist Non-dominated Sorting GA)

This Pareto based, an elitist approach which was proposed to remove the weaknesses of NSGA, especially its non-elitist nature and requirement of the sharing parameter. In this approach, the individuals in a population undergo non-dominated sorting as in NSGA, and individuals are given ranks based on this. A new selection technique, called crowded tournament selection, is proposed where the selection is made based on crowding distance (representing the neighborhood density of a solution). To implement elitism, the parent and child population are combined, and the non-dominated individuals from the population are propagated to the next generation. NSGA-II is one of the widely used MOO algorithms and is the method used in the thesis. It will be further explained in the methodology chapter (Deb et al. 2002).

2.7 Limitations of Previous Studies

Having conducted an assessmment on the previous research works in the field of renovations in buildings several gaps are discovered as described below:

- The uncertainty associated with the evaluation of objective functions in the optimizations has not been investigated.
- There is an absence of an innovative comprehensive set of sustainable materials as the renovation alternatives.
- In many research works, parametric studies were performed instead of optimization.
- Several studies did not address the envelope and merely focused on the HVAC systems.
- A lack of whole building performance analysis was observed in various research works.
- The cost objective was not considered as a performance criterion while assessing renovation alternatives

2.8 Summary

Conducting a literature review, it is revealed that energy assessment of renovation methods requires more efficient methods compared to simple trial and error or parametric study and iterative approaches. For this reason, a Building Performance Simulation (BPS) is used to evaluate the energy performance and address all the interactions among subsystems and building components. Within the process of renovation, since the innovative materials and strategies have not been widely used, they will be considered due to their potential to significantly reduce the energy consumption of buildings. With respect to the optimization algorithm, the Non-Dominated Sorting Genetic Algorithm (NSGA-II) is selected owing to the fact that it can handle large search spaces, continuous and discrete variables, and benefit from the elitist approach in contrast to the traditional GA. Finally, consideration of uncertainty involved with the objective functions' parameters is required to provide more precise results. In this study, the fuzzy set theory is integrated into the NSGA-II algorithm to address the mentioned uncertainties.

CHAPTER. 3 MODEL DEVELOPMENT

3. 1 Overview

The target end-users for the proposed model are designers, architects, or facility managers or their consultants. The renovations are related to the maintenance phase in the life cycle of a building as shown in Figure 5. To find the optimum solutions of renovating an existing building, the genetic algorithm is selected as the optimization method to handle the large search space of renovation alternatives, as well as addressing both discrete and continuous variables.

a genetic algorithm (NSGA-II) is used for the optimization, while a detailed whole-building simulation program, EnergyPlus in the DesignBuilder platform, is used for energy and cost analysis.

The simulation-based optimization system functions by means of 3 modules. The DesignBuilder is the platform in which optimization, data files, and simulation engine can intricately collaborate. The input and output are the means of connection with users; the optimizer module facilitates the optimization algorithm (NSGA-II), and the simulation program evaluates the objective functions, and the data files store the data required by the simulation program and the optimization algorithm (NSGA-II). All the modules are closely interrelated. To initiate the optimization process, optimization parameters, decision variables, and simulation inputs must be defined by referring to data files. As the optimizer module is initiated, close interaction is formed between the NSGA-II (optimization algorithm) and simulation engine (EnergyPlus). To be able to assess fitness values for all variables, the optimization module transfers the variables to the simulation module to evaluate their objective functions, and subsequently, they are returned to the optimization module. The two objective functions are assumed to consider the uncertainty. To address the uncertainty concerning the capital cost objective, the parameter “unit cost” which is used in the calculation of the cost objective for each renovation alternative is assumed to be a fuzzy number. The same assumption is held for the “u-value” parameter involved in the energy consumption calculations. Both these parameters are then defuzzified to be used in the simulation and optimization calculations. In the course of the simulation process, the simulation engine might regularly access data files (simulation parameters) to define the entity represented by a variable. When the mentioned values are calculated, they are sent back to the optimization for a fitness assessment. Consequently, after several iterations, the optimum or near optimum solutions are discovered and represented by the Pareto front. Figure **6** pictures a summary of the proposed model.

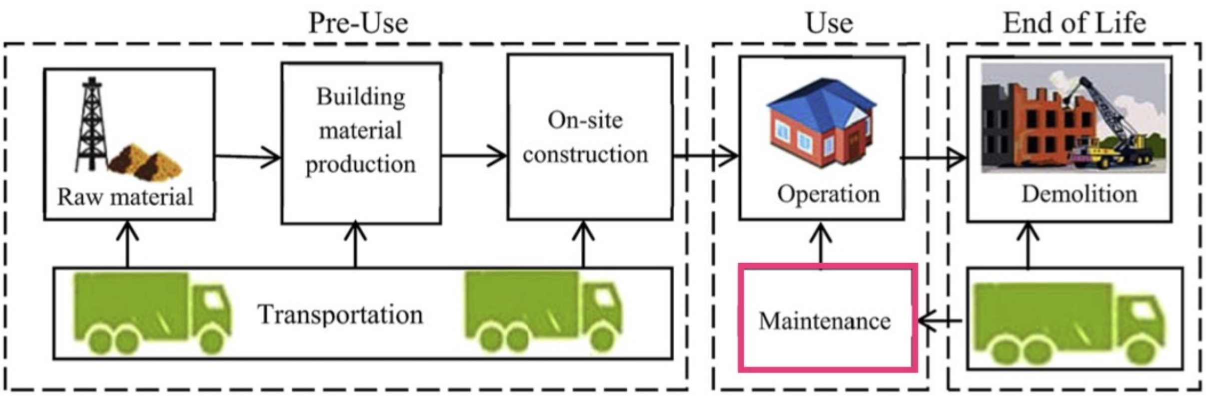
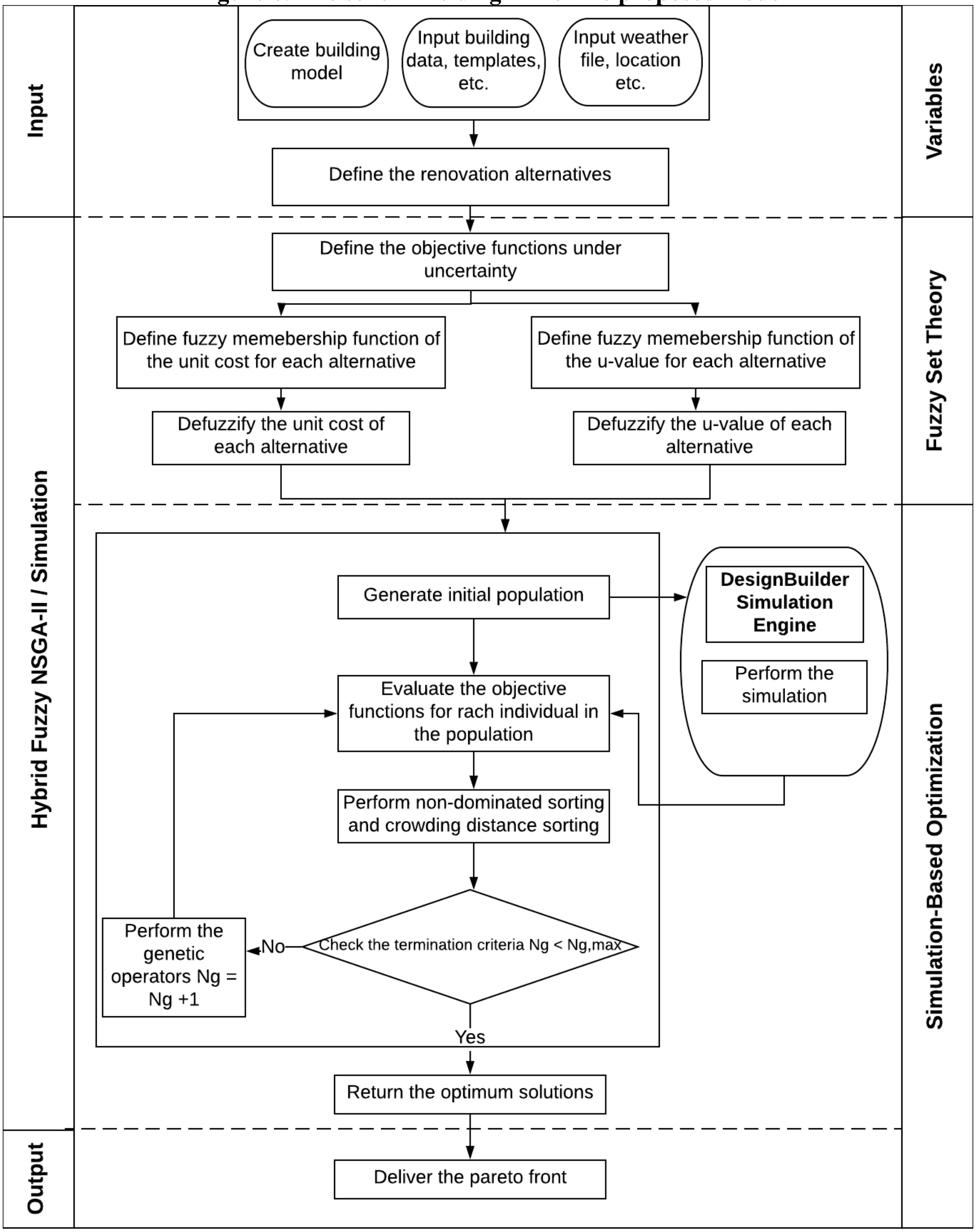


Figure 5. The life cycle of buildings (Fesanghary, Asadi, and Geem 2012)

3.2 Proposed Model

The aim of the proposed model is to identify the sets of renovation alternatives capable of minimizing capital constriction cost and annual energy consumption simultaneously in an existing office building. This thesis studies the renovation measures aimed at the envelope of the building excluding the roof. The renovation actions are mostly related to external walls and glazing, each of which is categorized in several types of innovative sustainable materials and strategies. Figure **6** describes the proposed model followed by a brief description of each step.

Figure 6. The schematic diagram of the proposed mode



Step 1: Creating the building model and inputting the relevant data

In the initial step, the building model is created in DesignBuilder. The required input data such as location, weather file, occupancy rates, as well as the ASHRAE standard templates, HVAC template, etc. are entered in the model.

Step.2 Defining the variables

Using the input data, the variables representing renovation alternatives are defined, forming the database for the simulation and optimization algorithm.

Step. 3 Defining the objective functions under uncertainty

Both capital cost and annual energy consumption objectives are assumed to incorporate uncertainty. To address the mentioned uncertainty, a fuzzy set theory is assigned for both objectives. A fuzzy membership function taking the shape of a triangular distribution is considered for the fuzzy sets. To defuzzify the fuzzy numbers, the graded mean integration approach is utilized, and the center of the area is identified. The defuzzified value for both parameters of cost and energy objectives is used in DesignBuilder for the computation of capital cost and annual energy consumption. Further details are provided in section 3.2.2.

Step. 4 Initializing the optimization

The NSGA-II is initiated, and GA parameters such as population size, the number of generations, crossover and mutation probability are specified. An initial population which is a set of possible individuals (renovation scenarios each consisting of decision variables) is randomly generated. In case constraints exist, the individuals will be checked against them.

Step. 5 Performing energy simulations integrated into the genetic algorithm

Energy simulations are performed for each set of variables. All individuals in the population which are decoded into their corresponding design are used for an annual simulation. The objective functions of each induvial are calculated by the simulation engine and simultaneously transferred to the optimization algorithm to be used for genetic algorithm fitness evaluation.

Step. 6 Perform non-dominated sorting and crowding distance

To sort all members of a population based on the values of their objective functions, the NSGA-II algorithm utilizes the non-dominated sorting algorithm to compare individuals. Afterward, according to crowding distance, the selected non-dominated solutions which are most widely spread are introduced to the offspring population.

Step. 7 Checking the termination criteria and constructing the Pareto front

If the number of iterations (N_g) is not equal to the maximum value ($N_{g,\ max}$), the individuals will go through crossover and mutation, and the algorithm will be repeated from step 5, otherwise the optimization process is terminated, and the non-dominated solutions at the last generation are designated as Pareto optimal set.

3.2.1 Model Inputs

The inputs required in the proposed model are divided into two categories: building model inputs and renovation alternatives, and the latter form the decision variables. Both categories will be explained in the following sections.

3.2.1.1 Building Model Inputs

In order for a building to operate in the simulation software, various parameters are to be set. After creating the 3D plan of a building in DesignBuilder, different properties of building systems are required to be defined. HVAC size and properties, activity templates, occupancy data, lighting template, etc. are some of the fundamental building model inputs. Table 1 summarizes several model inputs used.

Table 1. Simulation parameters and inputs

Location	QC, Montreal/ Mirabel INT' LA. ASHRAE climate zone: 6A
Occupancy schedule	Office_OpenOff_Occ
Weather data file	Montreal Mirabel PQ CAN WYEC2-B-75290 WMO#=716278
Simulation period	Annual simulation (Jan 1- Dec 31)
Solution algorithm for heat transfer	Finite difference
Solar distribution	Full interior and exterior
HVAC template	Fan coil Unit (4-Pipe), Air cooled chiller
HVAC heating set point	22℃
HVAC cooling set point	24℃

3.2.1.2 Renovation alternatives

The decision variables indicate the set of alternative measures that are available for building renovations. Several building renovation studies place emphasis on determining the suitable range and measurement of each component. For instance, those methodologies are defined in such a way to determine the optimum width of an external wall or sizing of a certain fenestration type. In this research, on the other hand, decision variables are defined based on the material types and strategies. Accordingly, the problem was sought to address the selection of renovation measures based on the sustainable components.

Decision variables are specified as the elements in a building envelope that play the most prominent role in causing higher energy consumption rates. To precisely pinpoint the aforementioned elements in an envelope is a challenging task as it involves numerous choices.
In building optimization, typically building parameters are defined as continuous variables merely since in numerical optimization methods it is difficult to deal with discrete variables (Fesanghary,

Asadi, and Geem 2012). In this research, however, the GA algorithm is selected to handle the discrete variables rather than avoiding discrete variables. Each variable is defined according to the materials and systems used in different layers (such as external walls and internal and external glazing). Consequently, each decision variable is associated with a table describing its construction (except window-to-wall ratio as it is a continuous variable).

The common elements in envelopes with the highest impact on energy consumption are found to be as follow (Asadi et al. 2014):

- window to wall ratio;
- external wall;
- glazing;
- orientation;
- shading;
- the windows type;
- the solar collector's type.

In the case of this thesis, the following decision variables in Table 2 are used and the options they cover consist of innovative material and strategies.

Table 2. Renovation alternatives (decision variables)

Variable	Variable type	Category	Variable ID	Construction detail
External wall	Discrete	PCM walls	InnoExW-PCM. 1-3	- Curtain wall (Spandrel glass, Insulation board, BioPCM- M, Gypsum board) - Curtain wall (Metal wall panel, Insulation board, BioPCM- M, Gypsum board) - Curtain wall (Stone, Insulation board, BioPCM- M, Gypsum board)
			InnoExW-PCM. 4-6	- Stud wall (metal wall panel, sheathing, batt insulation, BioPCM- M, gypsum board) - Stud wall (Wood siding, sheathing, batt insulation, BioPCM- M, wood) - Stud wall (Stucco sheathing, batt insulation, BioPCM- M, gypsum board)
			InnoExW-PCM.7-9	- EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, BioPCM-M, gypsum board) - EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, batt insulation, BioPCM-M, gypsum board) - EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, Lightweight concrete block, BioPCM-M, gypsum board)
			InnoExW-PCM.10-19	- Brick wall (Brick, insulation board, sheathing, gypsum board) - Brick wall (Brick, insulation board, sheathing, batt insulation, BioPCM-M, gypsum board)
			InnoExW-PCM. 20-25	- Concrete block (LW concrete block, batt insulation, BioPCM-M ,gypsum board) - Concrete block (stucco, HW CMU, fill insulation, gypsum board)
			InnoExW-PCM. 26-34	

				- Pre-cast and cast in place concrete block
		BIPV Walls	InnoExW-BIPV. 1-10	- Brickwork, Photovoltaic panel, XPS Extruded Polystyrene- CO2 Blowing, Concrete block, Gypsum plastering
		BIPV + PCM Walls	InnoExW-BIPV-PCM. 1-5	- Brickwork, Photovoltaic panel, XPS Extruded Polystyrene- CO2 Blowing, BioPCM-M/Q, Gypsum plastering
Glazing template	Discrete merge	Double glazing	InnoGlzTemp- Dbl. 1-20	-Double Glazing, Clear, Electrochromic (absorptive) switchable -Double Glazing, Clear, Electrochromic (reflective) switchable -Double Glazing, Clear, LoE, argon filled
		Triple glazing	InnoGlzTemp- Trp. 21-35	- Triple Glazing, Clear, - Triple Glazing, Clear, LoE, argon filled - Triple Glazing, Clear, LoE, argon filled+ BIPV - Triple Glazing, Clear, LoE, argon filled+ Thermochromic
		Quadruple glazing	InnoGlzTemp. 36	- Quadr, LoE, Krypton
		BIPV glazing	InnoGlzTemp. 37-42	- Triple Glazing, Clear, LoE, argon filled+ BIPV - Doble, Clear, BIPV
External glazing	Discrete	Pane material Gas Color	InnoExGlz. 1-60	Dbl, Air/Argon Dbl Elec Abs/Ref, Air/Argon Dbl LoE, Air/Argon Dbl LoE, Elec Abs/Ref, Air/Argon Electrochromic, absorptive Electrochromic, reflective LoE (coated) Thermochromic: Triple (thermo, air, thermo, air, clr
Internal glazing	Discrete		InnoIntGlz. 1-55	Dbl, Air/Argon Dbl Elec Abs/Ref, Air/Argon Dbl LoE, Air/Argon

				Dbl LoE, Elec Abs/Ref, Air/Argon Electrochromic, absorptive Electrochromic, reflective LoE (coated) Thermochromic: Triple (thermo, air, thermo, air, clr) Clear glass
Internal thermal mass	Discrete	BioPCM continuous layer	Inno. InternalThermalMass. 1-19	Concrete, BioPCM-M, Continuous layer
		Traditional construction (concrete)	Internal ThermalMass. 20-42	Concrete slab Reinforced concrete slab
Partition construction	Discrete			BioPCM-M, Continuous layer Expanded wood chipboard Brick cavity wall Reinforced concrete Single leaf brickwork Fiberboard, cavity Gypsum plasterboard, cavity
Facade type	Discrete			% fitted glazing % vertical glazing curtain wall, % glazing fixed height 1/1.5m. 20/30% glazing fixed window Horizontal strip, %glazed Preferred height, %glazed
Window to wall ratio	Continuous			20-100%
Shading (window blind)	Discrete		InnoShd. 1-50	- Electrochromic switchable - SageGlass Electrochromic - Slatted Blinds

				- Transparent Insulation
Window frame	Discrete			UPVC Aluminum PVC (with thermal break) Painted wooden wooden

3.2.2 Evaluation of Model Objectives: Hybrid Fuzzy Simulation-Based Optimization

3.2.2.1 Evaluation of objective functions under uncertainty

As the main objective of this study is to discover the optimum sets of renovation alternatives in an existing building, the defined decision variables (renovation alternatives) must be assessed against performance criteria which are addressed as objective functions. The following performance criteria are considered in this study, based on which the decision variables will be gauged:

1. Minimize: Annual energy consumption

As the annual energy consumption is calculated by the simulation engine using thermal calculation and directly transferred to the optimization module, no equation is defined for this objective.

