OPTIMIZING ENERGY PERFORMANCE OF BUILDING RENOVATION USING TRADITIONAL AND MACHINE LEARNING APPROACHES

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A Thesis
In the Department
of
Building, Civil, and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy at
Concordia University

Montreal, Quebec, Canada

April, 2020

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

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Entitled: Optimizing Energy Performance of Building Renovation Using Traditional and Machine Learning Approaches

and submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy (Building Engineering)

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ABSTRACT

Optimizing Energy Performance of Building Renovation Using Traditional and Machine Learning Approaches

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International Energy Agency (IEA) studies show that buildings are responsible for more than 30% of the total energy consumption and an equally large amount of related greenhouse gas emissions. Improving the energy performance of buildings is a critical element of building energy conservation. Furthermore, renovating existing buildings envelopes and systems offers significant opportunities for reducing Life-Cycle cost (LCC) and minimizing negative environmental impacts. This approach can be considered as one of the key strategies for achieving sustainable development goals at a relatively low cost, especially when compared with the demolition and reconstruction of new buildings. One of the main methodological and technical issues of this approach is selecting a desirable renovation strategy among a wide range of available options.

The main motivation behind this research relies on trying to bridge the gap between building simulation, optimization algorithms, and Artificial Intelligence (AI) techniques, to take full advantage of the value of their couplings. Furthermore, for a whole building simulation and optimization, current simulation-based optimization models, often need thousands of simulation evaluations. Therefore, the optimization becomes unfeasible because of the computation time and complexity of the dependent parameters. To this end, one feasible technique to solve this problem is to implement surrogate models to computationally imitate expensive real building simulation models.

The aim of this research is three-fold: (1) to propose a Simulation-Based Multi-Objective Optimization (SBMO) model for optimizing the selection of renovation scenarios for existing buildings by minimizing Total Energy Consumption (TEC), LCC and negative environmental impacts considering Life-Cycle Assessment (LCA); (2) to develop surrogate Artificial Neural Networks (ANNs) for selecting near-optimal building energy renovation methods; and (3) to develop generative deep Machine Learning Models (MLMs) to generate renovation scenarios

considering TEC and LCC. This study considers three main areas of building renovation, which are the building envelope, Heating, Ventilation and Air-Conditioning (HVAC) system, and lighting system; each of which has a significant impact on building energy performance.

On this premise, this research initially develops a framework for data collection and preparation to define the renovation strategies and proposes a comprehensive database including different renovation methods. Using this database, different renovation scenarios can be compared to find the near-optimal scenario based on the renovation strategy. Each scenario is created from the combination of several methods within the applicable strategy. The SBMO model simulates the process of renovating buildings by using the renovation data in energy analysis software to analyze TEC, LCC, and LCA and identifies the near-optimal renovation scenarios based on the selected renovation methods. Furthermore, an LCA tool is used to evaluate the environmental sustainability of the final decision.

It is found that, although the proposed SBMO is accurate, the process of simulation is time consuming. To this end, the second objective focuses on developing robust MLMs to explore vast and complex data generated from the SBMO model and develop a surrogate building energy model to predict TEC, LCC, and LCA for all building renovation scenarios. The main advantage of these MLMs is improving the computing time while achieving acceptable accuracy. More specifically, the second developed model integrates the optimization power of SBMO with the modeling capability of ANNs. While, the proposed ANNs are found to provide satisfactory approximation to the SBMO model in a very short period of time, they do not have the capability to generate renovation scenarios.

Finally, the third objective focuses on developing a generative deep learning building energy model using Variational Autoencoders (VAEs). The proposed semi-supervised VAEs extract deep features from a whole building renovation dataset and generate renovation scenarios considering TEC and LCC of existing institutional buildings. The proposed model also has the generalization ability due to its potential to reuse the dataset from a specific case in similar situations.

The proposed models will potentially offer new venues in two directions: (1) to predict TEC, LCC, and LCA for different renovation scenarios, and select the near-optimal scenario, and (2) to generate renovation scenarios considering TEC and LCC. Architects and engineers can see the effects of different materials, HVAC systems, etc., on the energy consumption, and make necessary changes to increase the energy performance of the building. The proposed models encourage the implementation of sustainable materials and components to decrease negative environmental impacts. The ultimate impact of the practical implementation of this research is significant savings in buildings' energy consumption and having more environmentally friendly buildings within the predefined renovation budget.

Dedicated to my parents and my wife for their endless love and unwavering support.

ACKNOWLEDGEMENTS

I would like to thank God for giving me the strength and encouragement in life especially during all the challenging moments in completing this thesis.

I would like to express my sincere gratitude to my supervisor Prof. Amin Hammad for the continuous support of my Ph.D. study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better supervisor for my Ph.D. study.

I would also like to thank the members of my committee, Dr. Fariborz Haghighat, Dr. Khaled El-Rayes, Dr. Hua Ge, and Dr. Mohsen Ghafouri for their constructive inputs and precious time.

Besides my supervisor, I would like to thank the rest of my research lab colleagues for their insightful comments and encouragement, and making the research lab a great research environment. Furthermore, I would like to thank Mr. Parsa Bagherzadeh, Ph.D. Student at Concordia University, for supporting me with useful information.

This research was made possible by “Fonds de recherche du Québec Nature et technologies” (FRQNT) award from the Quebec Government and a scholarship from the “Pierre Arbour Foundation”.

Last but not least, a special thank to my family. Words cannot express how grateful I am to my mother and father for all of the sacrifices that you have made for me. Your prayer for me was what sustained me thus far. At the end, I would like express appreciation to my beloved wife, Zahra Yousefli, and my two beloved children, Zahra Sadat and Seyed Amirreza, who were always my support in the moments when there was no one to answer my queries.

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LIST OF ABBREVIATIONS

μ	mean value
σ	variance value
AE	Autoencoder
ASGD	Averaged Stochastic Gradient Descent
ANN	Artificial Neural Network
ASHP	Air to Water Heat Pump
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEM	Building Energy Model
BIM	Building Information Model
BIPV	Building Integrated Photo Voltaic
BP	Back Propagation
BPNN	Back Propagation Neural Network
BNMI	Best Network after Multiple Iterations
CAE	Convolutional Autoencoder
CFL	Compact Fluorescent Lamp
DH	Percentage of Annual Discomfort Hours
DHW	Domestic Hot Water
CNN	Convolutional Neural Network
DNN	Deep Neural Network
CoP	Coefficient of Performance
COS	Cooling Operation Schedule
DOAS	Dedicated Outdoor Air System

EC	Energy Consumption
EE	Embodied Energy
f	Activation function
FT	Façade Type
EIFS	Exterior Insulation and Finishing Systems
ELM	Extreme Learning Machine
ES	Existing Situation
EW	External Walls
EWO	External Window Open
FPID	Fan-Powered Induction Unit
FSP	Fixed Set-Point
GA	Genetic Algorithm
GAN	Generative Adversarial Network
gbXML	green building Extensible Markup Language
GHG	Green House Gas
GRBFNN	Generalized Radial Basis Function Neural Network
GT	Glazing Type
HOS	Heating Operation Schedule
HR	Heat Recovery
HII	Heat Inertia Index
HTC	Heat Transfer Coefficient
HVAC	Heating, Ventilation and Air-Conditioning
ICF	Insulated Concrete Forms

KL	Kullback-Leibler
LCA	Life-Cycle Assessment
LCC	Life-Cycle Cost
LCEA	Life-Cycle Energy Assessment
LCIA	Life-Cycle Impact Assessment
LED	Light-Emitting Diode
LEED	Leadership in Energy and Environmental Design
LHS	Latin Hypercube Sampling
Li	Lighting systems
LMA	Levenberg-Marquardt Algorithm
Lr	Learning rate
MAPE	Mean Absolute Percentage Error
MARS	Multivariate Adaptive Regression Splines
MCA	Multi Criteria Analysis
MFM	Multifunctional Façade Modules
MLM	Machine learning model
MLR	Multiple Linear Regression
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
MOO	Multi-Objective Optimization
MPC	Model Predictive Control
MSE	Mean Squared Error
NTO	Material Take-Off

NA	Not Applicable
Nat. Vent.	Natural Ventilation
NoL	Number of Layers
NN	Neural Network
NSGA-II	Non-dominated Sorting and crowding Genetic Algorithm
NV	Natural Ventilation
OE	Operational Energy
PCA	Principal Component Analysis
PCM	Phase Change Material
PCM	Principal Component Analysis
PEC	Primary Energy Consumption
PMV	Predicted Mean Vote
PSO	Particle Swarm Optimization
PTAC	Packaged Terminal Air Conditioner
PTHP	Packaged Thermal Heat Pump
PV/T hybrid	Photovoltaic thermal hybrid
RBE	Responsive Building Elements
RBF	Radial Basis Function
RF	Random Forest
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RSA	Response Surface Approximation
RT	Roof Types

SAE	Stacked Autoencoder
SBMO	Simulation-Based Multi-Objective Optimization
SCG	Scaled Conjugate Gradient
SHGC	Solar Heat Gain Coefficient
SHG	Solar Heat Gain
SIPS	Structural Insulated Panel Systems
SVM	Support Vector Machines
SVR	Support Vector Regression
TEC	Total Energy Consumption
TPMVD	Total Percentage of Discomfort Hours
UPVC	Unplasticized polyvinyl chloride
VAV	Variable Air Volume
VAE	Variational Autoencoder
W	Window frame types
WWR	Window-to-Wall Ratios

CHAPTER 1. INTRODUCTION

1.1 General Background

Buildings are responsible for almost 30% of the world total energy consumption (Wang and Srinivasan 2017). Globally, buildings contribute towards over one-third of the associated greenhouse gas emissions (Ascione et al. 2017b). Therefore, considering methods for decreasing carbon emission and energy consumption related to buildings is vital for improving sustainability. The Government of Canada will develop a "net-zero energy ready" model building code, with the goal that provinces and territories adopt it by 2030 (Energy and Mines Ministers 2018). It will also develop a retrofit code for existing buildings and work towards energy labeling to support retrofits. Additionally, in 2030, 75% of Canada's buildings will continue to be the same buildings that are standing today; therefore, it is important to improve their energy efficiency. Moreover, the Quebec Government is announcing a $1.5 billion projected cost for renovating university buildings for energy optimization. In order to evaluate the sustainability of these renovation projects, planners should have access to the energy consumption of the buildings. Moreover, to analyze future strategies for improving energy performance, such as renovation scenarios, they also need accurate models.

On the other hand, buildings can be considered as nonlinear systems with dynamic and complex behaviors and with a relatively long lifecycle (U.S. Department of Energy, 2012). There are a significant number of components and systems in buildings that strongly affect building energy performance. This complexity causes difficulties in optimizing the whole building energy performance, while considering Total Energy Consumption (TEC), building Life-Cycle cost (LCC), and environmental impacts. Purdy and Beausoleil-Morrison (2001) showed that building envelope and mechanical systems contribute tremendously to the total building LCC. Furthermore, assessing the environmental impact of each process using a systematic approach is the main focus of Life-Cycle assessment (LCA).

Additionally, with increasing advancements in innovative energy management technologies and methods for renovation of existing buildings, such as efficient energy equipment, energy analysis tools, and Building Energy Models (BEMs), the opportunity to mitigate energy-related problems and implement new optimization methods for renovation projects becomes more feasible.

BEMs, such as those supported by EnergyPlus, DesignBuilder, TRNSYS, and eQuest, are widely used to simulate energy consumption and calculate the cost and other related parameters (Evins 2013). Simulation-Based Multi-Objective Optimization (SBMO) models are among the most popular and effective BEMs used in the building industry (Kim et al. 2016; Machairas et al. 2014). Furthermore, certification programs, such as Leadership in Energy and Environmental Design (LEED), and the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) have been extended to cover the renovation of buildings. On the other hand, decision-makers, energy managers and participants in energy renovation projects, primarily tested their assumptions using BEMs, which are time consuming.

1.2 Problem Statement

Improving the energy performance of existing buildings has a significant role in reducing negative environmental impacts (Ma et al. 2012). However, most of the existing institutional buildings' envelopes and systems are in poor condition (CBC news 2016). Therefore, an accurate energy predictive model is essential to facilitate better energy management systems. Ma et al. (2012) studied the significant role of the renovation of existing buildings in reducing energy intensity and negative environmental impacts. However, proposing a renovation strategy that takes full advantage of resources, while reducing the energy consumption and negative environmental impacts within an acceptable budget, is a big challenge for decision-makers due to the complexity of the subject and the large number of parameters involved. Despite the significant contribution of research on optimizing energy consumption, there is limited research focusing on the renovation of existing buildings to minimize their LCC and their environmental impact using LCA.

The problem of developing near-optimal renovation scenarios for whole building's renovation can become complex, in line with the consideration of TEC, LCC, and LCA. For such complex problems, the conventional approach of BEMs becomes far-fetched, because it is difficult or unfeasible to consider and analyze all dependent parameters, which are sometimes contradictory. SBMO can be designed to address such complex problems by integrating different types of optimization algorithm (e.g., Non-dominated Sorting and crowding Genetic Algorithm (NSGA-II)) and simulation tools. The benefits reached by integrating the optimization method with the simulation tools were discussed in (Sharif and Hammad 2018).