2. Minimize: Capital construction cost

Capital construction cost = $\sum_{i=1}^{n} Unit\ cost * Surface\ Area\ of\ construction\ components$ *Eq. 1*

Where n is the number of construction components.

The fuzzy set theory is selected to handle uncertainty in this study for the following reasons:

1. A large data base is not available for forming a probability set. In contrast, fuzzy sets require a limited number of datasets.
2. Fuzzy sets are expressed based on previous experience in a qualitative manner by experts.

Fuzzy Set Theory is explained below followed by its application in the model.

Fuzzy Set Theory

Fuzzy set theory (FS) was first developed specifically to handle uncertainties without statistical nature by Zadeh (Zadeh 1965). A fuzzy number, in contrast to a crisp number whose value is precisely defined, is a fuzzy set defined on the set of real numbers whose numeric meaning is vaguely defined. The fuzzy set is defined as below (Sadeghi, Fayek, and Pedrycz 2010):

$$A = \{(c, \mu_A(c)) | c \in C\} \qquad \textit{Eq. 2}$$

where A is a fuzzy number; i.e., a normalized convex fuzzy subset of real number C. $\mu_A(c)$ is a membership function which takes values between [0,1] indicating the degree c belongs to A. Several fuzzy systems with triangular fuzzy numbers, trapezoidal, Gaussian or similar ones could be used. Selection of the appropriate shape of fuzzy number highly relies on the stochastic nature of the parameter. Thus, their shape and value are usually defined based on the expert's opinion and varies for different projects.

Fuzzification is a procedure through which the input variables are converted into fuzzy numbers. Such conversion is accomplished through the membership functions (MFs). An MF is a function which associates a value (usually numerical) with the level of membership to the set. The grades of membership in fuzzy sets may take any values within the interval of 0 and 1. A degree of 0 denotes that an element is not a member of the set at all, whereas a degree of 1 indicates a full membership (Yeung, Chan, and Chan 2011). MFs can be of several types, the simplest is formed with straight lines, though the most used commonly used are triangular and trapezoidal shaped MFs. Figure 7 depicts the mentioned functions. Generally, in most cases, the fuzzy membership functions are triangular, where the lowest points are located on the feet of the triangle (also known as the lowest full memberships), and the highest point locates the peak (known as the highest full membership). (Che Ibrahim, Costello, and Wilkinson 2014). A triangular function is described as below:

$$TFN = \begin{cases} 0 & if \quad x < a \quad or \quad x > c \\ \left(\dfrac{x-a}{b-a}\right) & if \qquad a \le x \le b \\ \left(\dfrac{c-x}{c-b}\right) & if \qquad b \le x \le c \end{cases} \qquad \textit{Eq. 3}$$

where For TFN (triangular fuzzy number) *a* and *c* are the minimum and the maximum values respectively, and *b* is the most likely value.

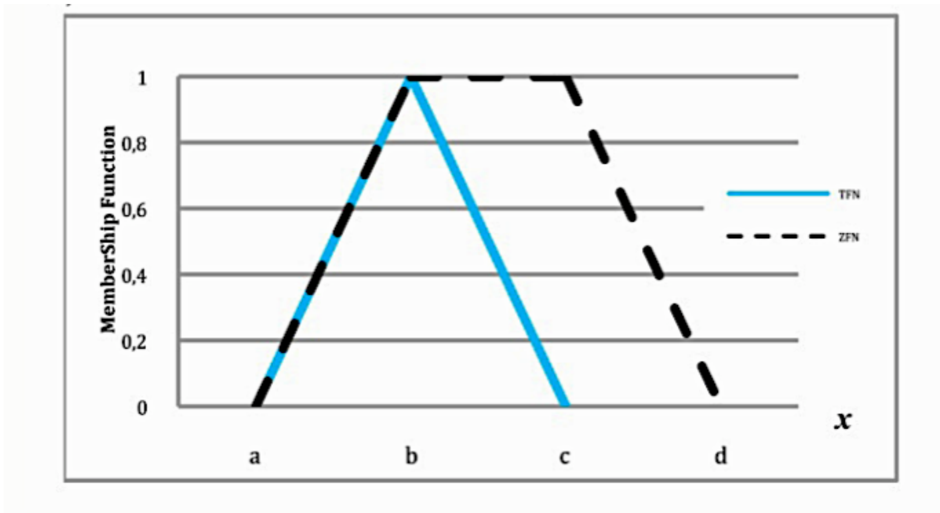


Figure 7. Triangular and trapezoidal fuzzy membership functions (Che Ibrahim, Costello, and Wilkinson 2014)

Fuzzy Set Theory in Calculation of Cost and Energy Consumption Objectives

Both objectives "capital construction cost, and energy consumption" are subject to uncertainty due to several factors such as weather, resource availability, etc. To address the uncertainty of the objectives functions which will be used in the optimization algorithm, the fuzzy set theory is utilized.

In this setting, the unit per surface cost and u-value (heat transfer coefficient) are the parameters respectively involved in the calculation of cost and energy objective functions which are fuzzy numbers. These fuzzy numbers are to be defuzzified so that they result in a crisp number which can be used in the optimization. To do so, a triangular distribution is used for the fuzzy membership function since Klir et al. have pointed out that most of the fuzzy set applications do not show significant sensitivity to the used shape of fuzzy membership function (Klir, Wang, and Harmanec 1997). Moreover, it is the simplest distribution, most commonly used in the literature and conclusively, it requires the smallest data set compared to a normal distribution, for instance. The fuzzy numbers in fuzzy sets for the "unit cost" and "u-value (heat transfer coefficient)" follow the membership function which has taken the form of the triangular distribution. As depicted in Figure 8, the fuzzy numbers are namely; *l, m, u* which are the lower-bound, most-likely, an upper-bound for the unit cost and u-value. The mentioned values are calculated for each renovation alternatives for all the envelope components which are intended to be optimized. The lower bound is defined as 98.5% of the most likely amount. Similarly, the upper bound is assumed 102% of the most likely amount. The most likely value for unit cost is the value recommended by DesignBuilder to be used in the cost calculations. Correspondingly, the most likely amount for the u-value is taken from DesignBuilder recommended by ASHRAE standard used in the energy consumption calculations. In order to defuzzify the fuzzy numbers, the graded mean integration approach is utilized (Mahata and Mahata 2011; Kutlu and Ekmekçioğlu 2012). According to this approach, a fuzzy number can be transformed into a crisp number by employing the equation below (Mahata and Mahata 2011; Kutlu and Ekmekçioğlu 2012):

$$\text{Graded mean} = \frac{l+4m+u}{6} \qquad \textit{Eq. 4}$$

Using the above Eq. 4 the value for the center of the area for each alternative is calculated and used in the optimization module for the objectives fitness evaluation.

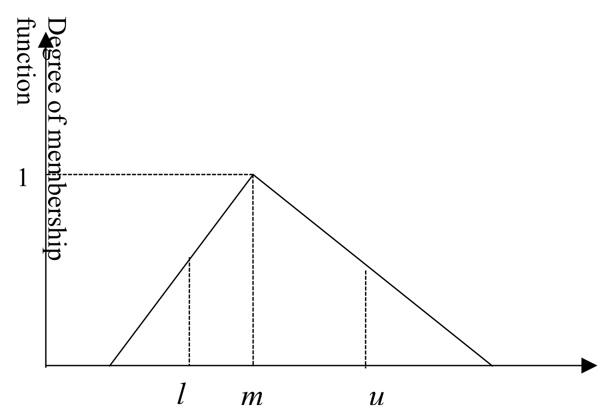


Figure 8. Triangular distribution

The uncertainty concerning each objective is explained as follows:

Capital Cost Objective Function

The defuzzified value of unit cost which is used in the capital cost calculations is computed for each renovation alternative using the Eq. 4 above and is stated in Table 3. As the description of alternatives is provided in previous section 3.2.1.2, only the alternatives IDs are provided in the following tables.

Table 3. Fuzzy and defuzzified numbers associated with unit cost

Alternatives	Triangular fuzzy membership function numbers of unit cost			Defuzzified value (Center of the area)
	Most likely	Lower bound	Upper bound	
InnExW-PCM1	879.27	866.08	896.85	880
InnExW-PCM2	714.40	703.69	728.69	715
InnExW-PCM3	864.28	851.32	881.57	865
InnExW-PCM4	524.56	516.69	535.05	525
InnExW-PCM5	464.61	457.64	473.91	465
InnExW-PCM6	464.61	457.64	473.91	465
InnExW-PCM7	459.62	452.72	468.81	460
InnExW-PCM8	679.43	669.24	693.02	680
InnExW-PCM9	489.59	482.25	499.38	490
InnExW-PCM10	709.41	698.77	723.60	710
InnExW-PCM11	924.23	910.37	942.71	925
InnExW-PCM12	724.40	713.53	738.88	725
InnExW-PCM13	734.39	723.37	749.08	735
InnExW-PCM14	714.40	703.69	728.69	715
InnExW-PCM15	744.38	733.21	759.27	745
InnExW-PCM16	714.40	703.69	728.69	715
InnExW-PCM17	714.40	703.69	728.69	715
InnExW-PCM18	944.21	930.05	963.10	945
InnExW-PCM19	954.20	939.89	973.29	955
InnExW-PCM20	749.38	738.13	764.36	750
InnExW-PCM21	469.61	462.56	479.00	470
InnExW-PCM22	469.61	462.56	479.00	470
InnExW-PCM23	479.60	472.41	489.19	480
InnExW-PCM24	659.45	649.56	672.64	660
InnExW-PCM25	659.45	649.56	672.64	660
InnExW-PCM26	659.45	649.56	672.64	660
InnExW-PCM27	659.45	649.56	672.64	660
InnExW-PCM28	459.62	452.72	468.81	460
InnExW-PCM29	449.63	442.88	458.62	450
InnExW-PCM30	499.58	492.09	509.58	500
InnExW-PCM31	469.61	462.56	479.00	470
InnExW-PCM32	504.58	497.01	514.67	505
InnExW-PCM33	474.60	467.49	484.10	475
InnExW-PCM34	479.60	472.41	489.19	480
InnoExW-BIPV	129.89	127.94	132.49	130

InnoExW-BIPV+PCM	294.75	290.33	300.65	295
InnoGlzTemp-Dbl	159.87	157.47	163.06	160
InnoGlzTemp-Dbl	209.83	206.68	214.02	210
InnoGlzTemp-Dbl	179.85	177.15	183.45	180
InnoGlzTemp-Trp	159.87	157.47	163.06	160
InnoGlzTemp-Trp	199.83	196.84	203.83	200
InnoGlzTemp-Trp	169.86	167.31	173.26	170
InnoGlzTemp-Trp	179.85	177.15	183.45	180
InnoGlzTemp-Qdr	299.75	295.25	305.75	300
InnoGlzTemp-BIPV	159.87	157.47	163.06	160
InnExtGlz-1	149.88	147.63	152.87	150
InnExtGlz-2	179.85	177.15	183.45	180
InnExtGlz-3	209.83	206.68	214.02	210
InnExtGlz-4	209.83	206.68	214.02	210
InnExtGlz-5	209.83	206.68	214.02	210
InnExtGlz-6	209.83	206.68	214.02	210
InnExtGlz-7	159.87	157.47	163.06	160
InnExtGlz-8	179.85	177.15	183.45	180
InnExtGlz-9	209.83	206.68	214.02	210
InnExtGlz-10	209.83	206.68	214.02	210
InnExtGlz-11	209.83	206.68	214.02	210
InnExtGlz-12	209.83	206.68	214.02	210
InnExtGlz-13	179.85	177.15	183.45	180
InnIntGlz 1	149.88	147.63	152.87	150
InnIntGlz 2	179.85	177.15	183.45	180
InnIntGlz 3	209.83	206.68	214.02	210
InnIntGlz 4	209.83	206.68	214.02	210
InnIntGlz 5	209.83	206.68	214.02	210
InnIntGlz 6	209.83	206.68	214.02	210
InnIntGlz 7	159.87	157.47	163.06	160
InnIntGlz 8	179.85	177.15	183.45	180
InnIntGlz 9	209.83	206.68	214.02	210
InnIntGlz 10	209.83	206.68	214.02	210
InnIntGlz 11	209.83	206.68	214.02	210
InnIntGlz 12	209.83	206.68	214.02	210
InnIntGlz 13	179.85	177.15	183.45	180
InternalThermalMass.	19.98	19.68	20.38	20
Inn.TraditionalthermalMass	209.83	206.68	214.02	210
PartitionConstruction	19.98	19.68	20.38	20
InnSh1	149.88	147.63	152.87	150
InnSh2	59.95	59.05	61.15	60
InnSh3	49.96	49.21	50.96	50
WindowFrame1	4.00	3.94	4.08	4
WindowFrame2	79.93	78.73	81.53	80
WindowFrame3	79.93	78.73	81.53	80

WindowFrame4	39.97	39.37	40.77	40
WindowFrame5	39.97	39.37	40.77	40

Energy Consumption Objective Function

As the energy consumed by components heavily relies on u-value (the thermal resistance) of components, this parameter is studied for uncertainty analysis. The defuzzified value of u-value which is used in the energy consumption calculations is computed for each renovation alternative using the Eq. 4 above and is stated in Table 4.

Table 4. Fuzzy and defuzzified numbers associated with u-value

Alternatives	Triangular fuzzy membership function numbers of u-value (W/m^2K)			Defuzzified value (Center of the area) (W/m^2K)
	Most likely	Lower bound	Upper bound	
InnExW-PCM1	0.122	0.120	0.124	0.122
InnExW-PCM2	0.111	0.109	0.113	0.111
InnExW-PCM3	0.068	0.067	0.069	0.068
InnExW-PCM4	0.436	0.429	0.444	0.436
InnExW-PCM5	0.422	0.415	0.430	0.422
InnExW-PCM6	0.422	0.415	0.430	0.422
InnExW-PCM7	0.466	0.459	0.475	0.466
InnExW-PCM8	0.143	0.141	0.146	0.143
InnExW-PCM9	0.317	0.312	0.323	0.317
InnExW-PCM10	0.135	0.133	0.138	0.135
InnExW-PCM11	0.079	0.078	0.081	0.079
InnExW-PCM12	0.125	0.123	0.127	0.125
InnExW-PCM13	0.113	0.111	0.115	0.113
InnExW-PCM14	0.145	0.143	0.148	0.145
InnExW-PCM15	0.121	0.119	0.123	0.121
InnExW-PCM16	0.145	0.143	0.148	0.145
InnExW-PCM17	0.145	0.143	0.148	0.145
InnExW-PCM18	0.779	0.768	0.795	0.78
InnExW-PCM19	0.789	0.778	0.805	0.79
InnExW-PCM20	0.126	0.124	0.128	0.126
InnExW-PCM21	0.397	0.391	0.405	0.397
InnExW-PCM22	0.346	0.341	0.353	0.346
InnExW-PCM23	1.840	1.813	1.877	1.842
InnExW-PCM24	0.149	0.147	0.152	0.149
InnExW-PCM25	0.149	0.147	0.152	0.149

InnExW-PCM26	0.143	0.141	0.146	0.143
InnExW-PCM27	0.143	0.141	0.146	0.143
InnExW-PCM28	0.434	0.427	0.442	0.434
InnExW-PCM29	0.434	0.427	0.442	0.434
InnExW-PCM30	0.637	0.628	0.650	0.638
InnExW-PCM31	0.401	0.395	0.409	0.401
InnExW-PCM32	0.468	0.461	0.477	0.468
InnExW-PCM33	0.451	0.444	0.460	0.451
InnExW-PCM34	0.280	0.276	0.285	0.28
InnoExW-BIPV	0.350	0.344	0.357	0.35
InnoExW-BIPV+PCM	0.316	0.311	0.322	0.316
InnoGlzTemp-Dbl	2.427	2.391	2.476	2.429
InnoGlzTemp-Dbl	2.427	2.391	2.476	2.429
InnoGlzTemp-Dbl	1.492	1.469	1.522	1.493
InnoGlzTemp-Trp	2.176	2.144	2.220	2.178
InnoGlzTemp-Trp	0.7794	0.768	0.795	0.78
InnoGlzTemp-Trp	1.9584	1.929	1.998	1.96
InnoGlzTemp-Trp	2.1272	2.095	2.170	2.129
InnoGlzTemp-Qdr	0.7803	0.769	0.796	0.781
InnoGlzTemp-BIPV	1.9584	1.929	1.998	1.96
InnExtGlz-1	2.6578	2.618	2.711	2.66
InnExtGlz-2	2.5089	2.471	2.559	2.511
InnExtGlz-3	1.7585	1.732	1.794	1.76
InnExtGlz-4	1.4918	1.469	1.522	1.493
InnExtGlz-5	1.7585	1.732	1.794	1.76
InnExtGlz-6	1.4918	1.469	1.522	1.493
InnExtGlz-7	1.7845	1.758	1.820	1.786
InnExtGlz-8	1.4918	1.469	1.522	1.493
InnExtGlz-9	1.6147	1.590	1.647	1.616
InnExtGlz-10	1.3219	1.302	1.348	1.323
InnExtGlz-11	1.6147	1.590	1.647	1.616
InnExtGlz-12	1.3219	1.302	1.348	1.323
InnExtGlz-13	2.1272	2.095	2.170	2.129
InnIntGlz 1	2.6578	2.618	2.711	2.66
InnIntGlz 2	2.5089	2.471	2.559	2.511
InnIntGlz 3	1.7585	1.732	1.794	1.76
InnIntGlz 4	1.4918	1.469	1.522	1.493
InnIntGlz 5	1.7585	1.732	1.794	1.76
InnIntGlz 6	1.4918	1.469	1.522	1.493
InnIntGlz 7	1.7845	1.758	1.820	1.786
InnIntGlz 8	1.4918	1.469	1.522	1.493
InnIntGlz 9	1.6147	1.590	1.647	1.616
InnIntGlz 10	1.3219	1.302	1.348	1.323
InnIntGlz 11	1.6147	1.590	1.647	1.616
InnIntGlz 12	1.3219	1.302	1.348	1.323

InnIntGlz 13	2.1272	2.095	2.170	2.129
Inno. InternalThermalMass.	1.1291	1.112	1.152	1.13
TraditionalthermalMass	3.0145	2.969	3.075	3.017
PartitionConstruction	1.1291	1.112	1.152	1.13
WindowFrame1	3.4731	3.421	3.543	3.476
WindowFrame2	5.8761	5.788	5.994	5.881
WindowFrame3	5.0098	4.935	5.110	5.014
WindowFrame4	3.6300	3.576	3.703	3.633
WindowFrame5	3.6300	3.576	3.703	3.633

The above objectives will be evaluated in the optimization algorithm. A Building Performance Simulation engine (BPS), EnergyPlus, embedded in the DesignBuilder software will calculate the energy consumption for each set of renovation alternatives in all optimization iterations. The cost function, alike, will be calculated through the simulation engine. As formerly explained, the simulation engine is selected for computation of objective function values to avoid using Response Surface Approximation Models (RSA) which first mimic the behavior of the base building model, and they are used within the GA for the evaluation of individuals (Magnier and Haghighat 2010). The rest of the chapter will introduce Building Performance Simulation engine (BPS), after which the integration of the simulation engine to the optimization module will be discussed. Further elucidation on both optimization module and the simulation engine will be provided in the subsequent chapter.

3.2.2.2 Building Performance Simulation

According to the section above, a Building Performance Simulation program (BPS) is selected as a means to evaluate objectives quantities. The objective functions, Annual energy consumption, and total construction cost require whole building evaluation; thus, rendering complex, non-linear computations. Although there are some equations available for calculating energy consumption and the relevant construction cost, elaborate substitutions such as the translation of a Window-to-Wall Ratio (WWR) into window coordinates or geometry studies beyond the basic figures cannot be handled (Bucking 2013).

Additionally, apart from the mentioned reasons, the complex nature of heat transfer calculations entails a more thorough and detailed computation method. For this reason, whole building simulations are normally used in building performance assessments. In this study, the commercial simulation program, DesignBuilder simulation with its EnergyPlus engine has been utilized. Even though the term simulation, ordinarily refers to stochastic programs (e.g., a discrete-event simulation programs using Monte Carlo methods), the area of simulation-based optimization mostly involves deterministic computer programs that are regularly used in building simulations (Gosavi 2003; Fu 2002).

3.2.2.3 Integration of the simulation and the optimization module

To address the interaction between the simulation and the optimization module, the nature of the simulation program should be considered. There are two types of simulation programs based on the means of their collaboration with the optimization module and three types of interactions. Simulations could be either internal or external. The external category does not include compiling together with the optimizer. In contrast, the internal type operates based on compiling with the optimizer. The types of interactions between simulation engines and optimizers have three types of interfaces namely external interface, an internal interface, and hybrid interface (Wang 2005). A brief description of each is as follows:

External interface: This is to address external simulations in which the communication with the optimization module is performed through files, thus necessitating the use of a translator to transfer the input and output to and from the optimization module.

Internal Interface: Addressing the internal simulations, the values of variables and functions are directly transferred between the simulation and optimization module. The primary advantage of this method is that since the variables are stored in the computer memory, they can be shared by the simulation and optimization module. In the case of this research, the DesignBuilder software is the platform facilitating the collaboration between simulation and optimization module. The first and foremost merit of the internal interface is its significantly less computation time and cost in comparison with the external version. Despite its substantial benefit, it suffers from the fact that the variables, performance criteria, and the optimization algorithm are required to be determined in advance. However, since every refurbishment project has its decision variables and decision criteria, this quality might, in fact, transpire as a benefit.

Hybrid Interface: This category incorporates both the internal and external simulations for calculating the objective functions amounts and requires both internal and external interfaces.

In this study, an internal simulation with an internal interface is employed to avoid the high computational time, transferring between optimization and simulation modules.

3.2.3 Model Output

The output of the simulation-based optimization model will be presented as optimal solutions sets of renovation alternatives. A Pareto front containing all these sets of optimal renovation scenario will summarize the optimization outcome. Each point on the Pareto front which is an optimal solution represents a renovation scenario consisting of renovation alternatives. A general form of a Pareto front resulted from optimization of two objective functions is presented in Figure 9 (The Pareto front from the model implemented in this thesis is present in chapter 5).

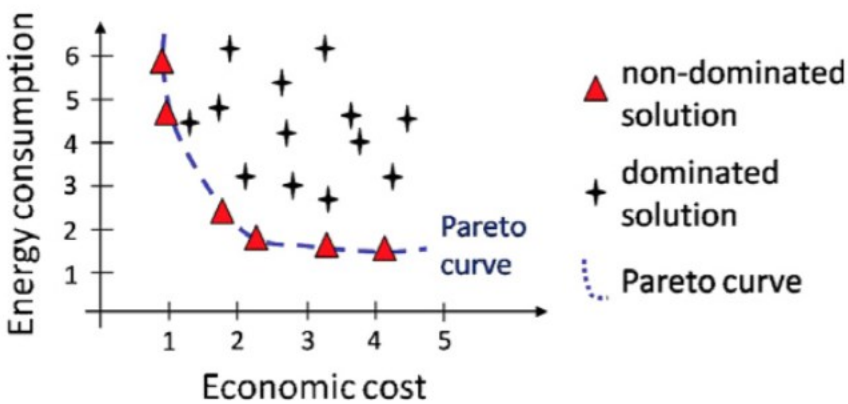


Figure 9. A sample of a Pareto front (Chantrelle et al. 2011)

3.3 Summary

This chapter included describing the proposed model; it is input consisting of building model input data needed for simulation and optimization as well as the decision variables defined in DesignBuilder to be used in the NSGA-II optimization algorithm. After this section, the objective functions including uncertainty, and fuzzy set theory were described, and the building performance simulation engine (BPS) was explained as the means of computing them. Afterward, the integration of the simulation to the optimization algorithm was demonstrated. At last, the outcome of simulation-based optimization, Pareto front, was discussed. The next chapter will incorporate further elaboration on the computation of objective functions in the simulation engine, along with the optimization algorithm and Pareto front.

CHAPTER. 4 OPTIMIZATION & SIMULATION INTEGRATION

4.1 General

As mentioned in previous chapters, there are numerous advantages pertaining to the use of BPS for building energy consumption calculation. Some of the benefits of performing whole building simulation are namely; accounting for interactions among all systems and subsystems in a building, higher precision, lower computational time in comparison with trial-and-error methods and so on. Another significant advantage of coupling a simulation engine to an optimization algorithm is that it eliminates the necessity of using surrogate models and thus for each iteration of the optimization algorithm, the values of objective functions are calculated simultaneously and transferred to the algorithm without incurring further burden (Magnier and Haghighat 2010). Conclusively, the building performance simulation engines for calculating the objective functions substantially reduce the computational time and cost. In the following section, the simulation engine used in this model followed by the optimization algorithm are explained. It should be noted that the consideration of uncertainty with the objective functions is discussed in the chapter. 3 and this chapter essentially introduces the above-mentioned objective functions.

4.2 Energy Simulations

The simulation engine used in this study is EnergyPlus which is embedded in DesignBuilder software. Simulations using EnergyPlus have the following characteristics: (DesignBuilder, v. 5.3, 2018)

- Weather data is derived hourly weather data file.
- Heat conduction and convection between zones of different temperatures are included.
- Solar gain through windows is included.
- Simulation of HVAC equipment is included.
- Includes one or more “warmup” (or pre-conditioning) days to ensure the correct distribution of heat in building thermal mass at the start of the simulation. Warmup continues until temperatures/heat flows in each zone have converged. If convergence does not occur, simulation continues for the maximum number of days as specified in the calculation options.

4.2.1 Simulation Inputs Parameters

In order to be able to perform simulations on thermal performance of retrofit measures on a building to calculate energy consumption and subsequently cost of retrofits, several inputs are required to be set for the simulation engine. Weather data files, building model (geometry), size and function (residential, office, etc.), occupancy patterns, activity templates, components construction and energy supply systems are the basic parameters. Apart from the construction components that are different in two random models, the rest of the parameters are similar in simulation engines and the models (DesignBuilder, v.5.3, 2018). As with the DesignBuilder, the required parameters for initiating thermal simulations run by the EnergyPlus engine are:

1. Standards in Building Performance Simulation
2. Weather, climate
3. Building geometry, model
4. Zones
5. Activity
6. Schedules
7. Time step
8. Occupancy.

They are explained as follow.

1. Standards in Building Performance Simulation: In this study building modeling and energy, assessment are performed in accordance with ASHRAE 90.1-2010 Appendix G PRM. DesignBuilder uses the ASHRAE climate zone site-level setting so that it can identify the climate zone for generating baseline constructions and glazing according to ASHRAE 90.1 The default climate can be loaded from the Locations template and its value derived from the Hourly weather data dialog which itself has bee was derived from .epw hourly weather data. When the energy code is set as ASHRAE 90.1 2007 or 2010, the appropriate model data settings such as Detailed HVAC and 6 time steps per hour are loaded to the building model accordingly The construction, glazing, lighting, activity templates, etc follow the standard set at the beginning at the site level.

2. Weather, climate: Weather data is derived from hourly weather data files. Hourly weather data in DesignBuilder are an EnergyPlus format with the extension 'epw' by the convention which can specify external conditions during simulations. The external temperature, solar radiation, atmospheric conditions, etc from each location's separate file. These hourly weather datasets are made available by DOE, U.S. [IWEC2012] Department of Energy, in order to be used in EnergyPlus simulation software website and imported in the model and are often 'typical' data derived from hourly observations at a specific location by national weather services. Examples of these typical data include TMY2 and WYEC2 in the United States and Canada and TRY (CEC 1985) in Europe. Figure 10 and Figure 11 show a weather data file for Montreal, and location respectively (DesignBuilder, v. 5.3, 2018).

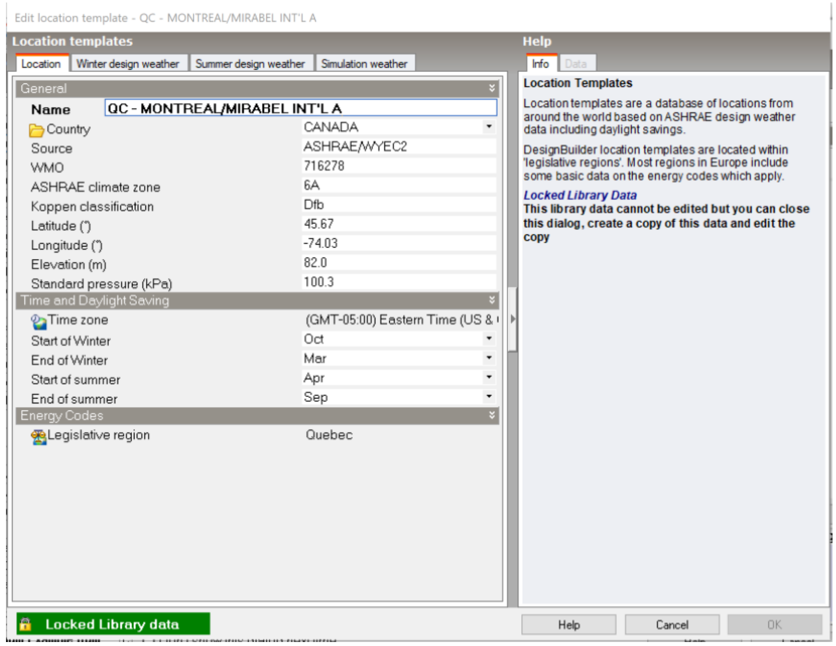


Figure 10. Representation of weather file settings in DesignBuilder

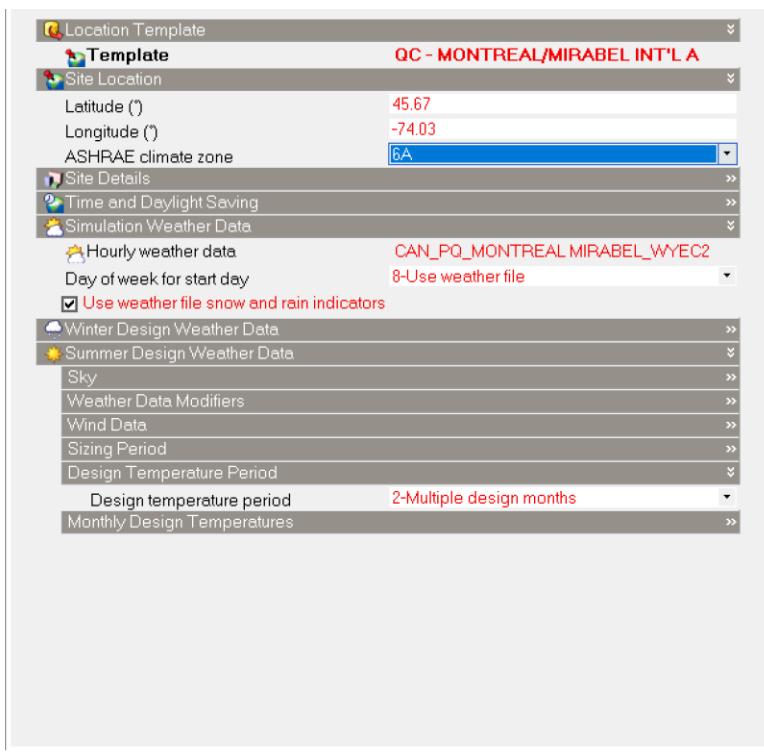


Figure 11. Representation of location settings in DesignBuilder

3. Building geometry, model: The specifications of the geometry of the model are specified in the modeling interface. DesignBuilder benefits from a user-friendly modeling interface in which models can be defined. As DesignBuilder is remarkably versatile, there is the possibility of either importing 2D floor plans from CAD files or paper drawings, or Importing 3D BIM data using the gbXML data format (DesignBuilder, v. 5.3, 2018).

4. Zones: Zones are part of the interior space that is required by thermal simulation to perform thermal calculations (Crawley et al. 2008). Spaces with similar thermal characteristics are categorized as one zone (Konstantinou 2014). The number of zones increases the complexity of the simulation escalades when multiple zones are modeled.

5. Activity: Data on the activity tab allows for defining the type of usage in each zone or general for the whole building. The data covers occupancy, equipment usage and suitable design internal temperatures, illuminance levels and ventilation rates per person. When the activity template is similar for the whole building, generic activity data can be selected. Figure 12 presents the activity template in DesignBuilder.