For a detailed model in a large project, SBMO often needs hundreds or thousands of simulations runs (Nguyen et al. 2014). Nevertheless, to achieve reliable results, the energy performance of each renovation scenario should be calculated by implementing whole building simulation tools that consider the specific characteristics of the building over the study period. It is clear that this procedure also results in a prohibitive computational time, even for simple buildings, and sometimes becomes unfeasible due to complexity of the dependent parameters (e.g., Magnier and Haghighat 2010a; Penna et al. 2015; Sharif and Hammad 2017).

New advancements in technologies relying on Machine Learning Models (MLMs) improve computational capabilities and accuracy of prediction models. One feasible method to resolve the above-mentioned problem is to implement surrogate models to computationally mimic expensive, real building simulation models with a more feasible model. Few studies have been conducted covering the integration of MLMs and building simulation or optimization (e.g., Abdallah and El-rayes 2015; Azari et al. 2016; Delgarm et al. 2016; Kim et al. 2016; Sharif and Hammad 2018). Also, the full integration between them, especially for building renovation, is still an open research problem.

Finally, in spite of the growing availability and huge improvement in MLM and especially Deep Neural Networks (DNNs), their application in the building industry is limited to some specific categories (e.g., Amasyali and El-Gohary 2018; Kim et al. 2018; Li et al. 2017; Mocanu et al. 2018; Naganathan et al. 2016; Paterakis et al. 2017; Singaravel et al. 2017). Based on the literature review, even less studies are available on developing generative DNNs for the design of new buildings or the renovation of existing ones. Moreover, the existing models do not take full advantage of semi-supervised Variational Autoencoders (VAEs) to generate scenarios of whole building renovation considering TEC and LCC.

1.3 Research Objectives and Scope

The aim of this research is three-fold: (1) to propose a SBMO model for optimizing the selection of renovation scenarios for existing buildings by minimizing TEC, LCC, and negative environmental impacts considering LCA; (2) to develop surrogate ANNs for selecting near-optimal building energy renovation methods; and (3) to develop generative deep MLMs to generate renovation scenarios considering TEC and LCC.

This study considers three main areas of building renovation, i.e., the building envelope, Heating, Ventilation and Air-Conditioning (HVAC) system, and lighting system; each of which has a noteworthy influence on building energy performance. The scope of this research is limited to applications in institutional buildings energy renovation and design. The case study is taken from an institutional building in Montreal to demonstrate the applicability of the models.

1.4 Research Significance

This study is implemented in the context of recent issues imposed by the Quebec government regarding the poor condition of university buildings, which accumulate about 40% of the existing buildings. The research aims to develop near-optimal scenarios for the renovation of buildings considering energy consumption, LCC, and LCA while providing an efficient method to deal with the limited renovation budget. This research also exploits the increasingly available MLMs and develops new methods and applications in the building industry. The overall proposed SBMO model encourages the implementation of sustainable materials and components to decrease TEC, LCC, and negative environmental impacts. Significant savings in buildings' energy consumption and having more environmentally friendly buildings within the predefined renovation budget are the ultimate results of the practical implementation of this research. On the other hand, the owners can benefit from this research to improve the energy performance of their buildings through the selection of optimum scenarios and fine-tuning the desired renovation methods with relatively low cost. Finally, decision-makers and energy advisors can benefit from this research through: (1) predicting TEC and LCC for their proposed renovation scenarios instantly and (2) generating new renovation scenarios for their projects automatically, which can be used to consider more options.

1.5 Thesis Layout

The structure of the thesis is as follows as shown in Figure 1-1:

Chapter 2 presents a comprehensive literature review that establishes baseline knowledge on (1) potential energy saving using energy efficiency technologies; (2) renovation methods for building envelope, HVAC systems, and lighting systems that are capable of reducing the TEC, LCC, and negative environmental impacts of existing buildings; (3) available decision-making methods for selecting building renovation models to improve sustainability in buildings while considering the renovation LCC; (4) challenges and limitations of SBMO in BEM; (5) surrogate MLMs in building application; and (6) machine learning-based surrogate models.

Chapter 3 describes an overview of the proposed framework that has four main parts including: (1) developing data management model including input data collection and preparation, database development, definition of the renovation strategies, and integration; (2) proposing the SBMO model for building renovation considering TEC, LCC, and LCA and validation of results; (3) data processing including data preprocessing, dataset preparation, and transformation; and (4) proposing two different MLMs to inform decision-makers of the various renovation scenarios that can be selected or generated, as well as the trade-off relationships between them.

Chapter 4 presents the development of the SBMO model, which is capable of optimizing the selection of renovation methods for envelope, HVAC, and lighting of existing buildings considering energy consumption and LCA while respecting the limited renovation budgets. A specific type of Genetic Algorithm (GA), coupled with a simulation tool, is used for the proposed SBMO model. This chapter includes data collection, database development and integration, definition of the renovation strategies, and SBMO development. To illustrate the applicability of the model, a case study was developed and the accuracy of the proposed model was cross-checked.

Chapter 5 focuses on coupling SBMO and MLMs and developing a prediction model. The MLMs are developed as surrogate models for emulating computationally expensive real building simulation models with more feasible models.

Chapter 6 focuses on developing a generative deep learning building energy model using Variational Autoencoders (VAEs). The proposed model extracts deep features from a whole building renovation dataset and generates renovation scenarios considering TEC and LCC of the existing institutional buildings.

Finally, **Chapter 7** summarizes the work presented in this thesis and provides research contributions, limitations and future works.

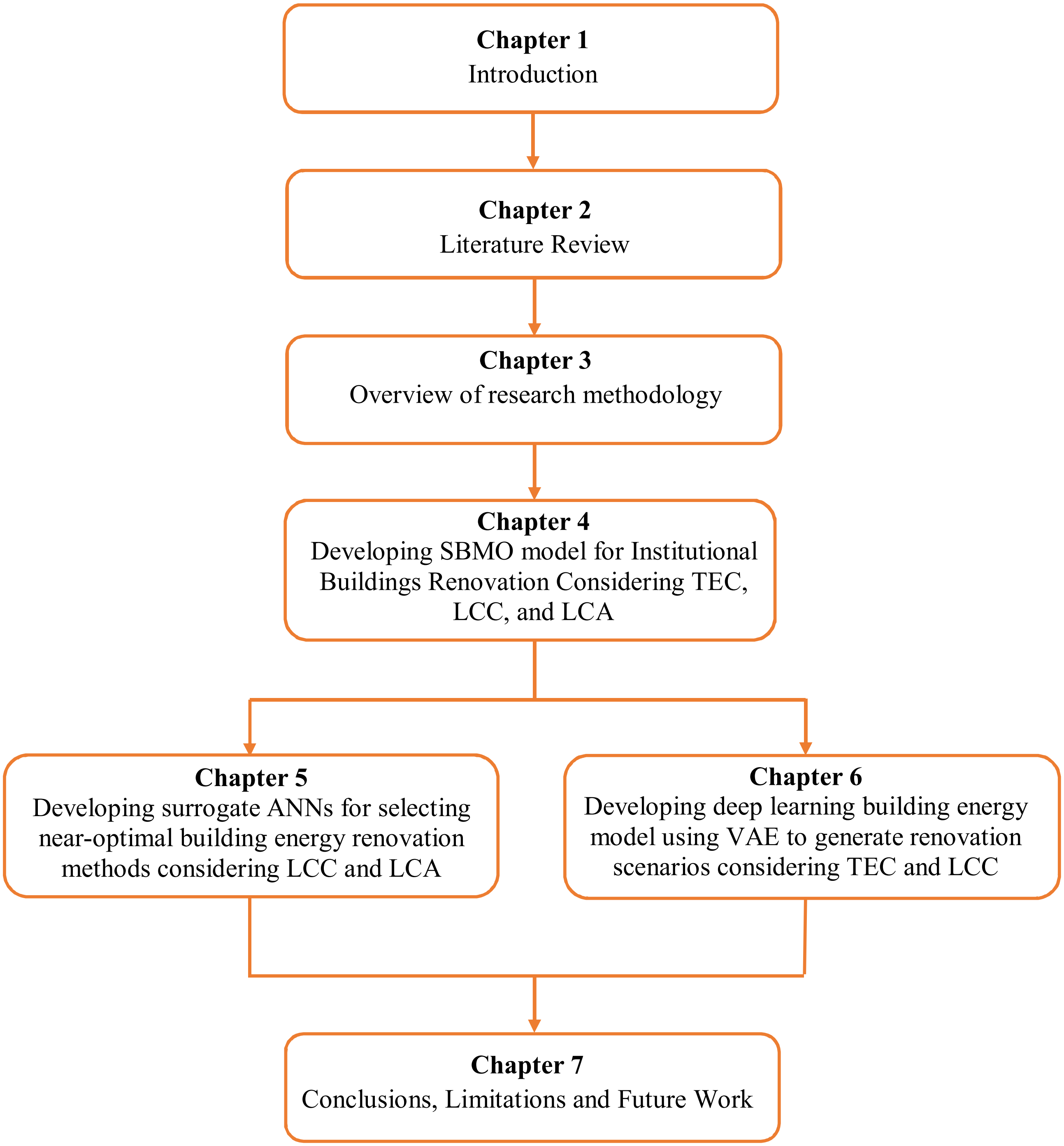


Figure 1-1. Thesis layout

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

In Canada, residential and commercial/institutional sectors consume approximately 20% of the total primary and secondary energy as shown in Figure 2-1 (Natural Resources Canada, 2016). Buildings also have significant impacts on the environment; thus, it is necessary to redress building energy consumption. Furthermore, energy use is the primary factor contributing to Green House Gas (GHG) emissions, which in turn cause climate change (Eurostat, 2010). The potential for reductions of secondary energy consumption and other negative environmental factors (e.g., GHG emissions) related to this sector are enormous. Consequently, a reduction in energy consumption will result in achieving the goals of sustainable development plans. The role of buildings in this critical task has been recognized and addressed by institutional and governmental organizations. However, it is not enough to build new energy efficient buildings; the renovation of existing buildings also needs to be considered (Neuhoff et al., 2011).

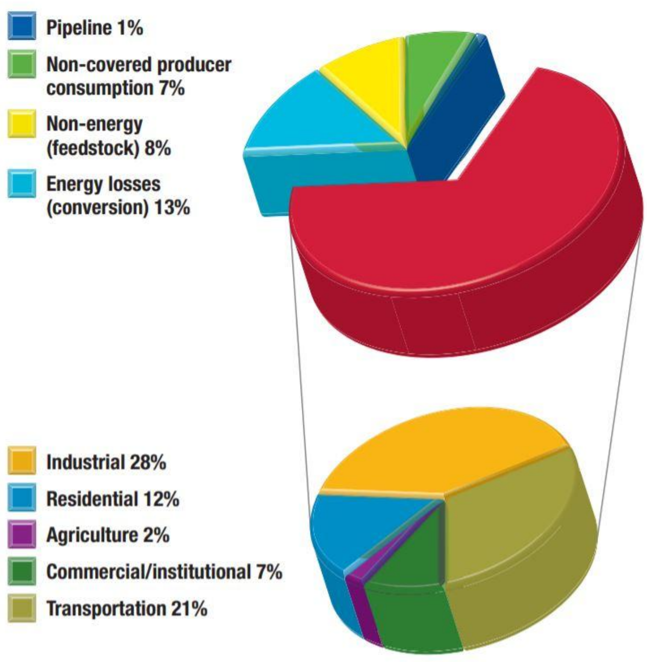


Figure 2-1. Primary and secondary energy use by sector, 2013 (Natural Resources Canada, 2016).

Buildings have a long life-cycle. During this extended period, operational energy systems, such as HVAC system, equipment, and lighting, are responsible for tremendous amount of total building energy consumption (Juan et al., 2010). Throughout the life-cycle of a building, the processes of construction and allocation of resources should be selected with consideration of environmental responsibility. This extended period starts from design and continues to construction, operation, maintenance, renovation and concludes with demolition (U.E.P.A., 2011).

Building renovation has received considerable attention as a viable alternative to new construction for reducing energy consumption and reducing a building’s Life-Cycle environmental impact (JCHS, 2019; Itard and Meijer, 2008). It is evident that existing buildings can achieve more energy conservation in comparison with newly built buildings’ and they need more attention regarding energy performance (Itard and Meijer, 2008). Therefore, it is vital to properly renew existing buildings in a manner that they will consume minimum energy and produce less adverse environmental impacts, all with reasonable renovation budgets and improving the aesthetic quality of the building façades (Konstantinou, 2014). Sustainable building renovation aims to integrate the sustainable development idea into existing buildings and renovation projects.

Furthermore, renovating building envelopes and energy systems to lessen energy losses is usually expensive and has a long payback period (Sharif and Hammad 2017). Major building renovation, e.g., changing envelopes and systems, is very costly and time-consuming; so, renovation planning should be comprehensive (Konstantinou, 2014). From the perspective of the energy performance, building envelope renovation is very challenging since many different factors must be considered for these projects. Key factors are energy efficiency, the well-being of occupants, new hygrothermal conditions, and durability. The renovation of the building's envelope significantly affects the future heating and cooling strategies (ASHRAE Design Guide, 2014). The patterns of energy demands will change after the renovation of the building envelope.