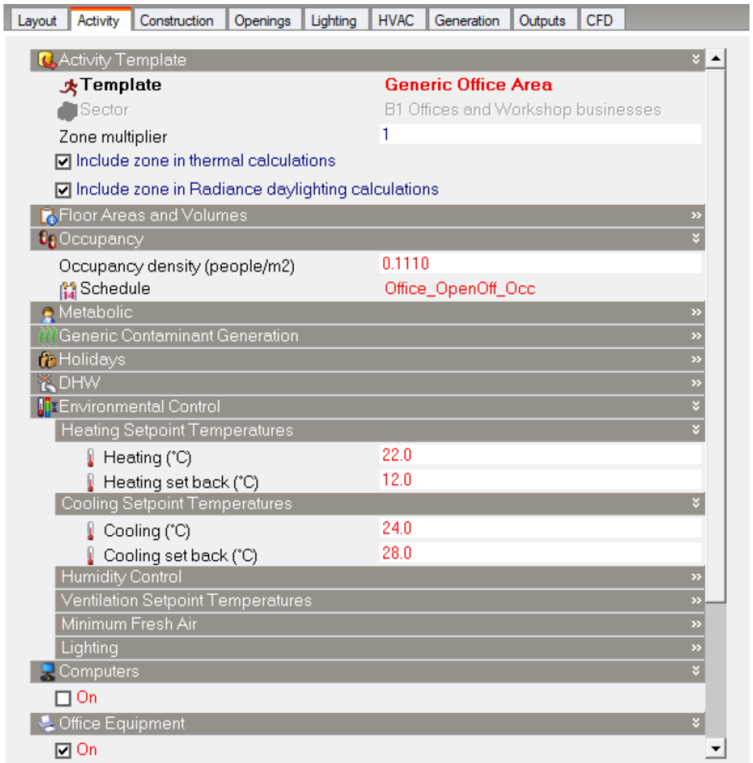


Figure 12. presentation of activity template in DesignBuilder

6. Schedules: The schedules define the hours of the day that the selected inputs come into effect. In addition to describing the hours when the zone is occupied, schedules also denote the following: (Konstantinou 2014)

- Occupancy times
- The use of Equipment, lighting HVAC operation
- Heating and Cooling temperature set points
- Transparency of component blocks (usually seasonal

7. Time step: "Step" is a process of calculating system's next state. "Timestep" is the time interval for which simulation will progress during next "step." Even though many buildings can be successfully simulated with 1 or 2-time steps per hour, EnergyPlus suggest a minimum of 4 for non-HVAC simulations and 6 for simulations with HVAC. When using the Finite difference solution method, 20 Time steps per hour is the minimum. Generally, as the number of time steps increases, the accuracy is improved. However, it might slow the simulation. (DesignBuilder, 2018)

8. Occupancy: When selecting the ASHRAE standard, and setting the activity template to generic office template this input parameter is automatically set based on person/m2

4.2.2 Energy Consumption Calculations

In EnergyPlus, the simulation engine of DesignBuilder, the thermal simulation of building surface constructions is performed by a conduction transfer function (CTF) transformation. Similar to other transformation-based solutions, CTF has several limitations such as constant properties, fixed values of some parameters, and do not produce results for the interior of the surface. In the case of conducting energy analysis by simulating more advanced constructions, such as phase change materials (PCM), it necessitates the inclusion of more fundamental forms. Consequently, a conduction finite difference (CondFD) solution algorithm has been incorporated into EnergyPlus. The two algorithms used in thermal evaluation, conduction, and convection, are explained as follow:

1. Conduction algorithm: In this thesis, the general solution algorithm used for heating and cooling calculations in DesignBuilder is Finite Difference is a solution technique using one dimension solution in the construction elements. It is a sensible heat only solution and does not take into account moisture storage or diffusion in the construction elements (DesignBuilder, 2018). This solution is mandatory for simulations of PCM including elements. According to DesignBuilder, it is also capable of improving accuracy for sheet metal material layers in constructions and chilled ceilings.

The Finite Difference settings used are described below:

The Finite Difference method is another numerical technique frequently used to solve differential equations by approximating them with difference equations, in which finite differences approximate the derivatives. FDMs are thus based on the concept of discretization (Grossmann, Roos, and Stynes 2007).

Assuming the function whose derivatives are to be approximated is properly-behaved, by Taylor's theorem we can create a Taylor series expansion (Anderson and Wendt 1995):

$$f\,(x+\Delta x) = f(x) + \frac{\partial f}{\partial x}\Delta x + \frac{\partial 2f}{\partial x^2}\frac{(\Delta x)2}{2} + \ldots\frac{\partial nf}{\partial x^n}\frac{(\Delta x)n}{n!} + R_n(x) \qquad \text{Eq.5}$$

Where *n*! denotes the factorial of *n*, and $R_n(x)$ is a remainder term denoting the difference between the Taylor polynomial of degree *n* and the original function. Then, an approximation for the first derivative of the function "f" will be derived by first truncating the Taylor polynomial:

for an $x=x_0$ and by setting $\Delta x= h$ we will have

$$f\,(x_0+ h) = f(x_0) + \frac{f\,\prime\,(x0)}{1!}h + \ldots + \frac{f\,(n)\;x0}{n!}h^n + R_n(x)\;, \qquad \text{Eq. 6}$$

$$f\,(x0+ h) = f(x0) + f\,'\,(x0)\;h + R1(x) \qquad \text{Eq. 7}$$

Setting, $x_0=a$ we have,

$$f\,(a+ h) = f\,(a) + f\,'\,(a)\;h + R1(x) \qquad \text{Eq. 8}$$

Dividing across by *h* gives:

$$\frac{f\,(a+h)}{h} = \frac{f\,(a)}{h} + f\,'\,(a) + \frac{R1\,(x)}{h} \qquad \text{Eq. 9}$$

Solving for f'(a):

$$f\,'\,(a) = \frac{f\,(a+h)-f(a)}{h} - \frac{R1\,(x)}{h} \qquad \text{Eq. 10}$$

Assuming that $R_1(x)$ is sufficiently small, the approximation of the first derivative of "f " is:

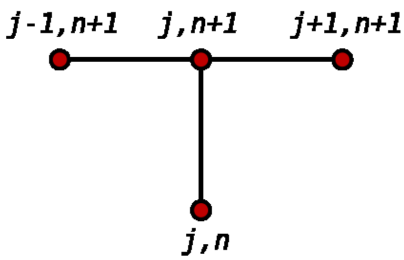
$$f\,'\,(a) \approx \frac{f\,(a+h)-f(a)}{h} \qquad \text{Eq.11}$$

In the case where the Finite Difference general solution algorithm is selected, or if this algorithm is to override any other construction in the simulation the settings below are required:

1. Fully implicit first order scheme, which is first order in time and is more stable over time. However, it may turn out to be slower than the second option below.

If we use the backward difference at time t $_{n+1}$ and a second-order central difference for the space derivative at position x_j (The Backward Time, Centered Space Method "BTCS") we obtain the recurrence equation (Anderson and Wendt 1995):

$$\frac{u_j^{n+1} - u_j^n}{k} = \frac{u_{j+1}^{n+1} - 2u_j^{n+1} + u_{j-1}^{n+1}}{h^2}$$ Eq. 12

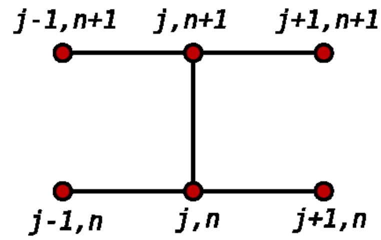


This is an implicit method for solving the one-dimensional heat equation. We can obtain u^n_j from solving a system of linear equations:

$$(1 + 2r)u_j^{n+1} - ru_{j-1}^{n+1} - ru_{j+1}^{n+1} = u_j^n$$ Eq.13

2. Crank Nicholson 2nd order, which is second order in time and may be faster than option 1 above. However, it might suffer from instability over time when boundary conditions change suddenly and severely.

Finally, if we use the central difference at time $t_{n+1/2}$ and a second-order central difference for the space derivative at position x_j ("CTCS") we get the recurrence equation (Anderson and Wendt 1995):



$$\frac{u_j^{n+1}-u_j^n}{k}=\frac{1}{2}\left(\frac{u_{j+1}^{n+1}-2u_j^{n+1}+u_{j-1}^{n+1}}{h^2}+\frac{u_{j+1}^{n}-2u_j^{n}+u_{j-1}^{n}}{h^2}\right)$$ Eq.14

This formula is known as the Crank–Nicolson method. We can obtain $u^{n+1}{}_j$ from solving a system of linear equations (Anderson and Wendt 1995):

$$(2+2r)u_j^{n+1}-ru_{j-1}^{n+1}-ru_{j+1}^{n+1}=(2-2r)u_j^n+ru_{j-1}^n+ru_{j+1}^n$$ Eq. 15

2. Convection Algorithm: The convection between the between internal zone surfaces and the rest of the zone air can be calculated in the simulation using several EnergyPlus inside convection algorithms. For the Inside Convection, The TARP algorithm is recommended by DesignBuilder based on variable natural convection relying on temperature difference from ASHRAE algorithms. As with the Outside Convection, The DOE-2 convection model which is a combination of the MoWiTT and BLAST Detailed convection models (LBL 1994) is recommended as the default algorithm by DesignBuilder (DesignBuilder, v.5.3, 2018)

4.3 Cost Calculations

In this model, the cost objective is defined as capital construction costs of renovation scenarios. Construction cost modeling provides an early design stage estimate of the initial construction costs. The cost calculations in DesignBuilder simulation are performed based on "surface area of each construction component." The capital cost function consists of structure costs, HVAC costs, lighting costs, sub-structure costs, renewable costs (such as those of PV panels).

Since the objective of the simulation is to be utilized in the NSGA-II optimization module, the costs outputs are used in tandem with that of annual energy consumption in the course of optimization. The uncertainty associated with the cost objective function is also considered as described in section 3.2.2. Figure 13 shows the subdivision of cost which is calculated per surface area for a sample building.

Structure Costs	Floor Area (m2)	Cost (GBP)
Sub Total	369.7	77627.5

HVAC Costs	Floor Area (m2)	Cost (GBP)
Sub Total	369.7	52159.9

Lighting Costs	Floor Area (m2)	Cost (GBP)
Sub Total	369.7	20864.0

Sub-Structure Costs	Floor Area (m2)	Cost (GBP)
Sub Total	400.0	44000.0

Super Structure Cost	Construction Area (m2)	Cost (GBP)
InnExW. 14 BIPV + PCM Project BIPV Wall	42.8	12631.6
Inn.5 internal mass	70.9	1417.4
Project wall	149.5	19431.6
Project partition	175.2	11212.2
Project flat roof	400.0	30000.0
Project ground floor	400.0	135600.0
Sub Total	1238.4	210292.7

Building Total Cost (GBP)		471819

Glazing Cost	Surface Area (m2)	Cost (GBP)
Copy of Thermochromic Glazing Example-revised	87.7	15787.6
Local shading		0.00
Blinds and internal shades		5262.50
Sub Total		21050.1

Renewables Cost	Area (m2)	Cost (GBP)
PV Panels	0.00	0.00
Solar Hot Water Panels	0.00	0.00
Wind Turbines	0.00	0.00
PV Electrical		1200.00
Wind Turbine Electrical		0.00
Sub Total		1200.0

Surface Finish Costs	Surface Area (m2)	Cost (GBP)
Walls	492.6	16869.9
Floors	370.1	16653.1
Ceiling	370.1	11102.0
Sub Total		44625

Figure 13. Subdivision of costs calculated per surface area for a sample building

4.4 Optimization

4.4.1 Multi-Objective Optimization

Satisfying multiple objectives in the course of optimization is known as multi-objective optimization. Generally, finding a single solution is a cumbersome task, if not impossible. It often happens that improving one objective would cause the other objective(s) to deteriorate (Bandyopadhyay and Saha 2012).

According to Coello et al. and Deb et al., multi-objective optimization (MOO) problems can be formally stated as follows (Coello 1999), (Deb 2001) :

Find the vector $x^* = [x_1^*, x_2^*, \ldots, x_n^*]^T$ of decision variables which will satisfy the m inequality constraints:

$g_i(x) \geq 0, i=1,2,...,m,$

and the p equality constraints:

$h_i(x)=0, i=1,2,...,p$

and simultaneously optimize the *M* objective values

$f_1(x), f_2(x), ..., f_M(x)$

The constraints given in equations above define the feasible region F which contains all the admissible solutions. Any solution outside this region is inadmissible since it violates one or more constraints. The vector x^* denotes an optimal solution in F. In the context of multi-objective optimization, the difficulty lies in the definition of optimality, since it is only rarely that a situation can be found where a single vector x^* represents the optimum solution to all the *M* objective functions.

Population-based methods such as genetic algorithms (GAs) can be easily extended to solve multi-objective optimization problems. As previously explained in the literature review an extension of GA is selected in this thesis to tackle to the presented multi-objective problem. For this reason, following is a further explanation of GA and its improved version, NSGA-II, which has been utilized in this study.

4.4.2 Genetic Algorithms

Genetic algorithms (GAs) known as efficient, adaptive, and robust search and optimization processes, use guided random choice as a tool for guiding the search in search spaces which are usually very large, complex, and multimodal. GAs are built on the principles of natural genetic selection, in which the genetic information of each or potential solution is encoded in arrangements called chromosomes.

GAs use domain or problem-related knowledge to direct the search to more promising areas in the search space; this process is known as the fitness function evaluation. Thus, each chromosome is assigned a fitness function which indicates its degree of acceptability with regard to the solution it represents. Various operators from biological origins such as selection, crossover, and mutation are applied to the chromosomes to produce potentially better solutions (Bandyopadhyay and Saha 2012).

Basic Principles and Features of GAs

Genetic algorithms (GAs) efficiently exploit historical information to reflect on new offspring with enhanced performance (Goldberg and Holland 1988). As previously mentioned, GAs encode the parameters of the search space in configurations called chromosomes (or *strings*). They implement repetitively on a set of chromosomes, called population, using three basic operators: selection/reproduction, crossover, and mutation. The distinction between GAs and most of the normal optimization and search processes are as follow (Holland and Goldberg 1989).

1. Gas operate with the coding of the parameters, not the parameters themselves.
2. GAs operate simultaneously with multiple points, rather than a single point.
3. GAs search via sampling (blind search).
4. GAs search using stochastic operators, rather than deterministic rules, to produce new solutions.

Advantages of GA algorithms

When used as an optimization technique, GAs are very unlikely to get stuck at a local optimum due to working simultaneously on a set of coded solutions. Additionally, the resolution of the possible search space is increased by operating on coded (possible) solutions, rather than the solutions themselves. A schematic diagram of the basic structure of a genetic algorithm is shown in Figure 14.

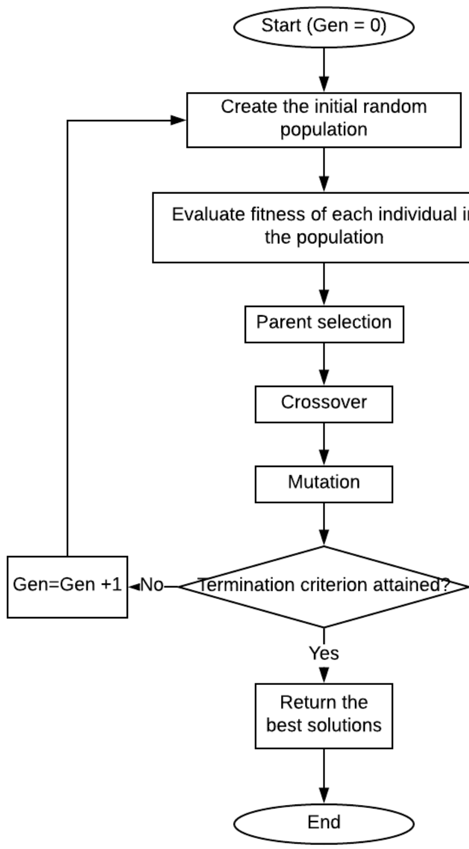


Figure 14. Schematic diagram of GAs

Basic components of GAs

The evolution of improving solutions starts from a set of chromosomes (representing a potential solution set for the objective function to be optimized) and advances to further generations through genetic operations. A generation or an iteration is defined as "replacement of an old population with a new one'. In order to evaluate the fitness of the derived solutions, GAs require a suitable objective function which links the chromosomal space to the solution space.

According to Bandyopadhyay et al. GAs normally consist of the following components (Bandyopadhyay and Saha 2012):

- A population of binary strings or coded possible solutions (biologically referred to as chromosomes).
- A mechanism to encode a possible solution (mostly as a binary string).
- An objective function and associated fitness evaluation techniques.
- A selection/reproduction procedure.
- Genetic operators (*crossover* and *mutation*).
- Probabilities to perform genetic operations.

These components are briefly described.

Population: To solve an optimization problem, GAs first turn a parameter set into a chromosomal representation of that set which is coded as a finite-length string. A set of these chromosomes in a generation is known as a population.

Encoding/Decoding Mechanism: To obtain a chromosome, the parameter values of a possible solution are converted into strings. Reversely, decoding is the task of retrieving the parameter values from the chromosomes.

Objective Function and Associated Fitness Evaluation Techniques: Being the only information (also known as the payoff information) that GAs use while searching for possible solutions, the fitness/objective function is chosen depending on the problem so that the strings (possible solutions) representative of suitable points in the search space have high fitness values.

Selection/Reproduction Procedure: The selection/reproduction process identifies certain individual strings (called parent chromosomes) from a population into a tentative new population (known as a mating pool) for genetic operations for further evolution. Roulette wheel parent selection(Holland and Goldberg 1989) and linear selection (Davis 1991)are two of the most commonly used selection operators.

Crossover: It is another operator with the goal of exchanging information between randomly selected parent chromosomes by switching parts of their respective strings so that offspring for the new generation will be produced. There are several types of crossover. In the single-point crossover, one of the most frequently used types, initially the members of the reproduced strings in the mating pool are randomly paired. Then a position of an integer such as k (known as the crossover point) is selected uniformly at random between 1 and $l - 1$, where l is the string length greater than 1. When all characters from position (k + 1) to l are exchanged, two new strings are created. For instance, let

a = 11000 10101 01000 . . . 01111 10001, b = 10001 01110 11101 . . . 00110 10100

be two strings (parents) selected from the mating pool for crossover. Let the crossover point be 11 (eleven). Then the newly produced offspring (switching all characters after position 11) will be

a' = 11000 10101 01101 . . . 00110 10100, b' = 10001 01110 11000 . . . 01111 10001.

Other crossover techniques are multiple-point crossover, shuffle-exchange crossover, and uniform crossover (Davis 1991).

Mutation: The primary goal of mutation, is to introduce genetic diversity into the population. Additionally, it sometimes helps to recover information lost in earlier generations. Similar to natural genetic systems, a mutation in GAs is generally performed sporadically. A random bit position of a randomly selected string is replaced by another character from the alphabet. For example, let the third bit of string a, given above, be selected for mutation. Then after mutation, the transformed string will be

11100 10101 01000 . . . 01111 10001.

A high mutation rate can cause the genetic algorithm to convert to a random search. It may change the value of an important bit and hence result in the fast convergence to a good solution. However, it may also slow down the process of convergence at the final stage of GAs.

Probabilities to perform genetic operations: Both the crossover and mutation operations are conducted stochastically. The probability of crossover operation is selected in such a way that recombination of potential strings (highly fit chromosomes) increases without any disruption. Generally, the crossover probability is placed between 0.6 and 0.9 (Davis 1991; Goldberg and Holland 1988). Due to its occasional occurrence, mutation operation will evidently have a low probability to be performed. Generally, the value is placed between $1/l$ and 0.1 (Goldberg and Holland 1988; Davis 1991) of which l is the length of the chromosome string.

Termination criteria: In order for a genetic algorithm to be terminated, according to Bandyopadhyay et al. one of the criteria below is to be met (Bandyopadhyay and Saha 2012):

1. The average fitness value of a population becomes more or less constant over a specified number of generations.

2. A desired objective function value is attained by at least one string in the population.

3. The number of generations (or iterations) is greater than some threshold.

4.4.3 Non-Dominated Sorting Genetic Algorithm (NSGA-II)

After closely examining several methods (fully covered in literature), GAs were selected as the optimization algorithm since they are capable of producing a Pareto front containing several optimum solutions. However, classic GA, and NSGA are non-elitist in nature. In this study, the NSGA-II algorithm is preferred over GA due to its ability to handle complexity in the search space.

Furthermore, since NSGA-II benefits from elitism, it can explore the search space more rapidly and provide a better diversity. Below is the description of this algorithm.

The individuals in a population undergo non-dominated sorting and are ranked based on this. A new selection technique, called crowded tournament selection, is performed where the selection is made on the basis of crowding distance (representing the neighborhood density of a solution). To implement elitism, the parent and child population are combined, and the non-dominated individuals from the combined population are directed to the next generation. (Bandyopadhyay and Saha 2012).

The non-dominated sorting, an important characteristic of NSGA-II, is performed as follows:

Given a set of solutions S, the non-dominated set of solutions $N \subseteq S$ is composed of those solutions of S which are not dominated by any other solution in S. To find the non-dominated set, the following steps are carried out (Bandyopadhyay and Pal 2007; Deb et al. 2002):

- Step 1: Set $i = 1$ and initialize the non-dominated set N to empty.
- Step 2: For each solution $j \in S$ $(j \neq i)$, if solution j dominates solution i then go to step 4.
- Step 3: If $j < \|S\|$, set $j=j+1$ and go to step 2. Otherwise, set $N=N \cup i$.
- Step 4: Set $i=i+1$. If $i \leq \|S\|$ then go to step2. Otherwise, output N as the non-dominated set.

The non-dominated sorting procedure first finds the non-dominated set N from the given set of solutions S. Each solution belonging to N is given the rank 1. Next, the same process is repeated on the set $S = S - N$ and the next set of non-dominated solutions N' is found. Each solution of the set N' is given the rank 2. This procedure continues until all the solutions in the initial set are given some rank i.e., S becomes empty. A measure called crowding distance had been defined on the solutions of the non-dominated front for diversity maintenance. The crowding distances for the boundary solutions are set to maximum values (logically infinite). For each solution i among the remaining solutions, the crowding distance is computed as the average distance of the $(i + 1)$th and $(i - 1)$th solutions along with all the objectives. Citing Deb et al., the following are the steps for computing the crowding distance d_i of each point i in the non-dominated front N (Deb et al. 2002):"

For i = 1,...,N, initialize $d_i = 0$.

For each objective function f_k, k = 1,..., M, do the following:

- Sort the set N according to f_k in ascending order.
- Set $d_1 = d_{\|N\|} = \infty$.
- For j=2 to (||N||-1), set $d_j = d_j + (f_{k(j+1)} - f_{k\,(j-1)})$.

In NSGA-II, a binary tournament selection operator works based on the crowding distance. If two solutions a and b are compared during a tournament, then solution a wins the tournament if either:

1. The rank of a is better (less) than the rank of b, i.e., a and b belong to two different non-dominated fronts, or

2. The ranks of a and b are the same (i.e., they belong to the same non-dominated front) and a has higher crowding distance than b; meaning that if two solutions belong to the same non-dominated front, the solution situated in the lesser crowded region is selected. (Bandyopadhyay and Saha 2012)

Having described the NS algorithm and concept of crowding distance used in tournament selection, the overall steps of the NSGA-II algorithm can be stated as below:

- Initialize the population.

- If termination criterion is not met, repeat the following:

    - Evaluate each solution in the population by computing the objective function values.
    - Rank the solutions in the population using Non-dominated Sorting (NS) algorithm.
    - Perform selection using the crowding binary tournament selection operator.

- Perform crossover and mutation (as in conventional GA) to generate the offspring population.
- Combine the parent and child populations.
- Replace the parent population with the best members (selected using non-dominated sorting and the crowded comparison operator) of the combined population.

- Output the first non-dominated front of the final population.

Figure 15 is an example of a Pareto curve for an optimization problem with two objectives. The optimization of three objectives results in a ''Pareto surface". For more than three objectives, a Pareto optimization can still be performed. However, direct visualization is not possible. (Dietz 2004).

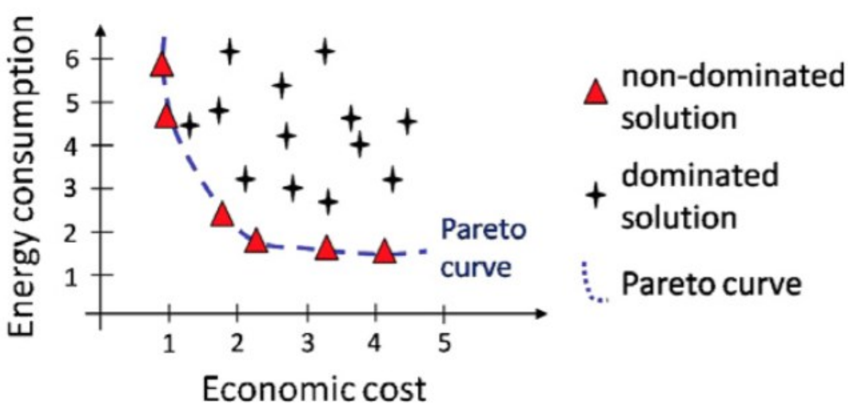


Figure 15. A sample of a Pareto front (Chantrelle et al. 2011)

4.5 Summary

This chapter which is an elaboration on methodology, involved explaining the simulation engine calculating objectives function values followed by the description of NSGA-II algorithm.

CHAPTER. 5 CASE STUDY (MODEL IMPLEMENTATION & VALIDATION)

5.1 Overview

This chapter employs the hybrid fuzzy simulation-based optimization that is developed in methodology part on a building model created in DesignBuilder. The proposed simulation-based optimization on sustainable renovations is conducted on a building model created in DesignBuilder, and a Pareto front containing the optimum solutions is obtained.

To verify the performance of NSGA-II optimization algorithm and to prove the improvements achieved by the proposed renovation alternatives, a base case building which represents the same building as the optimized model, containing the same activity, location, weather and input parameters is created. The only distinction between this base case and the optimized building is that only traditional construction has been used and no retrofit has been performed. Subsequently, a simulation is run on this base case building to evaluate the annual energy consumption. Conclusively, a random Pareto solution which comprises of a scenario of optimum renovation alternatives is selected, and its associated energy consumption is compared to the base case building which has not undergone a retrofit optimization.

5.2 Model Implementation

5.2.1 Case Description

A one-story office building with a total area of 371m^2 with activity template set to ASHRAE Generic Office Area; and HVAC template Fan Coil Unit (4-Pipe), Air Cooled Chiller is modeled in DesignBuilder. A double facade skin is used for the south facing facade. The building consists of 5 zones, one of which being the cavity zone forming. The 3D building model is presented in Figure 16.

It should be mentioned that the double-facade buildings are normally economically and environmentally feasible for high rise buildings. However, in this study to avoid high computational time the building is modeled as a one-story office building.

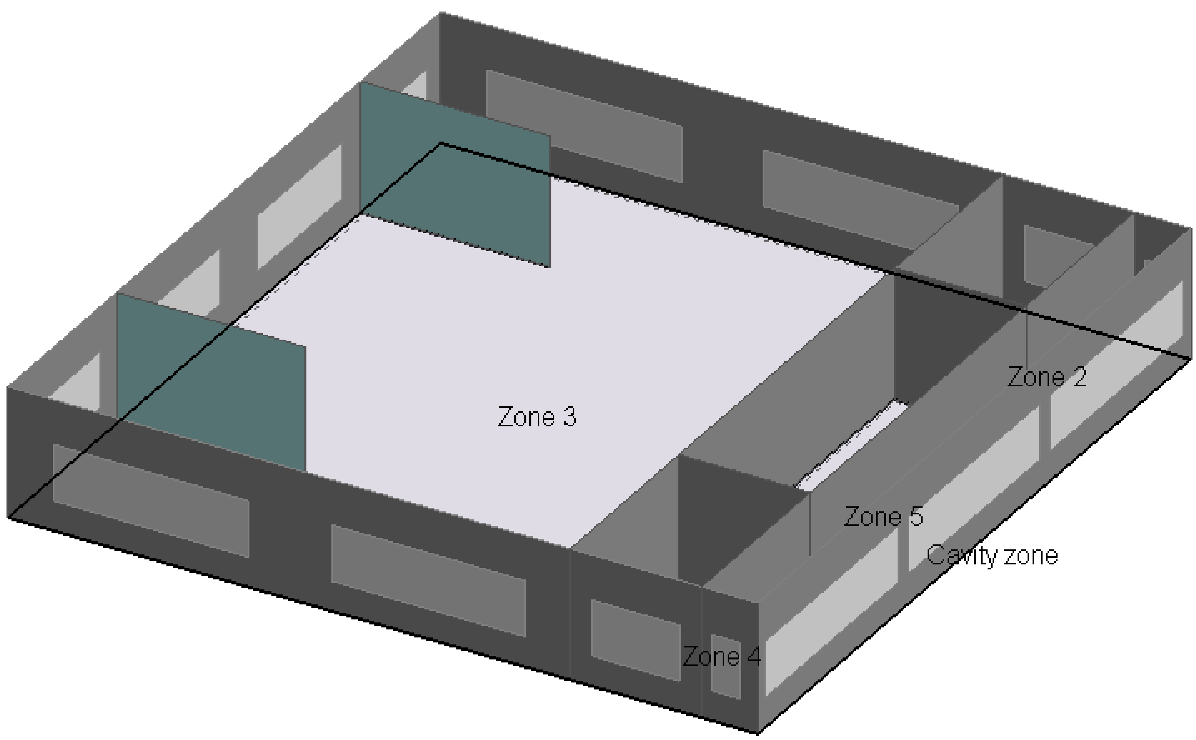


Figure 16. Floor layout of the sample case Building model created in DesignBuilder

5.2.2 Decision Variables

The decision variables used in the simulations which are subsequently incorporated in the optimization process are presented in Table 5. The table is followed by a more detailed description of several variables.

Table 5. Description of decision variables

Variable	Variable type	Category	Variable ID	Construction detail
External wall	Discrete	PCM walls	InnoExW-PCM. 1-3	- Curtain wall (Spandrel glass, Insulation board, BioPCM- M, Gypsum board) - Curtain wall (Metal wall panel, Insulation board, BioPCM- M, Gypsum board) - Curtain wall (Stone, Insulation board, BioPCM- M, Gypsum board)
			InnoExW-PCM. 4-6	- Stud wall (metal wall panel, sheathing, batt insulation, BioPCM- M, gypsum board) - Stud wall (Wood siding, sheathing, batt insulation, BioPCM- M, wood) - Stud wall (Stucco sheathing, batt insulation, BioPCM- M, gypsum board)
			InnoExW-PCM.7-9	- EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, BioPCM-M, gypsum board) - EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, batt insulation, BioPCM-M, gypsum board) - EIFs wall (EIFS finish, Insulation board, fiberboard sheathing, Lightweight concrete block, BioPCM-M, gypsum board)
			InnoExW-PCM.10-19	- Brick wall (Brick, insulation board, sheathing, gypsum board) - Brick wall (Brick, insulation board, sheathing, batt insulation, BioPCM-M, gypsum board)
			InnoExW-PCM. 20-25	- Concrete block (LW concrete block, batt insulation, BioPCM-M ,gypsum board) - Concrete block (stucco, HW CMU, fill insulation, gypsum board)
			InnoExW-PCM. 26-34	

				- Pre-cast and cast in place concrete block
		BIPV walls	InnoExW-BIPV. 1-10	-Brickwork, Photovoltaic panel, XPS Extruded Polystyrene- CO2 Blowing, Concrete block, Gypsum plastering
		BIPV + PCM walls	InnoExW-BIPV-PCM. 1-5	- Brickwork, Photovoltaic panel, XPS Extruded Polystyrene- CO2 Blowing, BioPCM-M/Q, Gypsum plastering
Glazing template	Discrete	Double glazing	InnoGlzTemp- Dbl. 1-20	-Double Glazing, Clear, Electrochromic (absorptive) switchable -Double Glazing, Clear, Electrochromic (reflective) switchable -Double Glazing, Clear, LoE, argon filled
		Triple glazing	InnoGlzTemp- Trp. 21-35	- Triple Glazing, Clear, - Triple Glazing, Clear, LoE, argon filled - Triple Glazing, Clear, LoE, argon filled+ BIPV - Triple Glazing, Clear, LoE, argon filled+ Thermochromic
		Quadruple glazing	InnoGlzTemp. 36	- Quadr, LoE, Krypton
		BIPV glazing	InnoGlzTemp. 37-42	- Triple Glazing, Clear, LoE, argon filled+ BIPV - Doble, Clear, BIPV
External glazing	Discrete	Pane material Gas Color	InnoExGlz. 1-60	Dbl, Air/Argon Dbl Elec Abs/Ref, Air/Argon Dbl LoE, Air/Argon Dbl LoE, Elec Abs/Ref, Air/Argon Electrochromic, absorptive Electrochromic, reflective LoE (coated)

				Thermochromic: Triple (thermo, air, thermo, air, clr
Internal glazing	Discrete		InnoIntGlz. 1-55	Dbl, Air/Argon Dbl Elec Abs/Ref, Air/Argon Dbl LoE, Air/Argon Dbl LoE, Elec Abs/Ref, Air/Argon Electrochromic, absorptive Electrochromic, reflective LoE (coated) Thermochromic: Triple (thermo, air, thermo, air, clr) Clear glass
Internal thermal mass	Discrete	BioPCM continuous layer	Inno. InternalThermalMass. 1-19	Concrete, BioPCM-M, Continuous layer
		Traditional construction (concrete)	Internal ThermalMass. 20-42	Concrete slab Reinforced concrete slab
Partition construction	Discrete			BioPCM-M, Continuous layer Expanded wood chipboard Brick cavity wall Reinforced concrete Single leaf brickwork

				Fiberboard, cavity Gypsum plasterboard, cavity
Facade type	Discrete			% fitted glazing % vertical glazing curtain wall, % glazing fixed height 1/1.5m. 20/30% glazing fixed window Horizontal strip, %glazed Preferred height, %glazed
Window to wall ratio	Continuous			20-100%
Shading (window blind)	Discrete		InnoShd. 1-50	- Electrochromic switchable - SageGlass Electrochromic - Slatted Blinds - Transparent Insulation
Window frame	Discrete			UPVC Aluminum PVC (with thermal break) Painted wooden wooden

External wall

The options in the external wall variable are categorized first based on the innovative sustainable materials/components/strategies which are then used in different construction types. To elucidate, take PCM walls category. There are various construction walls for an external wall such as curtain wall, stud wall, brick wall, concrete block and such, which themselves could have several variations based on the components used. For instance, 10 types of brickworks are used to form the variable options from InnoExW-PCM.10 to InnoExW-PCM.19. In the case of PCM walls, the phase change materials are embedded within each wall option in the innermost layer closest to the interior side of the wall and are selected based on the ASHRAE standard.