Recent environmental and financial concerns have revealed an immediate need for the recovery of the sustainability level of buildings. This need is more critical for existing buildings (U.S. Environmental Protection Agency, 2011). The construction sector is being pushed by different governmental and non-governmental organizations to implement sustainable innovation for its products and processes (Straube and Burnett, 2005).

In this chapter, initially energy-related renovation factors are briefly mentioned (Section 2.3) then the status of the recent practices promoting sustainability through renovation, building envelope (Section 2.4) and systems (Sections 2.5 and 2.6 for HVAC and lighting respectively) renovation methods, and technologies, for renovating existing buildings, are investigated. In Section 2.7, the application of decision-making methods and surrogate models for reducing energy consumption, LCC, and negative environmental impacts, is evaluated to select the near-optimal renovation scenario for building envelope, HVAC, and lighting. Section 2.8 provides an overview of challenges and limitations of SBMO in BEM. Different surrogate MLMs in building application are introduced and discussed in Section 2.9. Finally, Section 2.10 reviews a wide spectrum of literature on machine learning-based surrogate models in BEM. The limitations and research gaps in the available methods are highlighted in sections to be the baseline for the methodology of this research.

2.2 Potential of Energy Saving Using Energy Efficiency Technologies

One of the best approaches to decrease the TEC in buildings is improving energy performance. Energy efficiency is one method of reducing carbon dependence. Energy efficiency technologies are far cheaper to implement than other green energy sources like wind and solar. As shown in Figure 2-2, the levelized cost of energy efficiency is significantly lower than other new energy sources such as wind, solar, coal, natural gas, or nuclear. Furthermore, there is a significant potential for energy efficiency projects in Canada (Salimzadeh et al. 2016). It is estimated that it would be possible to reduce energy consumption by 23% by 2020 using current energy efficiency technologies (Howland 2013). Nevertheless, many of the energy efficiency potentials become unrealized due to the lack of knowledge (Howland 2013).

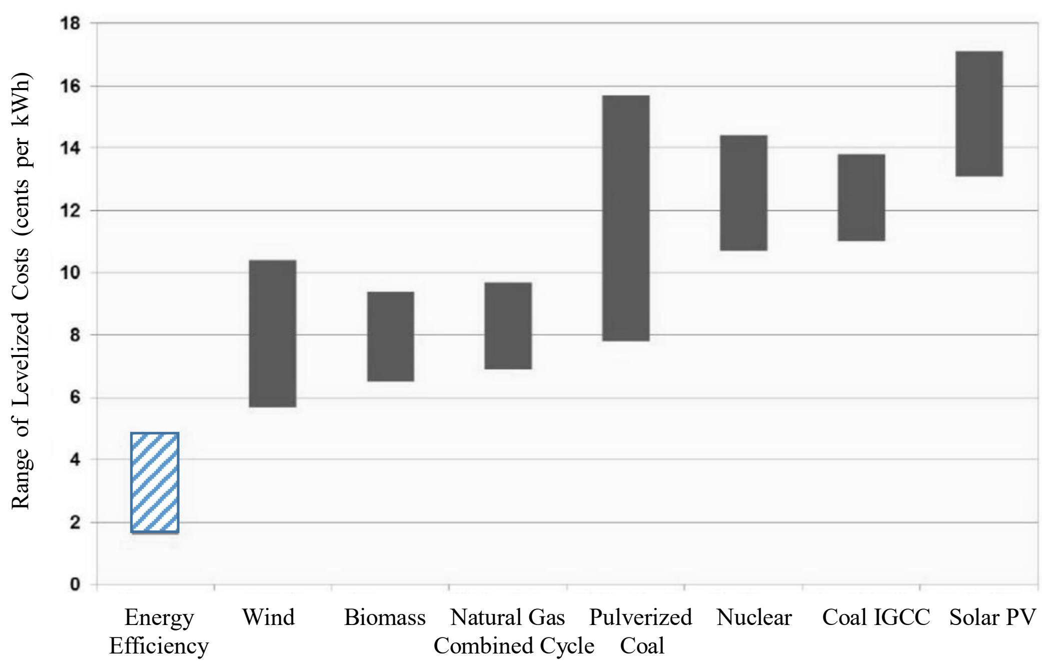


Figure 2-2. Levelized cost of new energy resources (Adapted from Howland, 2013).

2.3 Energy-Related Renovation Factors

Many important factors influence the energy consumption of buildings. The functionality of the building has a critical role, which must be a primary consideration. In general, choices related to building enclosures, HVAC systems, and lighting are responsible for the energy consumption of buildings. The building envelope has a very significant role in controlling and shaping the energy consumption of a building. Building enclosures can reduce heat transfer from surfaces, control solar gain and conduction, and decrease condensation. The selection and implementation of the proper insulation and glazing can be very useful in achieving the aims of energy renovation of the building envelope. Energy consumed associated with equipment and lighting should also be investigated since these devices have a tremendous role in the electricity consumption of buildings.

The local climate situation plays a vital role, especially in harsh climate zones and should be considered precisely in any renovation project. Furthermore, climate conditions should be taken into consideration by the designer, and in some cases, this consideration can lead to a renovation method based on the climate in the existing building site. For instance, natural ventilation is an important factor in almost all situations in which heating or cooling, gain or loss, through the envelope are necessary. Figure 2-3 depicts the interrelation between the major factors of buildings and the climate. It is entirely clear that decisions for the renovation of the building envelope heavily influences the future heating and cooling strategies (ASHRAE Design Guide, 2014).

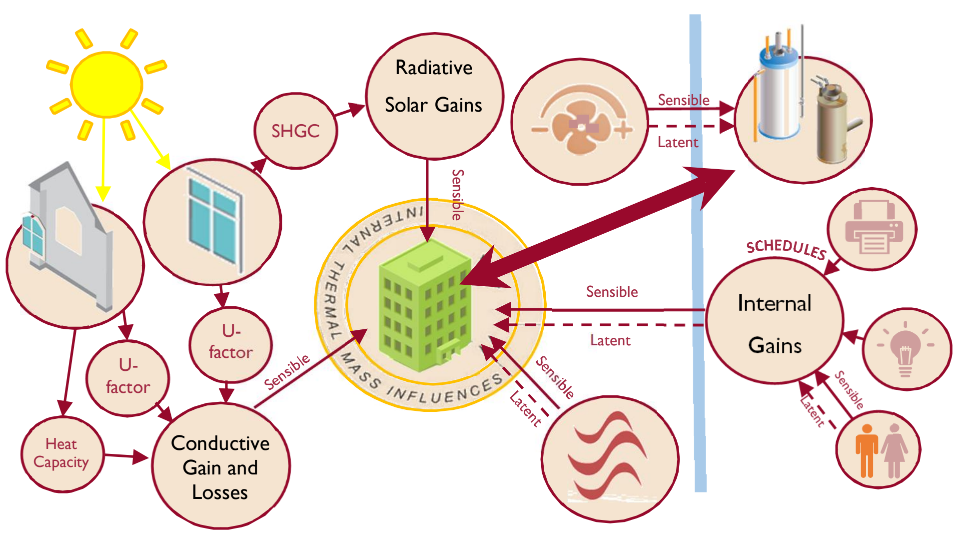


Figure 2-3. Heating and cooling influence (ASHRAE Design Guide, 2014).

2.4 Building Envelope Renovation Scenarios

In existing buildings, heat losses or gains through building envelopes affect the energy use and the indoor condition, and produce a significant amount of energy depletion. Therefore, renovating the external walls and fenestrations has a considerable impact on reducing energy consumption (Straube and Burnett, 2005). Building envelope renovation is very challenging from the perspective of energy performance because different factors must be considered for these projects. This kind of renovation should improve the thermal performance of the building and increase the property's value within reasonable renovation budget. Depending on the renovation objectives of each project, various results could be achieved. There are several factors which must be considered to develop renovation scenarios, including renovation methods, and building envelope materials and components (Konstantinou 2014).

2.4.1 Renovation Methods

There are different ways to categorize building envelope renovation according to the level of intervention, or the way building components are replaced, added or covered (Konstantinou 2014). Figure 2-4 shows different levels of intervention. They range from maintenance and repair to demolition (González et al., 2015). However, the renovation methods in this research mainly include the first three levels.

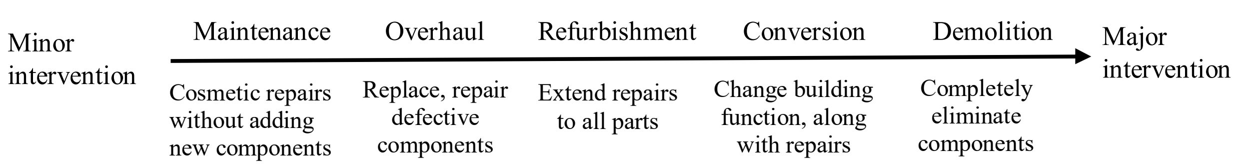


Figure 2-4. Levels of intervention (Adapted from Konstantinou, 2014).

The reviewed literature identified certain renovation methods i.e., Replace, Add-in, Wrap-it, Add-on, and Cover-it. These methods represent a systematic approach to the development of the renovation scenarios (Galiotto et al. 2015, Konstantinou 2014). Renovation methods can be classified based on the way building components are replaces, improved or added and their consequence on the building envelope performance. Furthermore, the combination of the renovation methods is also possible. The list of renovation scenarios cannot be comprehensive because the opportunities for combining different renovation methods are unlimited. Therefore, their classification is the first step for the development of a renovation scenario and identifying of the basic principles to help decide on the type of renovation method and emphasizing the advantages and disadvantages in each case is the first important step for the development of a renovation scenario.

Replace: A common method to upgrade a building envelope is the replacement of the façade or roof. In this method, a new façade will be implemented instead of the old one. This method could be comprehensive, which replaces the entire façade elements, or it can be a partial replacement, which focuses on specific parts of the façade. The benefits of this method are that novel, adequately performing elements replace the old ones, adding aesthetically pleasant features, and improving acoustic and thermal comfort. However, this method is usually costly.

Add-in: Add-in method is usually implemented in several situations, for instance, a heritage building with a great exterior or a monument building. This method usually upgrades the envelope from the interior. For example, a new insulation layer could be added to the internal side of the external walls to increase the thermal performance of the envelope and conform with new standards. However, thermal bridge issues are one of the major disadvantages of this method, and critical connections (e.g., slabs, balconies, window sills) particularly at the corners of the building, need extra attention.

Wrap-it: Covering the building with a second layer is termed wrapping. This method usually upgrades the building envelope from the exterior. This additional layer can contain external insulation, the cladding of the balconies or even a second envelope (e.g., double façade). This method is very beneficial especially for solving thermal bridge issues and adding more thermal resistance to the façade.

Add-on: Add-on method provides an additional function or extra space to the existing building. This new structure could be a small intervention (e.g., new balconies) or a comprehensive intervention, which adds a new building as an extension to the old one. Add-on has several benefits, such as adding to the floor area, climate consideration, and architectural aesthetic. Extended parts change the functionality of the old envelope, so it is no longer part of the building envelope. The new envelope can be built in a way to improve environmental performance.

Cover-it: Cover-it is a method to cover or upgrade a part of or the entire building envelope with external courtyards and atria. Transparent materials usually implemented in this method allow visual contact between the interior and exterior. This method usually improves the architectural appearance and useable space, and connects the adjacent area and the building itself. However, this method may have some disadvantages, such as insufficiency in thermal performance or technical implementation problems.

2.4.2 Building Envelope Materials

The selection of building envelope materials is usually very problematic due to several issues, namely, cost, implementation, performance, and environmental issues. This research focuses on the energy and environmental perspective of the material selection, so the materials presented in this research are mainly selected based on energy-saving measures. Several categories (i.e., insulation, glazing, fenestration, window frames, sealants, finishing, and cladding) should be considered to renovate a building envelope (Giebeler et al., 2009). Table 2-1 summarizes the materials used in the building envelope energy renovation (Konstantinou, 2014).

2.4.3 Building Envelope Components

Building envelope components consists of external walls (e.g., ventilated façades and double-skin façades), fenestration, roof, balconies, and ground floors. One important issue in this area is the technologies and systems using materials to improve the building envelope performance. The performance for each component can be measured based on its materials and the specific implemented method.

The use of innovative technologies and materials has been greatly improved in recent years and can lead to improvements in building energy efficiency. However, there are several barriers to their adoption, such as building integration problems. The main approachesof research are shifting from *static* to *responsive* and *dynamic* methods (e.g., Responsive Building Elements (RBE), and Multifunctional Façade Modules (MFM)) (Loonen et al., 2014). Loonen et al. (2014) categorized recent publications introducing research and development of building innovative envelopes based on the four phases in product development (i.e., laboratory scale, reduced-scale experiment, full-scale mock-up, and pilot study). There are several innovative products, such as Phase Change

Material (PCM), dynamic insulation, photovoltaics, electrochromic windows, which facilitate sustainable buildings (Kolokotsa et al., 2011).

Table 2-1. Overview of materials implemented in the building envelope energy renovation (Adapted from Konstantinou, 2014).