As with the BIPV walls, PV panels are applied in the outermost layer with the constant efficiency of 0.15. Conclusively, concerning the PCM and BIPV walls, the BIPV is installed on the outer layer and the PCM materials used in the innermost layer.
Defining all the mentioned options in DesignBuilder forms the database of variables which are subsequently used in simulation and NSGA-II optimization.

A screenshot of the definition of one of the options of BIPV and PCM walls in the DesignBuilder is provided below. Since the focus of this research is on the innovative sustainable material and strategies, only the characterization of these materials is described as compared to the rest of construction.
Figure 17 describes the formation of one of the options for the BIPV-PCM external wall. As previously presented the solution algorithm of simulation calculations is set as Finite Difference since as previously explained, in the case of PCM application the required simulation solution algorithm is the Finite Difference method. The outer layer is brickwork, and the BIPVs are installed on the outer layer. In order for the BIPVs to be integrated in some way with the underlying construction, one of the integrated heat transfer mode options is selected. Otherwise, the decoupled options will have a similar effect as drawing a separate PV panel on top of the surface at the building level. (DesignBuilder, v.5.3 2018)

The next layer consists of insulation material, XPS (Extruded Polystyrene- CO_2 Blowing). Afterward, a PCM, BioPCM M27/Q23 is included prior to the innermost layer, gypsum plastering. Figure 20 depicts a visual representation of external wall layers.

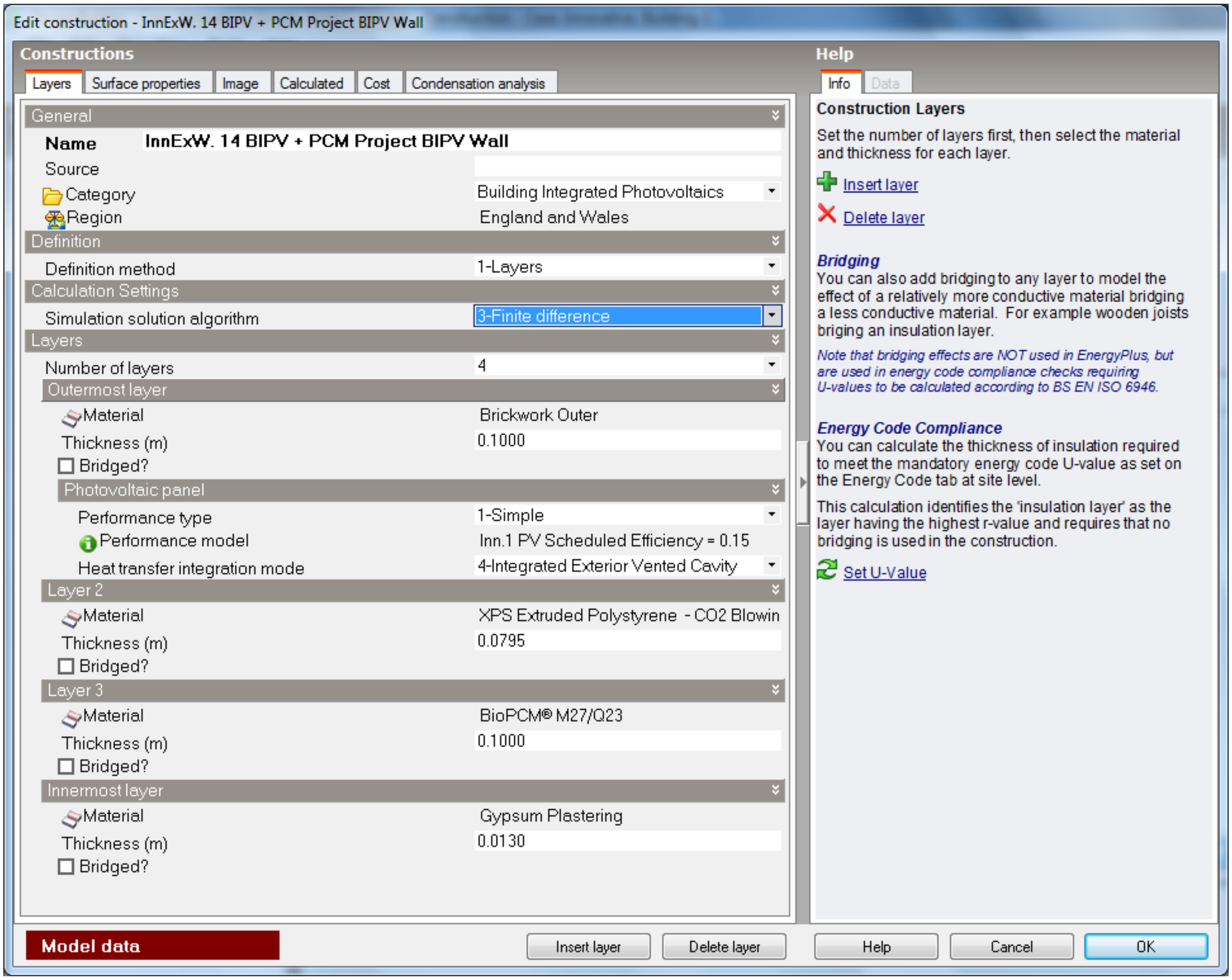


Figure 17. Representation of an option of an External Wall variable in DesignBuilder

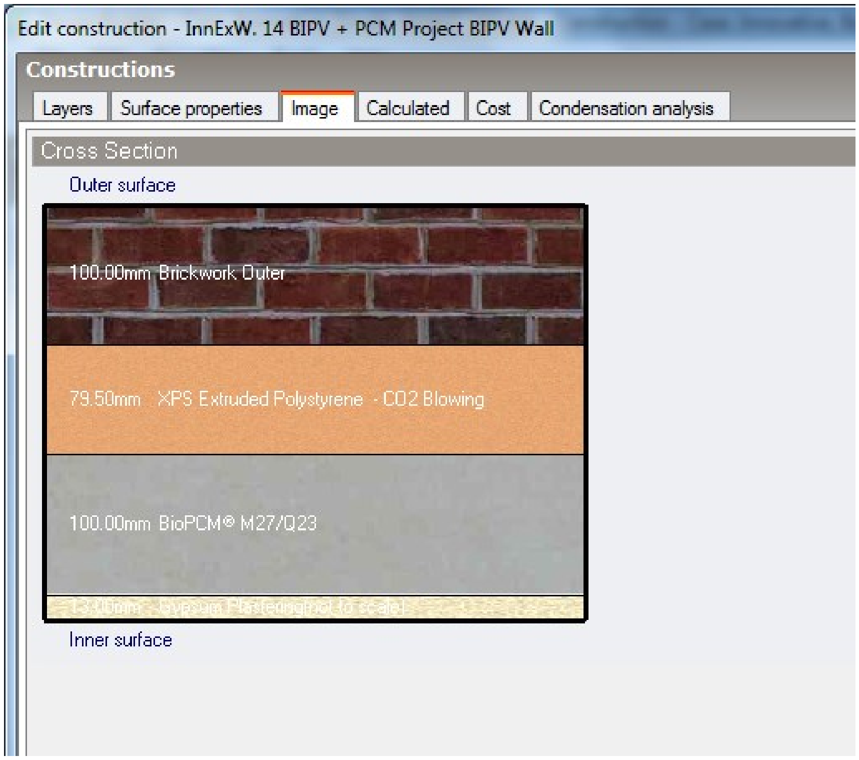


Figure 18. Visual representation of layers in an External wall option in DesignBuilder

Figure 19 displays thermal properties of the phase change material set in DesignBuilder used in the mentioned external wall option. The R-value (thermal resistance), though not selected below is 0.15 m2k/w for the PCM material BioPCM-M27.

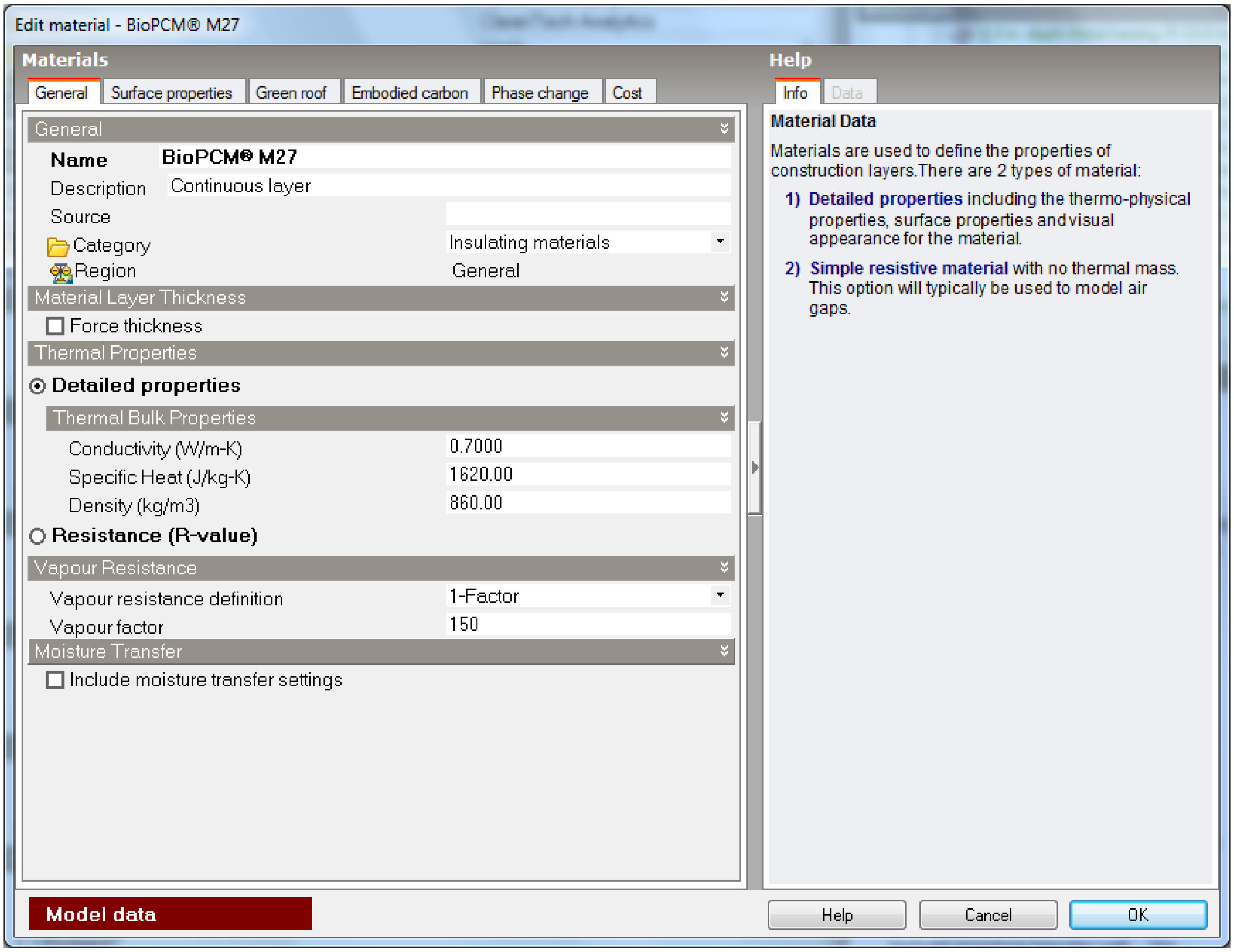


Figure 19. Thermal properties of a PCM

Glazing template: This variable defines the structure of the whole fenestration. Offering options of double, triple, quadruple and BIPV glazing, which are present in Table 6

External /Internal glazing: In this variable window pane material, gas layer between the two glass layers, and the color of panes is demonstrated. Owing to the fact the focus of this study is on selecting the material types, not the specifications, the dimensions are not addressed.

Table 6. Glazing components

External/Internal glazing		
Pane materials	**Gas types**	**colors**
electrochromic, absorptive electrochromic, reflective LoE (coated) Thermochromic Clear glass	Argon Xenon Krypton	Clear Bronze Grey Blue Green

Internal thermal mass: In this variable, the inclusion of a PCM type is included

Window Shading:

Window shading is included to reduce solar gains and improve resistance to heat conduction through windows (DesignBuilder, v. 5,3, 2018). Several of its types are as follow:

- Electrochromic switchable
- SageGlass Electrochromic
- Slatted Blinds
- Transparent Insulation

5.2.3 Simulation Parameters

Having created the sample 3D building model, in order for the genetic algorithm optimization to operate, several simulations are performed in parallel in each generation.
Using EnergyPlus as the core of the simulation engine the energy consumption of the created sample building and total construction cost is calculated in each generation for each

scenario consisting of renovation alternatives. Some of the settings used for simulation are listed in Table 7.

Table 7. Simulation parameters

Location	QC, Montreal/ Mirabel INT' LA. ASHRAE climate zone: 6A
Occupancy schedule	Office_OpenOff_Occ
Weather data file	Montreal Mirabel PQ CAN WYEC2-B-75290 WMO#=716278
Simulation period	Annual simulation (Jan 1- Dec 31)
Solution algorithm for heat transfer	Finite difference
Solar distribution	Full interior and exterior
HVAC template	Fan coil Unit (4-Pipe), Air cooled chiller
HVAC heating setpoint	22℃
HVAC cooling setpoint	24℃

Using the abovementioned parameters, the building of the base building case.1, is simulated to obtain the energy consumption of this building with conventional construction. The annual energy consumption rates for case.1 building calculated by DesignBuilder simulation engine are displayed on an HDML format report. A part of which is as follows.

Case. 1 Non-renovated envelope

The results of the annual simulation for the building on which renovation measures are not employed are depicted in Figure 20. **Energy consumption rates for the case. 1**

Program Version:**EnergyPlus, Version 8.6.0-198c6a3cff, YMD=2018.04.18 18:32**

Tabular Output Report in Format: **HTML**

Building: **Building**

Environment: **CASE. NON-INNOVATIVE-2 (SINGLE STOREY) (01-01:31-12) ** Montreal Mirabel PQ CAN WYEC2-B-75290 WMO#=716278**

Simulation Timestamp: **2018-04-18 18:32:55**

Report: **Annual Building Utility Performance Summary**

For: **Entire Facility**

Timestamp: **2018-04-18 18:32:55**

Values gathered over 8760.00 hours

Site and Source Energy

	Total Energy [kWh]	Energy Per Total Building Area [kWh/m2]	Energy Per Conditioned Building Area [kWh/m2]
Total Site Energy	141176.61	380.44	380.44
Net Site Energy	141176.61	380.44	380.44
Total Source Energy	441867.92	1190.73	1190.73
Net Source Energy	441867.92	1190.73	1190.73

Figure 20. Energy consumption rates for the case. 1Non-renovated envelope

5.2.5 Optimization

In order for the optimization to begin, the following steps proceed:

Step 1 - Create a base model. A one-story office building with the abovementioned parameters and templates following ASHRAE **90.1-2010**standard is created in DesignBuilder.

Step 2 - Run a standard simulation. Choosing random construction and material from the variables described above, an annual simulation is run. This simulation is merely to ensure the model would behave as expected in terms of hourly results, the temperature within the building, operation periods, etc. (DesignBuilder, V. 5.3, 2018)

Step 3 – Define the optimization problem in optimization analysis settings dialog.

Having performed a sample simulation on case.2 and gaining sufficient knowledge on how the model operates, an optimization can be initiated. In the optimization module, the NSGA-II (Non-dominated Sorting Genetic Algorithm) algorithm is utilized which is a "fast and elitist multi-objective" method providing a good trade-off between a well converged and a well-distributed solution set.