Material	Renovation principle	Description	Examples
Insulation	Heat losses or gains protection	High thermal resistance materials, which opposes the heat transfer	Organic and mineral materials, High-performance thermal insulation materials
Glazing	Heat losses or gains protection, passive solar heating, sun protection	Transparent material provides visual connection	Insulated glazing, Low-energy coating, Phase Change Material (PCM), Photochromic glazing
Window frames	Heat losses or gains protection, ventilation	Provide operation and fitting for glazing	Plastic (UPVC), Aluminum, Steel, Timber
Sealants	Heat losses or gains protection, airtightness, weatherproofing	Prevent uncontrolled air and water movement	Membranes, expanded foam, Tapes, Fillers
Finishing-Cladding	Construction protection, airtightness, heat losses or gains protection	Final rendering	Plaster, Paints, PCM, Cladding panels

2.5 HVAC Systems and Control Strategies

In 2012, about 70% of the total energy in commercial and institutional buildings in Canada was consumed by HVAC and lighting systems, which clarifies the need for optimization methods to improve energy performance (Natural Resources Canada, 2015). Studies show that HVAC and lighting systems are responsible for 33% and 25% of the total energy consumption in office buildings, respectively. Previous research shows that the most substantial energy saving potential can be achieved by improving the building service systems and the energy source (Alev et al., 2014). Due to the gap between predictions and actual measurements of energy performance of buildings (De Wilde 2014), there is a rise in the area of research focusing on the effect of building envelopes and HVAC optimization on buildings' energy consumption. Renovation projects usually include changes in the internal partitions and the outer envelope at the same time. The architectural plans will change, and consequently, the pattern of energy demands of the heating, cooling, and lighting will change. Therefore, the new energy consumption must be considered to provide an optimal comfort level for occupants and to guarantee the success of the project. As explained in Section 1.1, the HVAC system must be redesigned when renovating the envelope of the building to reflect the new energy demand and to avoid unwanted side effects.

HVAC control systems have an important impact on energy management. The primary task of HVAC control is optimizing operation systems, sequencing of system components, avoiding excessive cycling of system components and the conflicts between them (ASHRAE Design Guide, 2014). Adjustments in control strategies are critical and are sometimes the only possible way to manage the energy consumption. Furthermore, buildings use mechanical and/or natural ventilation. In renovation projects, however, the full integration between these two methods must be considered. There are several monitoring systems, which can be implemented to monitor the situation of a building after renovation. Energy audits and building automation and control are among the most popular systems.

2.6 Lighting Systems

As previously mentioned, improved lighting efficiency has a significant impact on the energy performance of a building. The lighting system affects the internal heat gain. Therefore, the lighting control should be addressed in the renovation project (DiLouie, 2008). A considerable number of studies have focused on the selection of the most appropriate lighting systems for building's renovation (e.g., energy efficient fluorescent, high-pressure sodium light, motion-activated lighting, Light-Emitting Diode (LED) lighting, and induction lighting). However, budget limitations, environmental issues, and applicability are the major factors that must be considered when selecting a new lighting system. Daylighting has impact on the electrical energy consumption; therefore, in the simulation of the case study daylighting factor was considered.

2.7 Decision-Making Methods for Building Renovation

Decision-making has several steps including explaining the goals and objectives of the decision, recognizing potential options with highest chance of success and constrains, and selecting the best or optimum options, which better solve the problem (Harris, 2012).

2.7.1 Energy Quantification Methods for Existing Buildings

An initial step in reducing the energy consumption of buildings is verifying the suitability of the building systems and equipment based on comparing the calculated energy consumption of the designed building at the time of its construction or renovation with the actual current pattern of energy consumption. In many cases, variations in the occupancy of the building after several years or some renovation can change the energy behavior of the building. There are several methods for energy quantification for buildings that are illustrated in Figure 2-5. Energy quantification is the method of defining the amount of energy consumption or energy performance indicators of a specific building according to related collected data. Computer simulations, building monitoring systems, end-use sub-metering system, building audit information, and utility bills are among the most popular sources to quantify building energy consumption (Wang et al. 2012). Three different approaches are proposed by scholars for energy quantification in an existing building, e.g., calculation-based approach (Jokisalo and Kurnitski 2007), hybrid approach (Sharif and Hammad 2017), and measurement-based approach (Polinder et al. 2013), as shown in the second sphere of Figure 2-5. Calculation-based approaches are very common and cover a wide range from dynamic simulations, which are complicated methods, to simple methods like steady-state methods. Inverse and forward modeling approaches are applicable to create steady-state energy calculation models. Hybrid quantification approaches have two main streams, which are calibrated simulation and dynamic inverse modeling. These models usually employ long or short-term monitoring data to improve, correct or validate the calculated results or to identify parameters of the dynamic model. In fact, hybrid quantification methods combine the benefits of two other approaches. The measurement-based approach is very practical for existing buildings due to the availability of energy bills and monitoring data (Wang et al. 2012). In this approach accurate, simple, or detailed information can be gathered using different methods (e.g., energy bill, building management system monitoring, end use sub-metering system, and non-intrusive load monitoring).

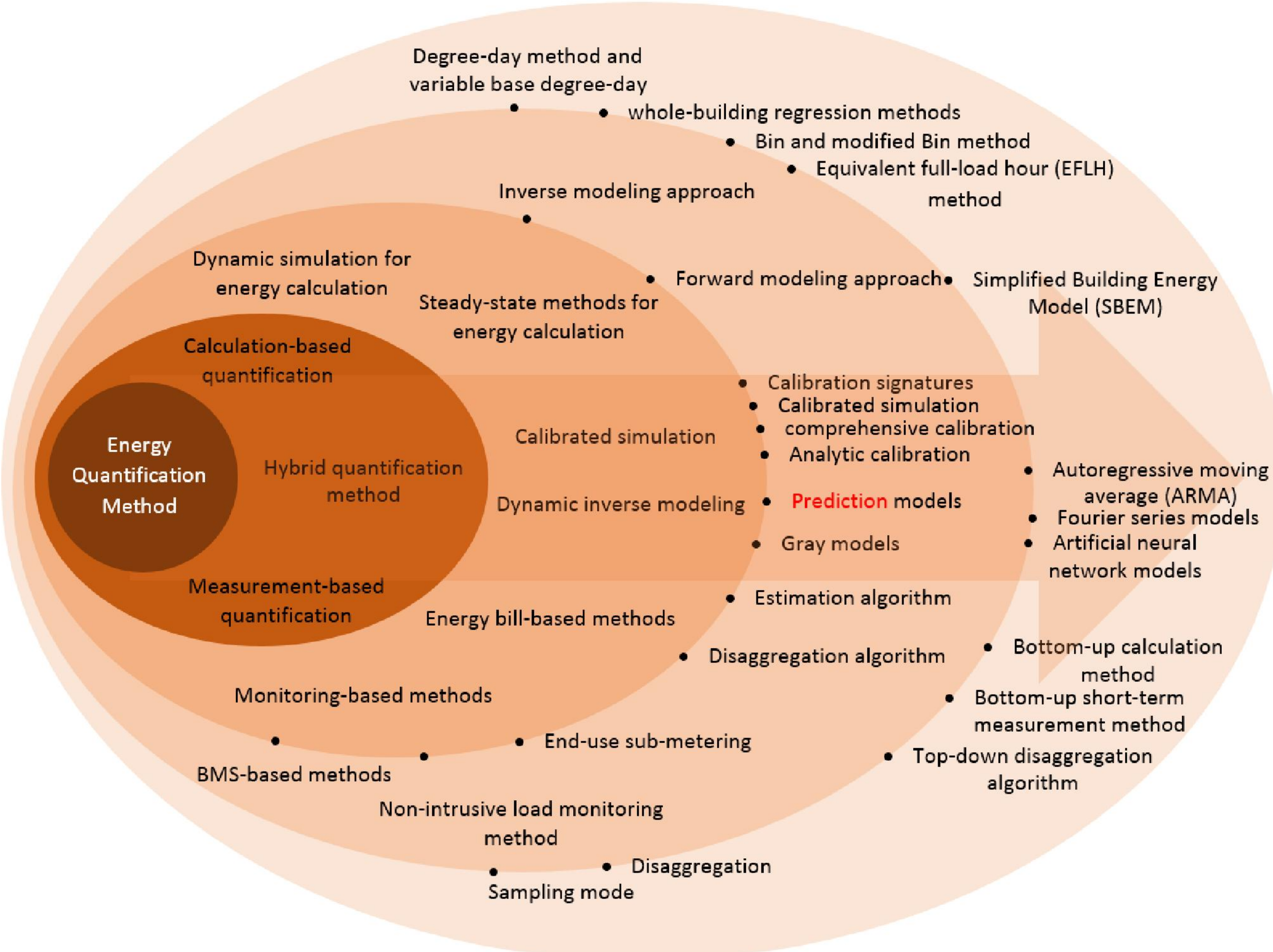


Figure 2-5. Overview of energy quantification methods for existing buildings.

2.7.2 Buildings Life-Cycle Cost

Buildings Life-Cycle Cost (LCC) is the main concern for any project that involves preliminary capital outflow and operational costs. The LCC of a renovation scenario is measured by summing up all costs starting from the procuring phase and construction phase until the conclusion of the study period. These costs include the initial costs (*IC*), present values of energy and water costs (PV_{En}, PV_{W}), operating and maintenance costs ($PV_{O\&M}$), replacement costs (PV_{Rep}) and residual values (PV_{Res}) as shown in the Equation (2.1) (Fuller et al., 1996). A reasonable discount rate must be considered to calculate the present value. Life-Cycle Cost Analysis (LCCA) recommends the best solution that offers the lowest LCC of all solutions considering the required functionality and quality.

$$LCC = IC + PV_{En} + PV_{W} + PV_{O\&M} + PV_{Rep} - PV_{Res} \qquad \textit{Eq. 2.1}$$

Sustainable buildings usually have higher initial capital investment than conventional ones (Kibert, 2008). However, during the life cycle of the project, the extra spending incurred in the original capital cost of sustainable buildings can be recovered within a relatively short period because of several factors, such as the reduction in the energy consumption (Kibert, 2008).

As previously discussed, whole building renovation comprising envelope, HVAC, and lighting systems, has a notable influence on optimizing the energy performance. Furthermore, there is a strong correlation between optimizing energy performance and the LCC as choosing different materials and components for renovation has a significant impact on LCC. On the other hand, when it comes to improving environmental sustainability, finding a correlation between optimizing energy performance and LCC is a challenge (Sharif and Hammad 2018). As a result, finding a balance between these important concepts is crucial to improving a building's energy performance.

2.7.3 Life-Cycle Assessment

A recent study shows that Life-Cycle Assessment (LCA) research is a growing area of study for buildings (Anand and Amor 2017; Wu and Apul 2015). Studies about LCA cover numerous topics, starting from manufacturing of building materials and components through to whole building analysis. The findings show that the operational phase, which is responsible for the highest energy consumption, is the main focus of research in recent years. Furthermore, integration of the building certification systems and LCA is another focus area, which has led to significant research and development in buildings' LCA.

This section discusses the definition and application of LCA methods to the different areas in the building industry. The section addresses issues based on ISO 14040 series (ISO, 2006), due to its broad international acceptance as a method to reduce negative environmental impacts, and because the majority of the methods being used are based on this standard. Moreover, this section reviews the implementation of LCA in the building industry and reports the related improvements and opportunities for future research. The research areas identified are: LCA definition and methods, Goal and Scope (G&S) definition, lifetime of the study, system boundaries, functional unit (FU), inventory analysis, impact assessment, interpretation, LCA implementation, and comparative analysis of LCA tools.

(a) Life-Cycle Assessment Definition and Methods

LCA is a comprehensive and systematic approach to evaluating environmental impacts of a product or process during its entire life cycle (Cabeza et al., 2014). LCA considers the extraction of raw materials, manufacturing, implementation, and End-of-Life (EoL) disposal and reuse. LCA can incorporate the selection of environmentally preferable materials and the optimization and evaluation of the construction processes (Asdrubali et al., 2013).

Three methods can be implemented for LCA: Process analysis and Input-Output (I-O) analysis, which are traditional Life Cycle Inventory (LCI) methods, and hybrid analysis (Crawford, 2008). The process analysis method aims to trace and evaluate all of the manufacturing processes of a product. Although the process analysis method is widely implemented, it has several disadvantages, such as the complexity of the upstream requirements for materials and services in this method. Furthermore, I-O analysis can be used as a *black box*, which provides little explanation of the values being presumed for each process (Crawford, 2008). These methods have different assumptions regarding the system boundaries (Chang et al., 2016). Furthermore, different databases are available to provide LCA information, such as Inventory of Carbon and Energy (ICE) (Hammond et al., 2008). It should be noted that data provided for these methods are locally based and grounded on many assumptions. On the other hand, hybrid methods strive to combine the advantages of traditional LCI methods while minimizing their individual limitations.

The American National Standards Institute (ANSI) and the International Organization for Standardization (ISO) have defined the standards for LCA with the ISO 14040 environmental management series, addressing national and international parties. By ISO definition, LCA is the "collecting and assessing of the inputs, outputs, and potential environmental impacts of a product or system throughout its life cycle" (ISO 14040, 1997) (ANSI/ISO, 1997). Based on ISO classification, LCA integrates four steps including: (1) Goal and Scope definition (G&S), (2) Life-Cycle Inventory Analysis (LCIA), (3) Life-Cycle Impact Assessment (LCIA), and (4) Interpretation. Furthermore, iteration between steps is essential; therefore each step is redefined frequently. Figure 2-6 represents the steps of ISO's LCA.

This research has implemented LCA as a method to analyze the environmental impacts of buildings. The economic evaluation of renovation scenarios and their energy performance are two essential evaluation criteria for optimization. In addition, LCA can be used to evaluate the sustainability of the renovation scenarios. Ideally, its application for the renovation of buildings will be valuable for decision makers.

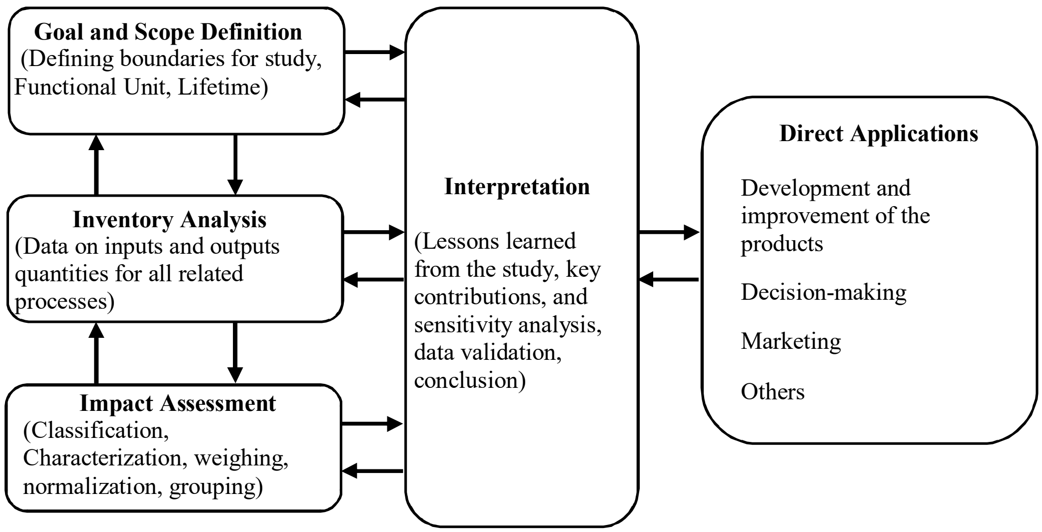


Figure 2-6. Steps of LCA (Adapted from ANSI/ISO, 1997).

(b) Goal and Scope (G&S) Definition

The aim of the G&S definition is to provide an understanding of the intended audience and applications in the study, and to outline the lifetime and scope of the study. G&S determine the use of the study and its breadth and depth. The scope definition of LCA also describes the system boundaries and the Functional Unit (FU) of the assessed building.

Different studies have focused on one or more aspects of the life cycle of the building; some only considered energy consumption or materials, while others measured the whole lifecycle but left out important elements, for instance, the demolition phase or transportation effects. The duration of the different studies also varied considerably, ranging from 30 to 100 years. This variety affects not only the scope of the selection of the renovation scenarios, but also the energy use of the building throughout its lifetime.

(c) Lifetime of the Study

There is no clear calculation process to define the lifetime of the study. It is usually assumed described based on a survey of the lifetime data of existing buildings, the commonly used lifetime for a specific type of building, or the usable life of the main elements of the building

(Vandenbroucke et al., 2015). The building's lifetime may be affected by market demands (obsolescence), which may lead to a major renovation or even demolition of the building before the end of its useful life. The lifetime is assumed in the range of 25–60 years, or investigated for the duration of one generation, which in turn decreases the ambiguity in operational results (Verbeeck et al., 2010). Research considering 100-year lifetimes, such as Borjesson and Gustavsson (2000), consider significant maintenance and renovation works as an important step of the case life cycle. Säynäjoki et al. (2012) considered shorter durations to develop applicable results in terms of achieving climate change mitigation goals (Säynäjoki et al., 2012). However, these assumptions can cause significant inaccuracy. Aktas and Bilec (2012) performed a statistical analysis to increase the accuracy of buildings' LCA considering the lifetimes of U.S. residential buildings. Their research suggested 61 years as the average lifetime of a building (Aktas and Bilec, 2012).

(d) System Boundaries

This section provides an outline of the boundary setting considerations within an LCA. Defining the system boundary is a key question in any LCA, which can produce a large potential variance in the results. Selecting the life cycle phases involved in the research is one key factor of boundary determining, an example of which is shown in Figure 2-7. In LCA, the environmental impacts of the building, such as equivalent CO_2 emissions, are analyzed in all phases of the life cycle of the building. These phases are grouped into pre-use (product) phase, construction and installation phase, use phase, and EoL phase. Figure 2-7 shows the system boundaries of the assessments. The pre-use phase contains raw material supply (A1), transportation (A2), and manufacturing (A3). The operation phase includes on-site construction and installation (A5), use (B1), maintenance (B2), repair (B3), replacement (B4), refurbishment (B5), operational energy and water use (B6, B7), and transportation related to the phase (A4). EoL includes demolition (C1), transportation (C2), waste processing (C3), and disposal (C4). Furthermore, current LCA studies comprise Embodied Energy (EE) and Operational Energy (OE) consumption during building life cycle. These studies usually consider maintenance during the O&M phase (Anand and Amor 2017, Cabeza et al. 2014).

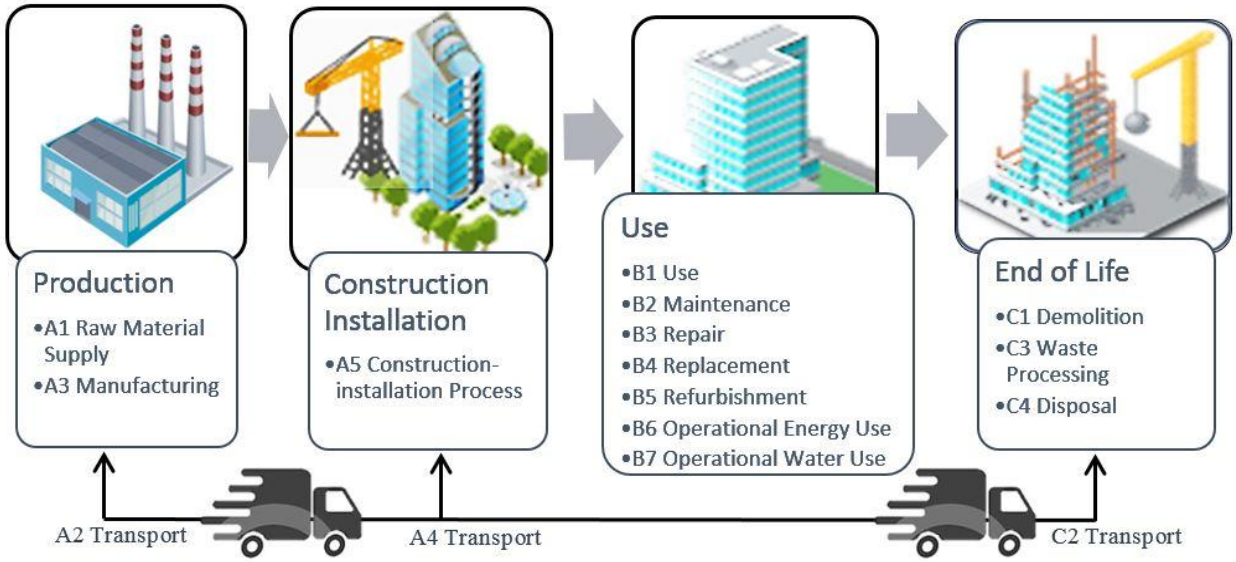


Figure 2-7. LCA system boundary of the assessments (Adapted from EN 15978:2012 and EN 15804:2014 standard).

(e) Functional Unit (FU)

Different Functional Units (FU) are implemented in the LCA of buildings (Cabeza et al., 2014). Based on the literature review, several factors determine the most commonly used FU in the LCA of buildings, such as building elements (e.g., roof), weight of the materials, and floor area. Selecting these factors may lead to neglecting the overall concept of the building or exaggerating the effect of one factor as compared to other building elements (Collinge et al. 2015). Islam et al. (2015) reported the floor area is the most commonly implemented FU for residential buildings. Furthermore, based on the definition of the goal of the study, heat delivery and heated floor area are used as FUs for LCA (Anand and Amor, 2017). Susie and Defne (2015) implemented various FUs for active equipment and passive products and integrated them for a more comprehensive study.

(f) Inventory Analysis

LCI analysis of buildings is very complicated because it is comprised of several processes and materials. Additionally, the operation of buildings, which has a dynamic nature, is very complex. LCI analysis gathers related data and calculates processes to determine the inputs and outputs of the system (Junnila, 2004). There are several challenges to having an accurate LCI, such as the availability of different calculation methods, missing data, unusable data, and restrictions to having access to the data (Abd Rashid and Yusoff, 2015).

Furthermore, data collection guidance in the current ISO standard is inadequate to provide a standardized methodology for embodied energy calculation (Dixit et al., 2012). At the data level, in addition to the issue of missing data, the quality of the gathered data is another concern for acceptable quality indicators to check for accuracy, especially at the product level (Peng 2016).

Building materials' data can be gathered from the table of materials. Some researchers calculate the construction data but neglect the waste generated during the process because it comprises a smaller portion of the total environmental impact (Rossi et al., 2012). In the use phase of a building, electricity is usually the main source of energy, followed by natural gas (Abd Rashid and Yusoff, 2015). Another important part of the use phase is maintenance works. Inventory data for maintenance is varied based on the researcher's assumptions.

Inventory data for buildings can be gathered from the industry market, available databases or environmental product declarations (EPD). For instance, the "Study of Life Expectancy of Housing Components" report produced by the US-based National Association of Home Builders (NAHB) is used by Iyer-Raniga and Wong (2012). They performed sensitivity analysis to check the applicability of information to the local environment (Iyer-Raniga and Wong, 2012). However, several discrepancies have been reported in applying generic information for products and EPD's (Lasvaux et al., 2015).

Recent research recognizes the EoL phase as a significant part of LCI analysis due to its capability of recycling building materials and reducing life cycle impacts (Blengini and Di Carlo, 2010). In construction projects, non-metallic materials are usually considered as waste and transported to landfills, except for concrete, which is sometimes recycled. Steel and aluminum are regularly considered as recyclable materials (Ochsendorf et al. 2011). Machines used for the demolition and transportation of the waste to the recycling center or landfill consume energy, which should be considered in EoL calculations.

(g) Impact Assessment

The impact assessment measures the potential impacts of a project on the environment by applying the outcomes of the inventory analysis phase. Consequently, during the interpretation phase, the findings of the impact assessment is calculated and validated based on to the G&S definition phase. Finally, the possible options for reducing the negative environmental impacts for the specific studied project are assessed, and recommendations and possible decisions are explored (ISO 14040, 1997). The selection of the impact categories and methodology are bound by the G&S definition and usually LCA experts implement available published methods instead of developing a new one (Goedkoop et al., 2016). Bare et al. (2000) explained two categorizations for impact assessment: problem oriented (midpoints) and damage-oriented (endpoint) methods. Midpoint approaches represent the links in the cause-effect chain (environmental mechanism) of a specific impact category before the endpoints, which are indicators or characterization factors and explain the relative importance of extractions or emissions. Global Warming Potentials (GWP) and ozone depletion potentials are common examples of midpoint characterization factors (Bare et al., 2000).

Various methodologies have implemented characterization factors at an endpoint step in the cause-effect chain for all classes of impact. For instance, some methodologies comprise human health assessment and ecosystem impacts at the endpoint, which can be considered as the outcomes of climate change, ozone depletion, and other indicators. In endpoint methodologies, the indicators are selected at the end point step and are generally quantitative and more understandable to decision makers. While in the midpoint methodologies, the environmental relations are usually explained in the form of qualitative relevancies, review articles, and statistics (Bare et al., 2000). Ortiz et al. (2009) proposed that Eco-indicator 99 and IMPACT 2002+ can be implemented for endpoint approaches, and that IMPACT 2002+, EDIP 97 and EDIP 2003 and CML 2002 baseline methods are recommended for midpoint methodologies.

(h) Interpretation

The concluding step merges the interpretation and analysis of the environmental impacts according to the goals of the LCA study (Ochsendorf et al. 2011). Usually the results of the study are compared with the results of the other published research for data validation and to assess the reliability of the external databases' sensitivity analysis, which would be extremely useful in making final decisions (Iyer-Raniga and Wong 2012).

Based on the literature review, several issues may affect in the interpretation step for LCA results, such as implementation of diverse energy measurement and inventory analysis methodologies, system boundaries definition, diverse calculation methodologies, such as Life-Cycle energy assessment (LCEA) or Life-Cycle impact assessment (LCIA), diverse impact assessment methodologies, project location, the manufacturing technologies, and the availability of accurate data (Anand and Amor 2017).