In order to initiate the optimization process, the optimization problem is defined by means of the following three components:

Objectives

Minimize: Total annual site energy

Minimize: Capital construction cost

Constraints: None

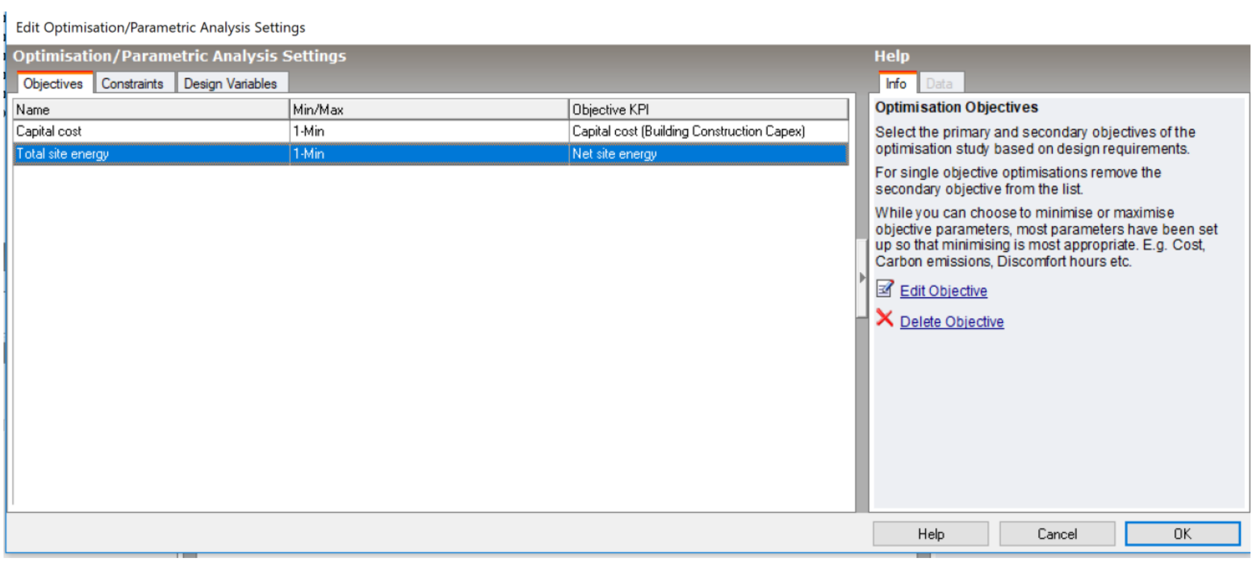
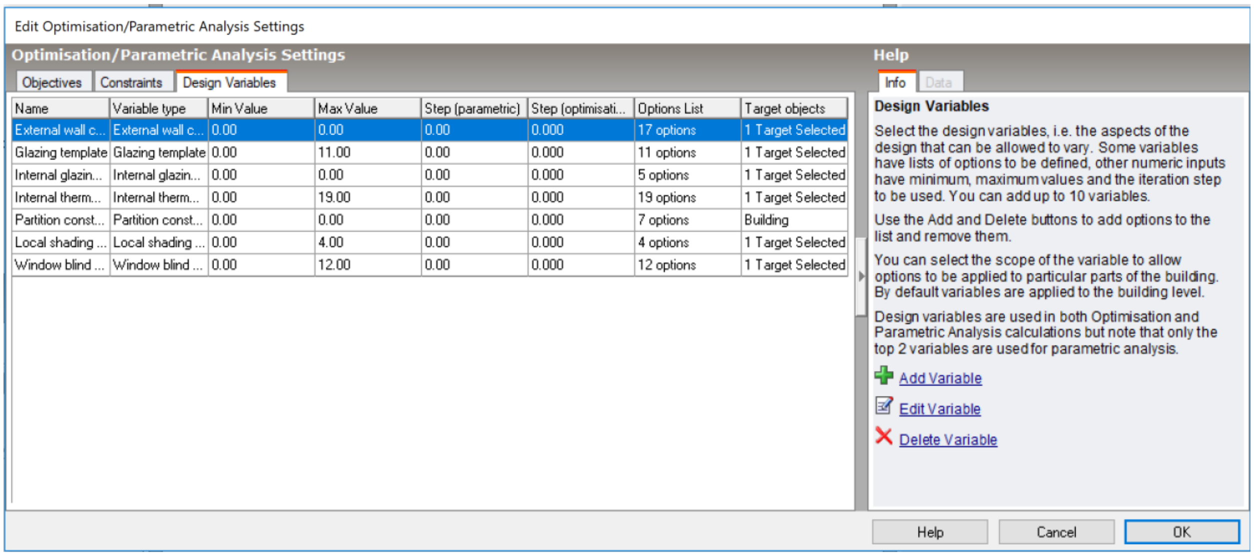


Figure 21. Representation of objective functions in DesignBuilder

Design variables:

The decision variables and their options that were previously developed and explained in the table. 1are defined in the optimization module. Figure 22 shows their list in the optimization module.



Name	Variable type	Min Value	Max Value	Step (parametric)	Step (optimisati...	Options List	Target objects
External wall c...	External wall c...	0.00	0.00	0.00	0.000	17 options	1 Target Selected
Glazing template	Glazing template	0.00	11.00	0.00	0.000	11 options	1 Target Selected
Internal glazin...	Internal glazin...	0.00	0.00	0.00	0.000	5 options	1 Target Selected
Internal therm...	Internal therm...	0.00	19.00	0.00	0.000	19 options	1 Target Selected
Partition const...	Partition const...	0.00	0.00	0.00	0.000	7 options	Building
Local shading ...	Local shading ...	0.00	4.00	0.00	0.000	4 options	1 Target Selected
Window blind ...	Window blind ...	0.00	12.00	0.00	0.000	12 options	1 Target Selected

Figure 22. Representation of decision variables in DesignBuilder

Step 4 - Define optimization calculation parameters

Following defining the variables, objective functions, and constraints the optimization parameters are defined which are presented as below. Figure 23 shows their representation in DesignBuilder.

Maximum generation:100

Initial population size: 20

Tournament size: 2

Crossover rate: 0.9

Mutation probability: 0.05

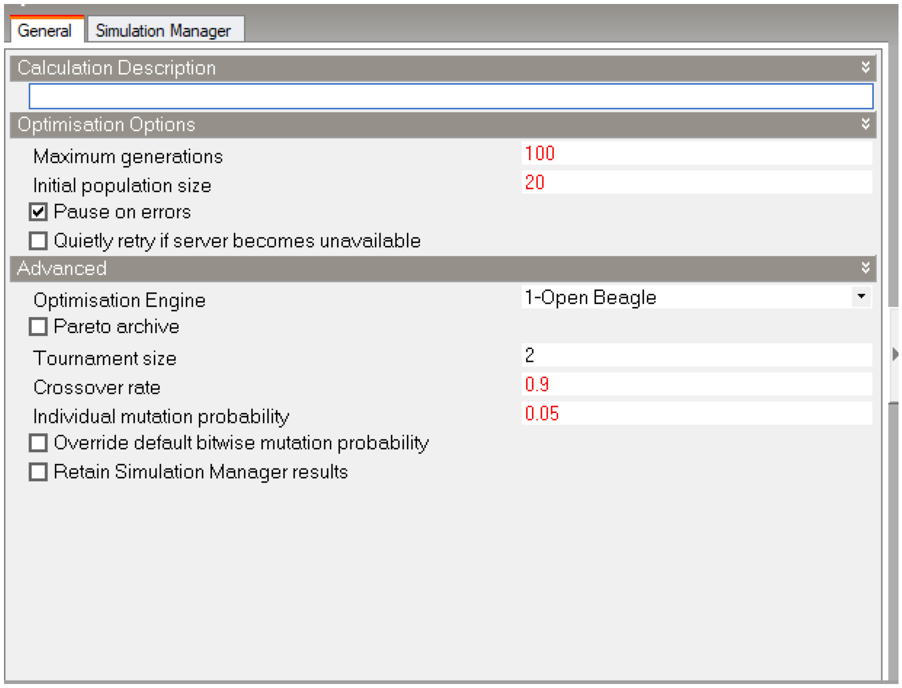


Figure 23. representation of optimization parameters in DesignBuilder.

Step 5 - Start optimization analysis

The optimization process will involve running a large number of simulations. With the recommended 100 generations with a population size of 20 in each, growing as Pareto solutions are added. That means that at least 100 x 20 = 2000 simulations will be run. The condition for the optimization termination in this study is the set number of the maximum generation which is 100. However, to ensure convergence has been achieved, the last monitors were closely monitored to determine if that the solution has converged and enough optimal solutions have been found. For example, if no new optimal solutions have been found in the last 10 generations, then that suggests convergence has been achieved.

5.2.5.1 Optimization Results

Several number of optimizations with a different number of generation of 25, 50, and 100, 200 were performed, and the graph below appeared as having the most convergent Pareto front. In this study, 4060 iterations (simulations) were performed for the 100 generations before achieving the Pareto front. The red points forming the Pareto solutions represent the optimal scenarios each forming sets of desired amounts of variables. The table below indicates the Pareto solutions.

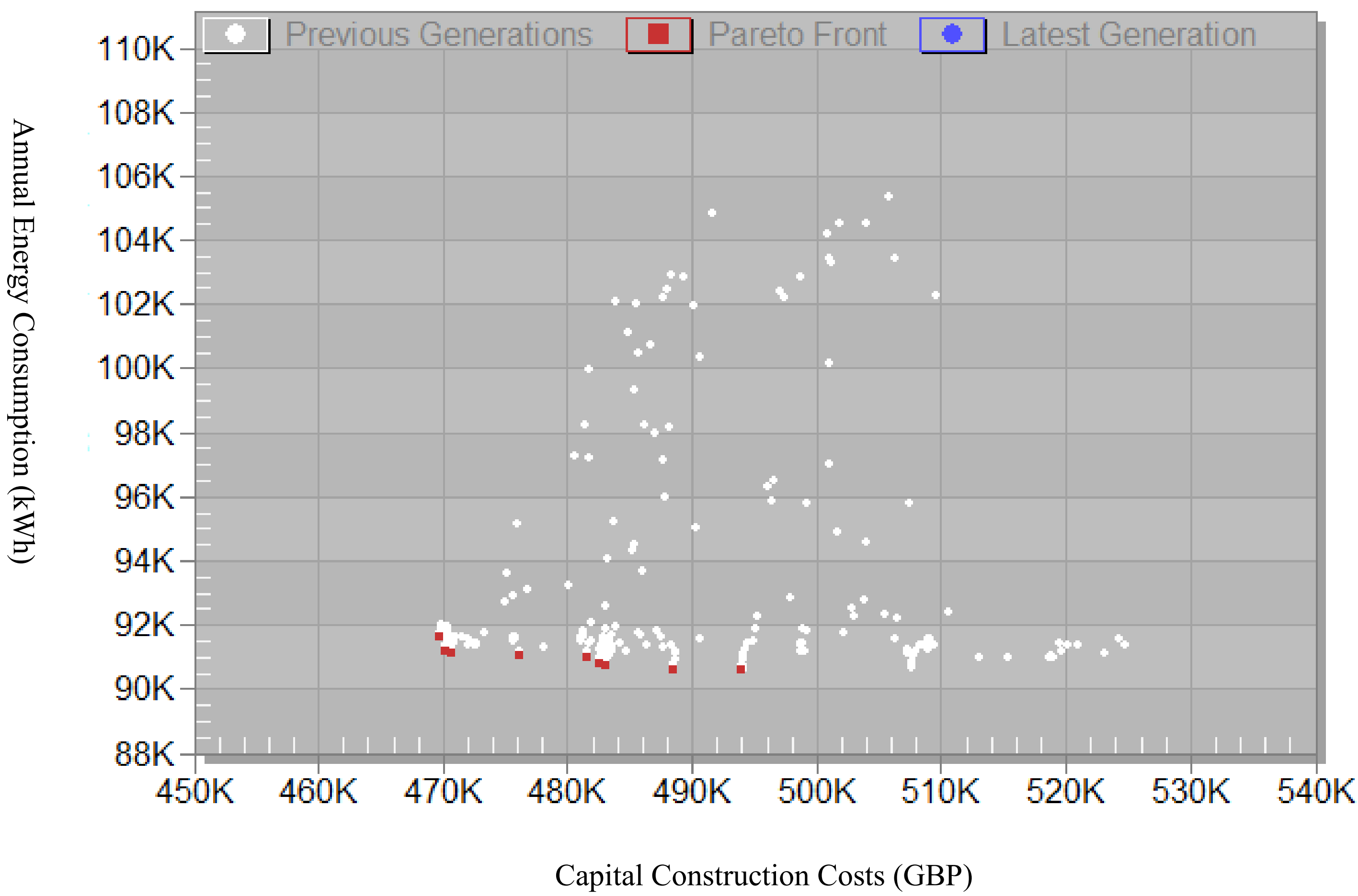


Figure 24. Optimization analysis results. Minimize capital construction costs and annual energy consumption

Scenario	Iteration	Generation	External wall	Glazing template	Internal thermal mass	Window to wall	Window blind type	Facade type	Partition construction	Internal glazing	External glazing type	Window frame	Capital Cost	Energy Consumption
1	1562	44	BioPCM Wall Above-Grade - ASHRAE 90.1 2007 - Steel-Framed	Uninsulated	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	115mm brick cavity wall with 12mm plaster both sides	Sgl Ref-A-M Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	481543.2334	91008.4616
2	2235	59	BioPCM Wall Above-Grade - ASHRAE 90.1 2007 - Steel-Framed	Double glazing, reflective, clear, internal blinds	Inn.6 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	Inn.4 internal mass	Sgl Ref-A-H Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	470683.1533	91136.51868
3	2258	59	BioPCM Wall Above-Grade - ASHRAE 90.1 2007 - Steel-Framed	Triple glazing, clear, LoE, argon-filled	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	360mm single leaf brick (plastered both sides)	Sgl Ref-A-M Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	476049.9833	91016.41421

4	2279	60	BioPCM Wall Above-Grade - ASHRAE 90.1 2007 - Steel-Framed	Triple glazing, clear, LoE, argon-filled	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	13mm expanded wood chipboard	Sgl Ref-A-H Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	470160.3933	91172.73466
5	2282	60	InnExW. 14 BIPV + PCM Project BIPV Wall	Uninsulated	Inn.19 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	360mm single leaf brick (plastered both sides)	Sgl Ref-A-M Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	488498.5634	90580.51346
6	2308	60	InnExW. 14 BIPV + PCM Project BIPV Wall	Uninsulated	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	13mm expanded wood chipboard	Sgl Ref-A-M Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	482608.9735	90758.82276
7	2345	62	BioPCM Wall Above-Grade - ASHRAE 90.1 2007 - Steel-Framed	Triple glazing, clear, LoE, argon-filled	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.0 m, width:0.5	13mm expanded wood chipboard	Sgl Ref-A-H Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	469705.3933	91644.24059
8	2392	63	InnExW. 14 BIPV + PCM Project BIPV Wall	Triple glazing, clear, LoE,	Inn.4 internal mass	40	InnShS. 7 Blind with medium	Fixed windows - height:1.5 m, width:1.0	Inn.3 internal mass	Sgl Ref-A-M Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	483131.5232	90718.0686

				argon-filled			reflectivity slats							
9	2412	63	InnExW. 14 BIPV + PCM Project BIPV Wall	Triple glazing, clear, LoE, argon-filled	Inn.15 internal mass	40	InnShS. 7 Blind with medium reflectivity slats	Fixed windows - height:1.5 m, width:1.0	115mm brick cavity wall with 12mm plaster both sides	Sgl Ref-A-H Clr 6mm	Sgl LoE (e2=.2) Clr 3mm	Painted Wooden window frame	493991.8132	90571.72701

Table 8. Pareto optimal solutions of the optimization

5.2.5.2 Discussion on pareto optimal solutions

The NSGA-II optimization has been performed multiple times to obtain the Pareto front, the convergence was achieved after 100 generations, and the last 10 generations were monitored for the possible occurrence of early convergence. The Pareto front shown above is the most convergent front obtained regarding convergence and diversity. The red points are the converged non-dominated optimum solutions in the last generation, and the whites are the dominated in previous generations. Close observations reveal that:

- The solutions of earlier generations are widely scattered with considerably higher amounts of annual energy consumption. In contrast, the solution of the final population is almost uniformly distributed. Furthermore, the observation in the last 10 generations indicated that a good convergence had been achieved.

- Comparing the maximum energy consumption and capital cost amounts in the initial generations with a random solution on the Pareto front, it is demonstrated that the initial values for annual energy consumption and capital cost have been respectively 105,500 kWh, and 506,000 GBP. While, they are reduced to 91,172 Kwh, and 470,160 GBP This comparison reveals a 14.3% reduction in annual energy consumption, as well as 7% in capital cost. Thus, it testifies that the optimization has been effective in terms of both objective functions.

- The optimum Pareto front indicates that the optimum solutions are almost uniformly spread and are placed in a close range with regard to energy consumption. However, this range constitutes a wider range for the capital cost objective function. To elucidate, the maximum difference between the energy consumption of Pareto solution is 1.7%. Conversely, the similar difference for the cost function is 5%. This comparison shows that for some variables even though the energy consumption has been in a more desirable status, they are not optimum due to their higher costs. Take the example of external glazing; In Table 9 the single glazing option has been preferred due to its lower cost, despite its higher u-value.

Table 9. comparison of options for external glazing variable

Renovation alternative option	**Unit cost (GBP/m^2)**	**U-value (W/m2K)**
Sgl LoE (e2=.2) Clr 3mm	120	3.835
Dbl LoE (e2=.2) Clr 3mm/13mm Arg	180	1.712
Glazing Integrated Photovoltaics	160	1.960
Trp LoE (e2=e5=.1) Clr 3mm/13mm Arg	200	0.780
Thermochromic External Glazing	180	2.130

- The fact that the optima are spread in a close range suggests that many optimum solutions have several parameters (decision variables) in common such as external glazing, window frame, facade type, window to wall ratio, and window blind type. Consequently, the mentioned variables show superiority over the rest of the variables.

5.3 Optimization validation

In order to verify the efficiency of the optimization algorithm, a random Pareto solution is selected from the Pareto front, and its annual energy consumption is compared to a sample base case building in which no retrofit optimization is performed. The base case. Building. 1 has a traditional concrete envelope and has not undergone any retrofit. Both building case. 1 (the base case) and building. 2 (the optimally retrofit) have the same building model, zones, activity, HAVC templates and so on. The mere distinction is that building. 1 is not retrofitted and building. 2 has undergone retrofitting by optimal renovation alternatives. Both buildings share the model was depicted in the figure. At the beginning of this chapter. Table 10 summarizes their respective annual energy consumption values.

Table 10. Comparison of energy consumption of an optimally renovated building with a non-renovated

Building	Annual energy consumption (kWh)
Renovated building. 2 with renovation scenario 5	90580.51346
Baseline building. 1 Non-innovative envelope	141167.61

As it can be noticed the optimized building manifests considerably lower energy consumption value proving that the optimization algorithm has been effective.

5.4 Summary

In this chapter, the proposed model is implemented on a sample case building created in DesignBuilder followed by the validation of the optimization algorithm.

CHAPTER. 6 CONCLUSION

6.1 Conclusion

A non-dominated sorting genetic algorithm (NSGA-II) has been performed in this study to discover the optimum renovation solutions forming the trade-off between annual energy consumption and capital cost. The following results have been achieved:

- 35% reduction in annual energy consumption after implementation of optimized sustainable renovations.
- 9 optimum renovation alternatives were found which are capable of causing the abovementioned reduction rate.