(i) Life-Cycle Assessment Implementation

The economic evaluation of renovation scenarios and their energy performance are two essential evaluation criteria for optimization. In addition, LCA can be implemented to evaluate the sustainability of the renovation strategy. The application of LCA in the building sector has become a focus of research in the last ten years (Buyle et al. 2013, Asdrubali et al. 2013). The number of published research papers about LCA related to buildings has more than doubled in the last five years (Anand and Amor, 2017). However, previous studies used LCA to compare only one aspect of the building separately, for instance, building envelope or explicit materials or building systems and control. There is limited research combining all aspects of the building simultaneously (e.g., Alshamrani et al. 2014, Vandenbroucke et al. 2015). Wang et al. (2005) and Asdrubali et al. (2013) focused on the design process, measuring or forecasting energy use for buildings and considering life-cycle environmental impacts.

In the LCA of buildings, some of the impacts are currently not sufficiently studied. One such impact is the results of changes that are made during renovations of a building throughout its life cycle (Anand and Amor, 2017 and Tabatabaee et al., 2015). Renovation changes should be considered as a part of the building's recurring embodied energy. Renovating existing buildings is costly and difficult to justify and approve, therefore maximizing the energy performance and reducing any negative environmental impacts plays an important role in any renovation. LCA studies have been conducted on whole building renovation (Schwartz et al., 2015) or considering refurbishments at the materials level (Nicolae and George-Vlad, 2015) to find optimum results.

Schwartz et al. (2016) implemented Multi Objective Genetic Algorithms (MOGA) to find optimal designs for a renovation of a residential multi-function building considering Life-Cycle carbon footprint (LCCF) and LCC. The expected life cycle in their research was 60 years. By applying MOGA, the renovation LCC and LCCF can be decreased. They considered insulating thermal bridges and utilizing different heating systems and fuels as two main correspondent factors in the optimization.

Alshamrani et al. (2014) focused on integrating LCA and LEED sustainability assessment considering the structure and envelope systems of school buildings. They considered three categories of the LEED system, which are materials and resources, energy and atmosphere, and the innovation and design process. They consider LCA under the third category of LEED. Different options, such as various structural combinations and envelope types, are tested using eQuest energy simulation software and ATHENA Impact Estimator (Alshamrani et al., 2014).

GHG emissions from construction and energy consumption in buildings result in a tremendous negative environmental impact. The main GHG emissions from building operation comprise carbon dioxide (CO_2), nitrous oxides (N_2O), methane (CH_4), and ozone (O_3) (Abdallah and El-rayes, 2015). The Intergovernmental Panel on Climate Change (IPCC) developed GWP factors, and these gases can be represented by equivalent quantities of CO_2 emission (IPCC, 2007).

In this research, LCA is defined based on the GWP, which is CO_2 equivalent and TEC. Also, during the life cycle of a project, the TEC is calculated as the summation of the energy consumption during the pre-use phase, construction and installation phase, and use phase. Although during the EoL phase the project has energy consumption, this amount is out of the scope of this research.

(j) Comparative Analysis of LCA Tools

LCA tools have various levels of detail and flexibility. These tools do not support all the aspects of building LCA, as shown in Table 2-2. Furthermore, some important parameters of buildings are neglected or simplified by these tools. For instance, building HVAC systems and lighting that have significant impact on the building operational energy consumption are excluded from ATHENA.

ATHENA Impact Estimator (referred to as ATHENA in this research) is frequently used by the North American construction industry due to its ability to assess the whole building and its components (Athena Impact Estimator, 2017). ATHENA for Buildings (ATHENA) conforms to the EN 15804/15978 system boundary and reporting format. However, the geographic coverage of ATHENA is limited to the United States and Canada (Athena Impact Estimator, 2017). ATHENA reports material costs, quantity of the materials in the building, and provides different reports and graphs for the environmental impact of different buildings. ATHENA software uses the European standard EN 15978, which embodies the life cycle of buildings processes (i.e., activities). ATHENA modeling capacity includes building's envelope, structure, and interior partitions and doors. Building products can also be added to the model. Based on the availability of data, LCA modeling can also calculate the operating energy consumption of the whole building. It is worthwhile to mention that LCA is not a method to estimate a building's annual operational energy (Athena Impact Estimator, 2017). ATHENA allows side-by-side comparisons for different renovation strategies.

DesignBuilder simplifies the process of building simulation and is capable of calculating the building and site operational energy consumption considering materials and components, HVAC and lighting, and comfort performance of buildings. Additionally, DesignBuilder calculates LCA based on bulk carbon data obtained from the Bath ICE and other data sources. However the embodied carbon related to several building services, such as HVAC and lighting, is not considered in the final results. DesignBuilder reports embodied carbon and equivalent carbon separately, although they overlap in some items. Equivalent carbon calculates the effects of other greenhouse gases based on the equivalent amount of CO_2. Furthermore, DesignBuilder calculates only operational energy (DesignBuilder, 2016).

SimaPro is a well-known tool that has large and comprehensive data libraries which include 6,000 processes. SimaPro can be used to design analysis models covering all the details of LCA in different fields of engineering. Furthermore, different methods are embodied in this tool (Goedkoop et al., 2016).

Table 2-2. Comparative analysis of LCA tools.

	LCA Tools	ATHENA	DesignBuilder	SimaPro
Software aspects	User-friendliness	Medium	Medium	Low
	Program complexity	Medium	Medium	High
	Level of interoperability	Medium	High	Medium
	Flexibility of the model	Medium	High	High
Analysis aspects (Environmental, Energy, Cost)	Analysis level	Building	Building	Variable
	Process contribution analysis	Yes	No	Yes
	Environmental impact	Yes	Yes	Yes
	Capital cost	Yes	Yes	Yes
	Life-Cycle cost	Yes	Yes	Yes
	Operational energy	Yes (simplified)	Yes	Yes
	Embodied energy	Yes	Yes	Yes
	Maintenance	Yes	Yes	No
	Transportation	No	Yes	Yes
	Demolition	No	Yes	No
Analysis aspects (Building)	Detail coverage	Medium	High	High
	Building construction components	Medium	High	No
	Building systems components	No	High	No
	Comprehensiveness of Database	Medium	High	High
Other aspects	Price	Free	Expensive	Expensive
	Developer	ATHENA (Canada)	Thermal Energy System Specialists, LLC (USA)	PRé Consultants (Netherlands)

2.7.4 Classification of Building Energy Optimization

According to the reviewed studies, simulation and optimization methods have been applied in the building industry for various purposes, such as improving energy performance, simulating and optimizing the energy consumption, improving the design of new buildings, and predicting future energy performance (Evins 2013; Nguyen et al. 2014). Optimization is the process of finding one or more solutions that consider all constraints and minimize (or maximize) one or more objective functions (Branke et al., 2008). The selection of the optimization technique depends on two main factors: the search method and the parameters to be optimized. There are three categorizations for optimization, which are based on the uncertainty in the decision variables, the number of parameters to be optimized (objective functions) and the value of the objective functions. If the value of the objective function can be estimated with certainty, the optimization is considered deterministic. Otherwise, the optimization is categorized as stochastic. If the optimization problem has only one single objective, it is called *single-objective optimization*; otherwise, it is called *multi-objective optimization* (Cohon, 1978). Multi-objective optimization problems often involve conflicting objectives (Nakayama et al., 2009).

Three widely used techniques in building optimization are evolutionary algorithms, dynamic programming, and weighted linear and integer programming (Abdallah, 2014). Also, Goldberg (1989), categorized optimization methods into three main groups including enumerative, systematic (exact or calculus-based) and stochastic (random or gradient-free).

Enumerative methods, which have simple principle, utilize algorithms that evaluate the objective function at every point in the search space sequentially and perform exactly that an exhaustive search. Enumerative methods have two limitations: the lack of real-world applicability and the magnitude of the search space, which can only be *finite* or *discretized* infinite. Therefore, the enumerative method is not commonly used in building optimization studies because the search space in the subject of the building optimization is usually too large for this method (Chantrelle et al. 2011).

Systematic methods, which are also referred to as gradient-based methods, are based on the mathematical calculations that can only be run for continuous and smooth functions. Linear programming, nonlinear programming, and discrete optimization are three different types of the calculation-based optimization (Diwekar, 2013). Systematic methods are more common in building optimization; for instance, to optimize the thickness of the insulation considering derivative methods (Bolattürk, 2008). Optimization of the passive thermal performance of buildings considering building envelopes was done by Bouchlaghem and Letherman (1990). The researchers coupled the simplex method and the non-random complex method to develop a thermal prediction program (Bouchlaghem and Letherman 1990).

Gradient-based methods are vulnerable by being dependent on the initial prediction, regularity of the objective function, and exposure to be trapped at local minimums when traversing parameter(s) (Deb, 2001). Furthermore, building optimization is very complex and could be considered as a nonlinear topic, which can be evaluated utilizing a building simulation program in some situations (Wetter and Wright, 2004). Therefore, gradient-based methods are not preferred for complex building renovation studies. While stochastic methods, i.e., ant colony algorithm, simulated annealing, and Genetic Algorithm (GA), which are based on stochastic approaches, are more applicable. Furthermore, stochastic (gradient-free) methods can be easily integrated with building assessment tools because they do not require a hypothesis about the regularity of the objective functions. GA is one of efficient and widely recognized stochastic methods and was developed by Holland (Holland, 1975). GA contains various algorithms from *simple genetic algorithm* to very complex algorithms and is widely implemented in the field of building optimization (Deb et al. 2002). Stochastic and calculus-based optimization methods are more commonly used in complex optimization studies (Diwekar, 2013).

A Non-dominated Sorting and crowding Genetic Algorithm (NSGA-II) is based on the evolution of a population of "individuals," each of which is a solution to an optimization problem. NSGA-II is one of the most efficient genetic algorithms for multi-objective optimization and is often used for multi-criteria optimization in different domains (Deb et al. 2002). A flowchart of NSGA-II, which is implemented by Palonen et al. (2009), is shown in Figure 2-8.

The majority of optimization research focused on building envelope, building form, HVAC systems, and renewable energy. Energy, construction costs, LCC, operational costs, and comfort are among the most selected objective functions of optimization studies (Evins 2013). An overview of some simulation and/or optimization papers on building renovation is given in Table 2-3 and compared with the current study in terms of methods, renovation parameters, objective functions, and selected tools. These papers have some overlaps with the current study. However, none of them has brought together all decision variables, i.e., envelope, HVAC, and lighting, and objective functions, i.e., TEC, LCC, and LCA for optimizing the renovation of the existing buildings. For instance, Chantrelle et al. (2011), used NSGA-II optimization method (MultiOpt tool) and TRNSYS as simulation tool to optimize energy use, comfort, and investment. Jin and Overend (2012), identified optimal façade solutions for a renovation project using EnergyPlus simulation and assessing the trade-off between cost, energy use and user productivity. Several recent studies considered a reference building for comparing and reviewing appropriate optimization strategies for existing buildings, but in this way, the characteristics of the reference building and the case study should be similar, which is not possible in all circumstances (Ascione et al. 2017, de Vasconcelos et al. 2015).

2.7.5 Integrating Building Information Modeling with Energy Simulation, LCC, and LCA

Evaluating the energy consumption and environmental impacts of a project using simulation has attracted tremendous interest in recent years (Abaza 2008; Iyer-Raniga and Wong 2012; Jalaei and Jrade 2014; Sharif and Hammad 2017). Different energy simulation and analysis tools have been established during the past 50 years (Jalaei and Jrade, 2014). DOE2, EnergyPlus (Crawley et al. 2001), Ecotect, TRNSYS (Machairas et al., 2014), DesignBuilder (DesignBuilder, 2016), Integrated Environmental Solution (IES-VE) (Jalaei and Jrade, 2014), and eQUEST (Alshamrani et al., 2014) are among several practical and effective software used in the building industry. The accuracy of the BEM is very critical. If the building model has errors or miscalculations, it would result in an incorrect database. Therefore, the final optimized model could be inaccurate and far from the real building scenario.

BIM tools, such as Revit, have the potential to connect with energy analysis applications. Furthermore, energy and daylighting simulation were added to new versions of BIM tools. Research on energy use and environmental issues using these tools offers a striking opportunity to make cost-effective choices, which have a positive effect on the building LCC and facilitate achieving the energy performance goals. BIM aids decision-makers to visualize the spatial model of the building and explain the sequence of construction activities (Eastman et al., 2008). Also, BIM models can provide input data for energy simulation and present the results. On the other hand, LCA tools have the capacity to process and analyze the environmental issues of the building. BIM tools (e.g., Revit) have been recently developed with environmental analysis add-ins.

The integration of BIM and LCA was proposed in several studies, such as Häkkinen and Kiviniemi (2008). They developed a three-step method for integration. Their method initially linked separate tools through file exchange. Consequently, the required functionality was added to the existing BIM tool. Jalaei and Jrade (2014) proposed a methodology to integrate BIM, LCA, and Management Information Systems (MIS), which can be used to implement sustainable design for buildings at the conceptual phase and to consider their environmental influences.

Table 2-3. Overview of simulation and/or optimization literature on building renovation.