- The initial values for annual energy consumption and capital cost in the early generations have been respectively 105,500 kWh, and 506,000 GBP. While, they are reduced to 91,172 kWh, and 470,160 GBP. This comparison reveals that the optimization algorithm was able to improve the alternatives 14.3 % in terms of energy consumption function, and 7% with respect to the cost function.

6.2 Research Contributions

The research contributions are summarized as follow:

1. Integration of fuzzy set theory to the simulation-based optimization to account for the uncertainty associated with the objective functions in the NSGA-II simulation-based optimization:

    - Fuzzy set theory is utilized to address the uncertainty pertaining to cost and energy consumption objective functions.
    - Defining fuzzy membership functions of the unit cost for all renovation alternatives.
    - Defining fuzzy membership functions of the u-value for all renovation alternatives.
    - The defuzzified unit cost and u-value parameters were transferred to simulation-based NSGA-II optimization to be utilized in the evaluation of fitness functions

2. Use of innovative sustainable components as the renovation alternatives such as BIPV panels in external walls, PCM material, electrochromic glazing, etc.

6.3 Recommendation for Future Work

This research offers the following recommendations for future work:

- The same model could be performed on a high-rise building, as the double facades and BIPVs are most efficient in high rise buildings.
- Use of innovative components could be expanded to other building parts such as roof, as well as the inclusion of a wider range of innovative sustainable components.
- In the optimization section, the environmental performance criterion can also be considered, leading to a Pareto surface of optimal solutions.

REFERENCES

Abdallah, Moatassem, Khaled El-Rayes, and Caroline Clevenger. 2015. 'Minimizing energy consumption and carbon emissions of aging buildings', *Procedia Engineering*, 118: 886-93.

Adams, Brian M, WJ Bohnhoff, KR Dalbey, JP Eddy, MS Eldred, DM Gay, K Haskell, Patricia D Hough, and Laura P Swiler. 2009. 'DAKOTA, a multilevel parallel object-oriented framework for design optimization, parameter estimation, uncertainty quantification, and sensitivity analysis: version 5.0 user's manual', *Sandia National Laboratories, Tech. Rep. SAND2010-2183*.

Ali Al-Arja, Omaimah, and Tala Samir Awadallah. 2016. 'Energy consumption optimization in schools sector in Jordan', *Architectural Science Review*, 59: 400-12.

Anderson, John David, and J Wendt. 1995. *Computational fluid dynamics* (Springer).

Ardente, Fulvio, Marco Beccali, Maurizio Cellura, and Marina Mistretta. 2011. 'Energy and environmental benefits in public buildings as a result of retrofit actions', *Renewable and sustainable energy reviews*, 15: 460-70.

Arndt, Derek S, Molly O Baringer, and Michael R Johnson. 2010. 'State of the climate in 2009', *Bulletin of the American Meteorological Society*, 91: s1-s222.

Asadi, Ehsan, Manuel Gameiro da Silva, Carlos Henggeler Antunes, Luís Dias, and Leon Glicksman. 2014. 'Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application', *Energy and Buildings*, 81: 444-56.

Ascione, Fabrizio, Nicola Bianco, Claudio De Stasio, Gerardo Maria Mauro, and Giuseppe Peter Vanoli. 2015. 'A new methodology for cost-optimal analysis by means of the multi-objective optimization of building energy performance', *Energy and Buildings*, 88: 78-90.

Athienitis, Andreas K, James Bambara, Brendan O'Neill, and Jonathan Faille. 2011. 'A prototype photovoltaic/thermal system integrated with transpired collector', *Solar Energy*, 85: 139-53.

Attia, Shady. 2012. "Computational Optimisation for Zero Energy Building Design, Interviews with Twenty Eight International Experts." In.: Architecture et climat.

Bahaj, AbuBakr S, Patrick AB James, and Mark F Jentsch. 2008. 'Potential of emerging glazing technologies for highly glazed buildings in hot arid climates', *Energy and Buildings*, 40: 720-31.

Bandyopadhyay, Sanghamitra, and Sankar Kumar Pal. 2007. *Classification and learning using genetic algorithms: applications in bioinformatics and web intelligence* (Springer Science & Business Media).

Bandyopadhyay, Sanghamitra, and Sriparna Saha. 2012. *Unsupervised classification: similarity measures, classical and metaheuristic approaches, and applications* (Springer Science & Business Media).

Barbosa, Sabrina, and Kenneth Ip. 2014. 'Perspectives of double skin façades for naturally ventilated buildings: A review', *Renewable and sustainable energy reviews*, 40: 1019-29.

Beale, Mark Hudson, Martin T Hagan, and Howard B Demuth. 1992. 'Neural Network Toolbox™ getting started guide', *Matlab, Mathworks, R2012b*.
Bolattürk, Ali. 2006. 'Determination of optimum insulation thickness for building walls with respect to various fuels and climate zones in Turkey', *Applied thermal engineering*, 26: 1301-09.
Bouchlaghem, NM, and KM Letherman. 1990. 'Numerical optimization applied to the thermal design of buildings', *Building and environment*, 25: 117-24.
Bourazza, Saïd. 2006. 'Variantes d'algorithmes génétiques appliquéees aux problèmes d'ordonnancement', Université du Havre.
Bradshaw, Robert W, Joseph G Cordaro, and Nathan P Siegel. 2009. "Molten nitrate salt development for thermal energy storage in parabolic trough solar power systems." In *ASME 2009 3rd International Conference on Energy Sustainability collocated with the Heat Transfer and InterPACK09 Conferences*, 615-24. American Society of Mechanical Engineers.
Bucking, Scott. 2013. 'Pathways to net-zero energy buildings: An optimization methodology', Concordia University.
Chan, ALS, Tin Tai Chow, KF Fong, and Z Lin. 2009. 'Investigation on energy performance of double skin facade in Hong Kong', *Energy and Buildings*, 41: 1135-42.
Chantrelle, Fanny Pernodet, Hicham Lahmidi, Werner Keilholz, Mohamed El Mankibi, and Pierre Michel. 2011. 'Development of a multicriteria tool for optimizing the renovation of buildings', *Applied Energy*, 88: 1386-94.
Che Ibrahim, Che Khairil Izam, Seosamh B Costello, and Suzanne Wilkinson. 2014. 'A fuzzy approach to developing scales for performance levels of alliance team integration assessment', *Journal of Construction Engineering and Management*, 141: 04014094.
Coello, Carlos A Coello. 1999. 'A comprehensive survey of evolutionary-based multiobjective optimization techniques', *Knowledge and Information systems*, 1: 269-308.
Coley, David A, and Stefan Schukat. 2002. 'Low-energy design: combining computer-based optimisation and human judgement', *Building and environment*, 37: 1241-47.
Crawley, Drury B, Jon W Hand, Michaël Kummert, and Brent T Griffith. 2008. 'Contrasting the capabilities of building energy performance simulation programs', *Building and environment*, 43: 661-73.
Davis, L. 1991. 'Handbook of Genetic Algorithms Van Nostrand Reinhold New York Google Scholar'.
Deb, Kalyanmoy. 2001. *Multi-objective optimization using evolutionary algorithms* (John Wiley & Sons).
Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. 2002. 'A fast and elitist multiobjective genetic algorithm: NSGA-II', *IEEE transactions on evolutionary computation*, 6: 182-97.
Dietz, Adrian. 2004. 'Optimisation multicritère pour la conception d'ateliers discontinus multiproduits: aspects économique et environnemental'.
Erickson, Mark, Alex Mayer, and Jeffrey Horn. 2002. 'Multi-objective optimal design of groundwater remediation systems: application of the niched Pareto genetic algorithm (NPGA)', *Advances in Water Resources*, 25: 51-65.
Fesanghary, Mohammad, Somayeh Asadi, and Zong Woo Geem. 2012. 'Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm', *Building and environment*, 49: 245-50.

Fu, Michael C. 2002. 'Optimization for simulation: Theory vs. practice', *INFORMS Journal on Computing*, 14: 192-215.
Ghaffarianhoseini, Ali, Amirhosein Ghaffarianhoseini, Umberto Berardi, John Tookey, Danny Hin Wa Li, and Shahab Kariminia. 2016. 'Exploring the advantages and challenges of double-skin façades (DSFs)', *Renewable and sustainable energy reviews*, 60: 1052-65.
Goldberg, David E, and John H Holland. 1988. 'Genetic algorithms and machine learning', *Machine learning*, 3: 95-99.
Gosavi, Abhijit. 2003. 'Simulation-based optimization', *parametric optimization techniques and reinforcement learning*.
Grossmann, Christian, Hans-Görg Roos, and Martin Stynes. 2007. *Numerical treatment of partial differential equations* (Springer).
Holland, JH, and D Goldberg. 1989. 'Genetic algorithms in search, optimization and machine learning', *Massachusetts: Addison-Wesley*.
https://www.nrcan.gc.ca/home
https://openei.org/doe-opendata/dataset/buildings-energy-data-book
Ioannidis, Zissis. 2016. 'Double Skin Facades Integrating Photovoltaic Panels, Motorized Shades and Controlled Air Flow', Concordia University.
Jelle, Bjørn Petter, and Christer Breivik. 2012. 'State-of-the-art building integrated photovoltaics', *Energy Procedia*, 20: 68-77.
Klir, George J, Zhenyuan Wang, and David Harmanec. 1997. 'Constructing fuzzy measures in expert systems', *Fuzzy sets and systems*, 92: 251-64.
Konstantinou, Thaleia. 2014. *Facade Refurbishment Toolbox.: Supporting the Design of Residential Energy Upgrades* (TU Delft).
Kutlu, Ahmet Can, and Mehmet Ekmekçioğlu. 2012. 'Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP', *Expert systems with Applications*, 39: 61-67.
Lee, Kyoung Ok, Mario A Medina, Erik Raith, and Xiaoqin Sun. 2015. 'Assessing the integration of a thin phase change material (PCM) layer in a residential building wall for heat transfer reduction and management', *Applied Energy*, 137: 699-706.
Ma, Zhenjun, Paul Cooper, Daniel Daly, and Laia Ledo. 2012. 'Existing building retrofits: Methodology and state-of-the-art', *Energy and Buildings*, 55: 889-902.
Machairas, Vasileios, Aris Tsangrassoulis, and Kleo Axarli. 2014. 'Algorithms for optimization of building design: A review', *Renewable and sustainable energy reviews*, 31: 101-12.
Magnier, Laurent, and Fariborz Haghighat. 2010. 'Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network', *Building and environment*, 45: 739-46.
Mahata, Gour Chandra, and Puspita Mahata. 2011. 'Analysis of a fuzzy economic order quantity model for deteriorating items under retailer partial trade credit financing in a supply chain', *Mathematical and Computer Modelling*, 53: 1621-36.
Marzouk, Mohammad, and Eslam Mohammed Abdelkader. 2017. 'Minimizing Construction Emissions Using Building Information Modeling and Decision-Making Techniques', *International Journal of 3-D Information Modeling (IJ3DIM)*, 6: 14-35.
Nemry, Françoise, Andreas Uihlein, Cecilia Makishi Colodel, Christian Wetzel, Anna Braune, Bastian Wittstock, Ivana Hasan, Johannes Kreißig, Nicole Gallon, and Sigrid Niemeier. 2010. 'Options to reduce the environmental impacts of residential buildings in the European Union—Potential and costs', *Energy and Buildings*, 42: 976-84.

Nguyen, Anh-Tuan, Sigrid Reiter, and Philippe Rigo. 2014. 'A review on simulation-based optimization methods applied to building performance analysis', *Applied Energy*, 113: 1043-58.

Nielsen, Toke Rammer. 2002. 'Optimization of buildings with respect to energy and indoor environment', PhD Dissertation, Technical University of Denmark, online at: http://www/. byg. dtu. dk/upload/institutter/byg/publications/rapporter/byg-r036. pdf,[accessed 22 January 2012].

Omrany, Hossein, Ali Ghaffarianhoseini, Amirhosein Ghaffarianhoseini, Kaamran Raahemifar, and John Tookey. 2016. 'Application of passive wall systems for improving the energy efficiency in buildings: A comprehensive review', *Renewable and sustainable energy reviews*, 62: 1252-69.

Panão, Marta JN Oliveira, Helder JP Gonçalves, and Paulo MC Ferrão. 2008. 'Optimization of the urban building efficiency potential for mid-latitude climates using a genetic algorithm approach', *Renewable Energy*, 33: 887-96.

Papaefthimiou, S, E Syrrakou, and P Yianoulis. 2006. 'Energy performance assessment of an electrochromic window', *Thin Solid Films*, 502: 257-64.

Parry, Martin, Osvaldo Canziani, Jean Palutikof, Paul J van der Linden, and Clair E Hanson. 2007. *Climate change 2007: impacts, adaptation and vulnerability* (Cambridge University Press Cambridge).

Pedrycz, Witold, and Fernando Gomide. 2007. *Fuzzy systems engineering: toward human-centric computing* (John Wiley & Sons).

Peippo, K, PD Lund, and E Vartiainen. 1999. 'Multivariate optimization of design trade-offs for solar low energy buildings', *Energy and Buildings*, 29: 189-205.

Pielichowska, Kinga, and Krzysztof Pielichowski. 2014. 'Phase change materials for thermal energy storage', *Progress in materials science*, 65: 67-123.

Poel, Bart, Gerelle van Cruchten, and Constantinos A. Balaras. 2007. "Energy performance assessment of existing dwellings." *Energy and Buildings* 39, no. 4: 393-403.

Rakha, Tarek, and Khaled Nassar. 2011. 'Genetic algorithms for ceiling form optimization in response to daylight levels', *Renewable Energy*, 36: 2348-56.

Roberts, Simon. 2008. 'Altering existing buildings in the UK', *Energy policy*, 36: 4482-86.

Sadeghi, Naimeh, Aminah Robinson Fayek, and Witold Pedrycz. 2010. 'Fuzzy Monte Carlo simulation and risk assessment in construction', *Computer-Aided Civil and Infrastructure Engineering*, 25: 238-52.

Safer, Nassim, Monika Woloszyn, and Jean Jacques Roux. 2005. 'Three-dimensional simulation with a CFD tool of the airflow phenomena in single floor double-skin facade equipped with a venetian blind', *Solar Energy*, 79: 193-203.

Schaffer, J David. 1985. "Multiple objective optimization with vector evaluated genetic algorithms." In *Proceedings of the First International Conference on Genetic Algorithms and Their Applications, 1985*. Lawrence Erlbaum Associates. Inc., Publishers.

Shameri, MA, MA Alghoul, Kamaruzzaman Sopian, M Fauzi M Zain, and Omkalthum Elayeb. 2011. 'Perspectives of double skin façade systems in buildings and energy saving', *Renewable and sustainable energy reviews*, 15: 1468-75.

Sharif, Seyed Amirhosain, and Amin Hammad. 'Simulation-Based Optimization of Building Renovation Considering Energy Consumption and Life-Cycle Assessment.' in, *Computing in Civil Engineering 2017*.

Srinivas, Nidamarthi, and Kalyanmoy Deb. 1994. 'Muiltiobjective optimization using nondominated sorting in genetic algorithms', *Evolutionary computation*, 2: 221-48.
Sullivan, Robert, F Beck, D Arasteh, and Stephen E Selkowitz. 1995. 'Energy performance of evacuated glazings in residential buildings'.
Thomsen, AF, and CL van Der Flier. 2008. 'Replacement or reuse? The choice between demolition and life cycle extension from a sustainable viewpoint'.
Wang, Weimin. 2005. 'A simulation-based optimization system for green building design', Concordia University.
Wetter, Michael. 2003. 'GenOpt (R), generic optimization program, User Manual, Version 2.0. 0'.
Woolley, T, S Kimmins, P Harrison, and R Harrison. 1997. "Green Building Handbook: A Guide to Building." In.: Taylor & Francis, UK.
Wright, Jonathan, and Raziyeh Farmani. 2001. "The simultaneous optimization of building fabric construction, HVAC system size, and the plant control strategy." In *Proceedings of the 7th IBPSA Conference: Building Simulation, Rio de Janeiro, Brazil*, 865-72.
Xing, Yangang, Neil Hewitt, and Philip Griffiths. 2011. 'Zero carbon buildings refurbishment—A Hierarchical pathway', *Renewable and sustainable energy reviews*, 15: 3229-36.
Xu, Ben, Peiwen Li, and Cholik Chan. 2015. 'Application of phase change materials for thermal energy storage in concentrated solar thermal power plants: a review to recent developments', *Applied Energy*, 160: 286-307.
Yeung, John FY, Albert PC Chan, and Daniel WM Chan. 2011. 'Fuzzy set theory approach for measuring the performance of relationship-based construction projects in Australia', *Journal of management in engineering*, 28: 181-92.
Zadeh, Lofti A. 1965. 'Information and control', *Fuzzy sets*, 8: 338-53.
Zadeh, Lotfi A. 1975. 'Fuzzy logic and approximate reasoning', *Synthese*, 30: 407-28.
Zahraie, Banafsheh, and Mehdi Tavakolan. 2009. 'Stochastic time-cost-resource utilization optimization using nondominated sorting genetic algorithm and discrete fuzzy sets', *Journal of Construction Engineering and Management*, 135: 1162-71.
Znouda, Essia, Nadia Ghrab-Morcos, and Atidel Hadj-Alouane. 2007. 'Optimization of Mediterranean building design using genetic algorithms', *Energy and Buildings*, 39: 148-