Author	Title	Method		Decision Variables				Objective Functions				Tool
				Env	HVAC	Li	Comments	TEC	LCC	LCA	Comments	
Abdallah and El-Rayes 2015	Optimizing the selection of building upgrade measures to minimize the operational negative environmental impacts	S O	NSGA-II	-	✓	✓	GHG emissions, refrigerant impacts, mercury-vapor emissions, lighting pollution, water use	-	✓	✓	Upgrade cost and building environmental impacts index	eQUEST
Asadi et al., 2014	Multi-objective optimization for building retrofit	S O	NSGA-II (MOGA)	✓	✓	-	EW and R insulation material, W, solar collector, HVAC	✓	-	-	EC, retrofit cost, and thermal discomfort hours	TRNSYS and ANN in MATLAB
Ascione et al., 2017	Cost-optimal analysis, Robust assessment of cost-optimal energy retrofit (CASA)	S O	NSGA-II (MOO) and ANN	✓	✓	-	Geometry, envelope, operation, and HVAC	✓	✓	-	EC, thermal comfort and global cost	EnergyPlus and MATLAB
Ascione et al., 2011	Energy retrofit of historical buildings	S	Dynamic energy simulation	✓	✓	✓	W, thermal insulation of the envelope, HVAC, control set-point, Li (Specific options)	-	-	-		EnergyPlus
Bolattürk, 2008	Optimum insulation thicknesses for building walls with respect to cooling and heating degree hours	O		✓	-	-	Insulation material for building EWs	-	✓	-	Insulation thicknesses, energy savings, payback period using LCCA	
Chantrelle et al., 2011	Development of a multicriteria tool for optimizing the renovation of buildings	S O	NSGA-II (MOGA)	✓	✓	-	Building envelopes, heating and cooling loads and control strategies	-	-	✓	Energy consumption, cost, thermal comfort, and life-cycle environmental impact	MultiOpt, TRNSYS, COMIS
Flores-Colen, de Brito, 2010	A systematic approach for maintenance budgeting of buildings façades	S		✓	-	-	Five façades' claddings; (service life, performance, quality, maintenance operations, frequency, and costs)	-	✓	-	Budget allocation and performance of buildings during their LCC using EUAC	Simulation of performance degradation models
Magnier and Haghighat, 2010	MOO of building design using TRNSYS simulations, GA, and ANN	O S	NSGA-II, GAINN	✓	✓	-	HVAC system settings, thermostat programming, and passive solar design	✓	-	-	Thermal comfort (Predicted Mean Vote) and energy consumption	TRNSYS and MATLAB
Huang et al., 2014	Thermal properties optimization of envelope in energy-saving renovation of existing buildings	O	Math Model	✓	-	-	Shape factor, WWR, W, and wall (thermal insulation thickness of envelope and thermal properties)	-	✓	-	Energy-saving renovation costs, performance of the windows and requirements for the insulation layer	

Author	Title	Method		Decision Variables				Objective Functions				Tool
				Env	HVAC	Li	Comments	TEC	LCC	LCA	Comments	
Jin and Overend, 2012	Façade renovation for a public building based on a whole-life value approach	S O	MOO	✓	-	-	Façade materials and products	-	✓	✓	Cash payback period, carbon payback period, and occupant productivity	EnergyPlus and MATLAB
Juan et al., 2010	A hybrid decision support system for sustainable office building renovation	S O	Hybrid GA and A* (GAA*)	✓	✓	-	Sustainable site, energy efficiency, water efficiency, material and resources, and indoor environmental quality	✓	-	✓	Renovation cost, building quality, and environmental impacts	GAA* and ZOGP, MIT Design Advisor
Loonen et al., 2014	Simulation-based support for product development of innovative building envelope components	S	SA and structured parametric studies	✓	-	-	W position, orientation and WWR, room depth, wall insulation, and thickness of thermal mass layer	✓	-	-	Total energy savings, daylight illuminance, glare discomfort, and overheating hours	TRNSYS and DAYSIM
Ouyang et al., 2009	Economic analysis of energy-saving renovation measures for urban existing residential buildings in China based on thermal simulation and site	S	Thermal simulation	✓	-	-	Layout, orientation, shape, WWR, heat transmission, shadow, airproof degree of W, thermal inertia of R, EW, partition wall, exterior door, floor, ground floor, absorption of R and EW surface and green vegetation	-	✓	-	Economic benefit using LCC method	DOE-2
Palonen et al., 2009	A genetic algorithm for optimization of building envelope and HVAC system parameters (Design)	S O	NSGA-II and Hooke-Jeeves	✓	✓	-	additional insulation thickness of the existing insulation material (EW, R and floor), U-value of W, and type of heat recovery	-	✓	-	Investment cost (insulations and windows) and ventilation heat recovery	GenOpt, NSGA-II and Omni-optimizer, MINLP
Penna et al., 2015	MOO of Energy Efficiency Measures in existing buildings	S O	NSGA-II	✓	✓	-	Insulation of the walls, R, and floor, G, heating generator, MVS, thermal bridges and air tightness of the building	✓	✓	-	Energy efficiency and global costs (EP, WDT, NPV)	TRNSYS
Schwartz et al., 2015	Multi-objective GA for the minimization of the life cycle carbon footprint and LCC	S O	GA	✓	-	-	Panel, EW, internal wall, W, interior floor,concrete frame, and street ceiling and floor	-	✓	✓	LCA vs. LCC and embodied vs. operational carbon emissions	Sketchup, Bath ICE, and EnergyPlus
Sharif and Hammad, 2018	SBMO of institutional building renovation considering TEC, LCC, and LCA	S O	NSGA-II	✓	✓	✓	R, EW, FT, W, WWR, HVAC, COS, HOS, Li, EWO	✓	✓	✓	TEC, LCC, and LCA pairwise	Design-Builder

A*: Best-first algorithm
EC: Energy Consumption
EP: Energy Performance
Env: Envelope
EW: External wall
EWO: External Window Open
EUAC: Equivalent Uniform Annual Cost
FT: Façade Type
Li: Lighting
MINLP: mixed integer (Nonlinear) programming
MVS: Mechanical ventilation system
NPV: Net Present Value
O: Optimization
R: Roof
S: Simulation
SA: Sensitivity Analyses
W: Window
WDT: Weighted Discomfort Time
WWR: Window to Wall Ratio
ZOGP: Zero-one goal programming

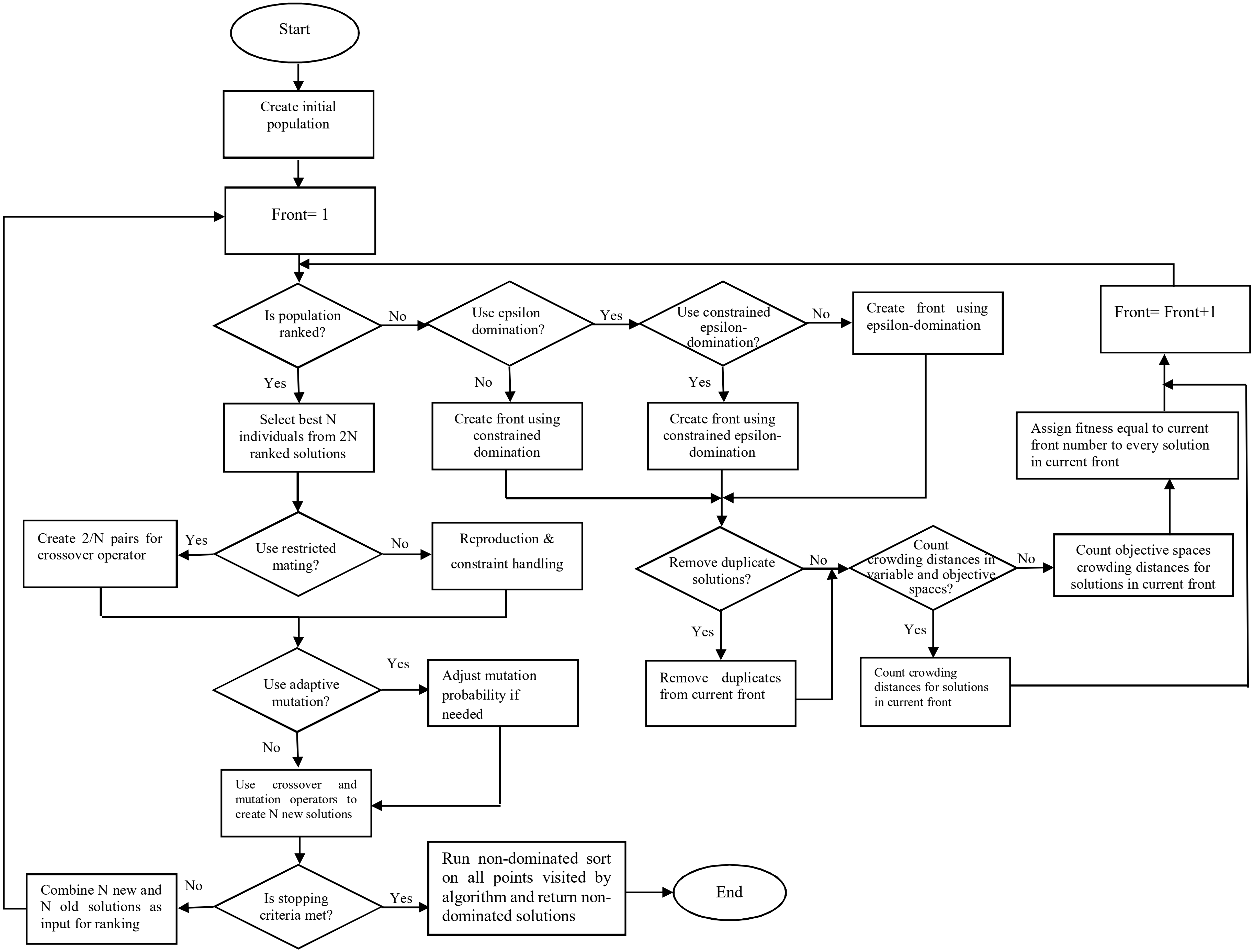


Figure 2-8. Flowchart of implemented NSGA-II (Adapted from Palonen et al., 2009).

2.8 Challenges of Simulation-Based Optimization in BEM

BEMs may be simplified (Xu and Wang 2008) or comprehensive, which take significant computational time (Chantrelle et al. 2011). Also, several BEMs, e.g., EnergyPlus, TRNSYS, DOE-2, e-QUEST (building performance simulation tools), and GenOpt (optimization tool), are widely used to simulate energy consumption and calculate the cost and other related parameters, and apply different renovation scenarios based on the available building components and materials (Evins 2013).

The application of BEMs in the building sector has become a focus of research in recent years (Fumo 2014; Harish and Kumar 2016; Kavgic et al. 2010; Zhu 2006). The number of published research papers about building energy efficiency has significantly increased and a large diversity of methods have been developed in the last ten years (e.g., Coakley et al. 2014; Wang and Srinivasan 2017; Amirifard et al. 2018). The objectives of these studies can be categorized into four main groups: (1) improving the building characteristics (i.e., building envelope, systems, equipment, and occupant behavior); (2) increasing the implementation of the innovative techniques and materials (i.e., automating building control and operation, Phase Change Materials (PCMs), dynamic insulation, and electrochromic windows); (3) increasing the use of renewable energy sources (i.e., solar panels, photovoltaics, geothermal heat pumps, biomass heating, and aerothermal system); and (4) recommending new rules, regulations, and governmental incentives (Ayoub and Yuji 2012; Huang and Niu 2015; Resch et al. 2014; Zhang et al. 2015). To fulfill these objectives, better energy consumption prediction algorithms and more accurate and comprehensive BEMs are required.

Furthermore, energy advisors, engineers, mechanical designers, and architects at energy engineering and efficiency consulting firms use BEMs for analyzing the energy consumption in buildings. However, the current BEMs have the following limitations: high computation time and complexity of the dependent parameters; accuracy issues; being non-user-friendly and expensive; not considering governmental incentives for energy renovation projects; not using comprehensive, integrated and interactive databases; neglected historical data of buildings; and lacking in generalization capability (Coakley et al. 2014; Fumo 2014; Maile et al. 2010; Naganathan et al. 2016).

A multitude of recent studies have been conducted on the development of the SBMO models, which integrate optimization and simulation into BEMs (Delgarm et al. 2016; Gosavi 2015; Machairas et al. 2014). However, despite its strength, SBMOs are not able to guarantee optimal solutions from among the many possibilities of different scenarios (Nguyen et al. 2014). Therefore, integration of the BEMs and optimization algorithms i.e., SBMO, is necessary that provides an opportunity for decision makers and practitioners to improve the energy performance of buildings through selection of optimum scenarios, and the fine-tuning of the desired renovation methods, and as a result, to accurately estimate the energy consumption of buildings (Delgarm et al. 2016; Gosavi 2015; Machairas et al. 2014).

The main obstacles in current SBMOs can be categorized in two main groups. From simulation point of view, the complexity of the dependent parameter and the computational time are the main issues (Sharif and Hammad 2019). Moreover, from the optimization point of view, the uncertainty of many parameters should be considered during the optimization, including the optimization engine, the decision variables, the number of parameters to be optimized, the value of the objective functions, and constraints. Furthermore, current SBMOs are not user-friendly and do not consider different parameters for a comprehensive assessment. Due to these limitations, consulting firms use very simplified models that can cause accuracy problems.

2.9 Surrogate Models in Building Applications

Simulation-based optimization methods, which are the focus of recent studies, often need hundreds or thousands of simulation evaluations. Therefore, for a big project, SBMO models may become infeasible because of the aforementioned problems. To solve the problem of infeasibility of SBMO, two techniques can be used. The first technique is to implement very simplified models instead of a detailed simulation model. This technique has many drawbacks, such as increasing the chance of inaccuracy, or oversimplification of the existing building, or even the inability of modeling complex building characteristics. For instance, Lee (2007) used a two-step method to solve this problem. In the first step, a simple model was implemented, and then more detailed simulation models were developed considering the outcomes of the previous model. The second step reduces the number of generations or the population size of the optimization model (Lee , 2007). It is clear that these reductions also decrease the performance of the optimization algorithms significantly, or may even lead to sub-optimal solutions (Wang, et al., 2005).

Another technique is to implement surrogate models (approximation models) to imitate computationally expensive, real building simulation models, with an appropriately representative model.

Surrogate models are usually used at the preprocessing and post-processing steps in simulation-based optimization studies of buildings (Nguyen et al. 2014). The reliability of the surrogate model can be tested by comparing the results of the surrogate models with the original BEM (Eisenhower et al., 2012). Furthermore, several research studies have been conducted considering MLMs for buildings as surrogate models (Ascione et al. 2017a; Choliet 2013; Marasco and Kontokosta 2016; and Naganathan et al. 2016). Also, a few studies addressing the integration of MLM and simulation, or optimization, have been conducted. However, full integration between them, especially for building renovation, is still an open research problem.

Surrogate models are among the promising solutions to improve convergence speed in optimization problems, while maintaining accuracy, as they can reduce the function evaluation computation cost and smooth noisy response functions (Nguyen et al. 2014; Kleijnen, 1987).

2.10 Machine Learning-Based Surrogate Models in BEMs

MLMs are a subset of Artificial Intelligence (AI) that often apply statistical techniques on a simple input structure (e.g., historical data) to emulate detailed simulations and define relations between attributes. MLMs imitate the behavior of the original simulation model to be able to produce the model responses at reduced computational time. A large variety of MLMs have been used by scholars for building energy prediction. Among them, Artificial Neural Networks (ANN) (Escandón et al. 2019), linear regression analysis, Support Vector Machines (SVM), and decision trees (Tardioli et al. 2015) are popular in the building industry (Chalal et al. 2016).

MLMs use data-driven techniques to train data from BEMs as an alternative approach (Gallagher et al. 2018). Wei et al. (2018) reviewed different data-driven methods implemented in building energy consumption. They categorized current methods in two main groups, which are prediction methods (e.g., ANN, GA, SVM, statistical regression, and decision tree) and classification methods (e.g., K-mean clustering, hierarchy clustering, and self-organizing map). Ensemble, Radial Basis Function, ANN, multivariate adaptive regression splines, autoencoders, principal component analysis, K-means, Support Vector Regression (SVR), and Kriging are several efficient techniques for surrogate modeling (Ascione et al. 2017a; Choliet 2013; Marasco and Kontokosta 2016). The prediction accuracy of Conditional Restricted Boltzmann Machines (CRBM) and Factored Conditional Restricted Boltzmann Machines (FCRBM) are also studied by Mocanu et al. (2016).

MLMs offer a variety of models, from simple curve fitting models to more complicated models, such as deep learning models. High accuracy while maintaining high calculation speed could turn MLMs into a perfect replacement for comprehensive simulations, covering huge datasets, especially for renovation projects (Sharif and Hammad 2019).

MLMs can utilize a simple input structure to mimic detailed simulations and define relations between features (Horsey et al., 2016). MLMS learn the statistical *latent space* of datasets, and then *samples* from this space, generating new outcomes with features similar to the model that was captured in its training data. The data mining method has been utilized for load profiling studies in which seasonal energy consumption changes are addressed to predict the energy performance of future buildings (Pitt and Kitschen, 1999).

MLMs are more likely to improve performance over other analytic tools in many cases (Wei et al. 2018a; Zhao and Magoulès 2012). The advantages of using small datasets, while maintaining the high accuracy of forecasting for energy consumption analysis using different MLMs have been proven by several researchers (Li et al., 2017). Therefore, using MLM techniques can save a lot of computational time and cost, yet with a higher degree of accuracy.

Creating an MLM often involves the following three main steps: (1) Sampling input features as the dataset, which creates a dataset for training the surrogate model; (2) Applying a suitable MLM (e.g., ANN, AE, and GAN) based on the dataset, training, validating, and testing before using it as a ‘‘surrogate’’ of the original model; (3) deploying MLM as a prediction model. In more detail, the first step includes data collection and processing, while the second step focuses on the MLMs development. During the second step, the processes of the selection and development of MLM, training, validation, and testing take place. The first and second steps may be iteratively repeated for the MLM until the convergence happens or validation achieves success. Finally, in the third step, the MLM can be utilized as a prediction model. Figure 2-9 describes the stepwise procedure of the methodology.

The preprocessing step is needed to eliminate missing or repeated values, and inconsistencies for different features through data transformation and integration (Yu, 2012). For instance, Amasyali and El-Gohary (2018b) preprocessed outdoor weather-related parameters to develop possible feature pool for their MLM, which is used to predict hourly cooling energy consumption. They removed non-occupied hours data (e.g., weekend hours) from the dataset because their case study has altered operational features in these hours. They performed a stepwise regression for feature selection. The results indicated that out of 22 weather-related variables, only 14 features should be utilized for MLM. Consequently, they used mean and standard deviation to center and scale each feature of the dataset, respectively (Amasyali and El-Gohary 2018).

There are many techniques for assessing the MLM performance (e.g., leave-one-out cross-validation and cross-validation) (Edwards et al. 2012). However, cross-validation is an objective strategy in terms of identifying regression algorithms and feature selection (Ma and Cheng 2016). A quantitative and practical Bayesian method called Bayesian regularization backpropagation is proposed by MacKay (1992) for learning of mappings in feedforward networks. This method is used for the fine-tuning step in several studies (e.g., Singaravel et al. 2017; Yildiz et al. 2017).

ANN and SVM are the most widely used MLMs for energy prediction (Fan and Hyndman, 2012). Among different types of surrogate models, ANN models have been successfully used in many building energy consumption prediction studies (Amasyali and El-Gohary 2018; Melo et al. 2014). The number of published research papers about surrogate models related to buildings has been increased in recent years (Amasyali and El-Gohary 2018a; Wei et al. 2018; Ahmad et al. 2014). The study of Amasyali and El-Gohary in (2018a) shows that a significant number of previous MLM studies (47% out of 63 studies) have used ANN to predict building energy consumption. Using ANN has a high potential for improving energy consumption modeling, analysis, and long-term forecasts for industries (Azadeh et al. 2008).

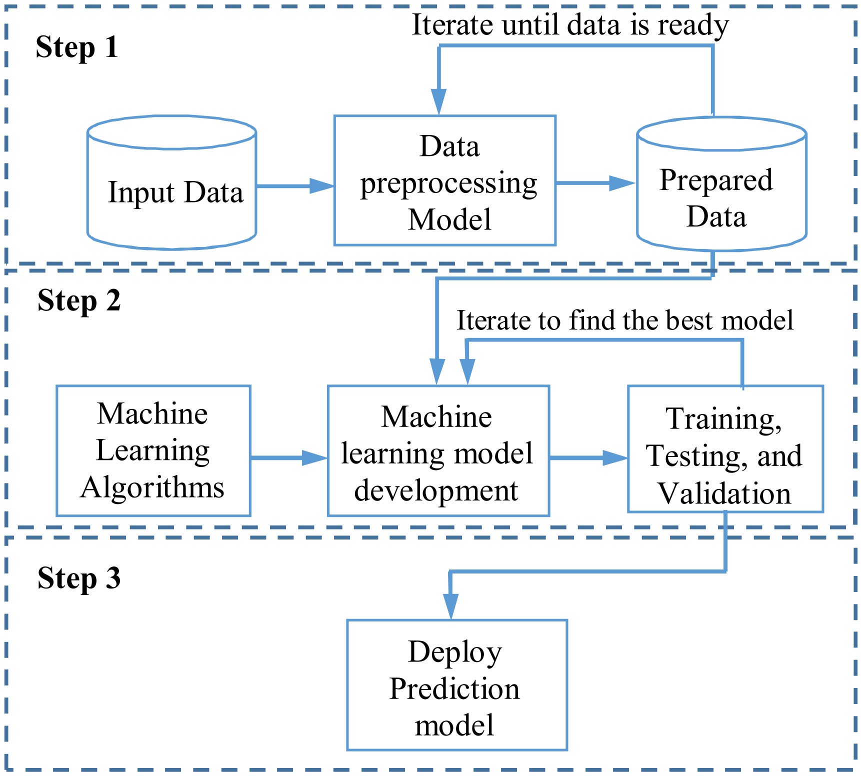


Figure 2-9. Machine learning process for creating surrogate model.

2.10.1 Artificial Neural Networks (ANNs)

ANNs are a type of AI modeling method that imitates the human brain's behavior (Yang et al., 2005). ANNs efficiently emulate the complex relationships of biological networks to answer complex nonlinear problems (Gurney, 2005). By doing so, accurate results are maintained, while the computational time becomes insignificant.

ANNs model the relationship between inputs and outputs by learning from the recorded data. Neurons are the fundamental computation units for ANN, which are connected by weighted links (synapses connections). Information transmission and manipulation occurred using these networks. Input data from previous neurons is received by the following neurons. The learning process in ANN, called "network training", is the ability to learn ''rules'' based on previous known relationships, and using them to control physical phenomena and generalize results for new situations (Neto and Fiorelli 2008). A transfer function is used to translate and manage these data and combine them to generate output data that are sent to the neurons in the next layer. Each neuron has associated weight and bias, which makes the network learn from provided inputs and outputs using training techniques. This iterative procedure continues until a stopping criterion is achieved, that can be the maximum number of iterations defined as epochs or the goals that are obtained, which properly set the weights of the synaptic connections by minimizing certain factors, for example the root mean squared error (RMSE) (Afram et al. 2017; Asadi et al. 2014) or the sum of squared errors (SSE) (Magnier, 2008).

Feedforward Multi-Layer Perceptron (MLP) with linear or nonlinear neurons, Recurrent Neutral Network (RNN), and Radial Basis Function neural network are among the different types of ANN structures. However, MLP feedforward algorithm is the most popular ANN (Afram et al. 2017). An ANN generally has three parts: an input layer, hidden layers, and an output layer. Back Propagation Neural Network (BPNN) and RNN are two architectures, which are used in recent studies (Wei et al. 2018a). In BPNNs, the computed output errors are consistently propagated to neurons, as negative feedback, to modify the weights of the input neurons. Therefore, by minimizing output errors, the accuracy of the ANN can be gradually improved. RNNs involve feedback results as inputs of the model using a loop. The backward connection in RNNs enables the former layers to process their current inputs, as well as what they have learned from the inputs. RNNs have internal memory. Therefore, they are able to recall their input and accurately predict future outcomes. RNNs are suitable for computing sequential data, e.g., time series datasets without random data for the prediction of the energy consumption of a passive solar building (Kalogirou and Bojic 2000), speech recognition (Li and Wu 2015), and connected handwriting recognition (Graves et al. 2009).

ANNs have been used in various research areas, including energy performance prediction, energy and cost optimization, and energy retrofitting (Ascione et al. 2017b; Yu et al. 2015). Several studies have been proposed to minimize energy consumption using ANN (Garnier et al. 2015; Huang et al. 2015; and Ning and Zaheeruddin 2010). Several recent publications introducing ANN methods are categorized in Table 2-4. ANNs are pre-programmed in many tools such as MATLAB® and their efficiency is demonstrated in various building studies (Wei et al. 2018; Magnier and Haghighat 2010, Azari et al., 2016). Melo et al. (2014) explained different capabilities of ANN models and proposed them as a surrogate approach of energy performance assessment tool in labeling programs.

The integration of optimization and ANN initiated in early 1993. However, integrated models have been rarely used on BEMs (Amasyali and El-Gohary 2018; Magnier 2008). Concurred with the previous studies, this kind of integrated model can be very practical for SBMOs.

Chen et al. (2010) proposed a method of temperature identification in intelligent buildings using a BPNN with one hidden layer coupled with the Particle Swarm Optimization (PSO). The authors stated that the time for generating the database was small, so the proposed BPNN is acceptable from the time prospect while it has high accuracy and stability (Chen et al. 2010).

Magnier and Haghighat (2010) trained an ANN using TRNSYS simulation data. Then they coupled trained-validated ANN with NSGA-II to optimize energy consumption and thermal comfort considering HVAC system settings, thermostat programming, and passive solar design (called GAINN). Obviously, the time of the simulation by using TRNSYS is far greater than the time needed by the ANN. The direct coupling between TRNSYS and NSGA-II would take more than 10 years; while using the GAINN approach, this time is reduced to 3 weeks for the whole methodology, which is mainly the simulation time required to generate the dataset (Magnier and Haghighat 2010b).

Asadi et al. (2013) proposed a Multi-Objective Optimization (MOO) considering five decision variables, i.e., insulation material for roof and external walls, windows, HVAC systems, and solar collector types for building retrofitting and three objective functions, i.e., energy consumption, thermal discomfort hours, and overall investment costs. The energy consumption for lighting is excluded from their study. Consequently, a three-layer feedforward ANN with input, hidden, and output layers, was utilized to combine with the MOO to quantitatively evaluate the selection of different technologies for retrofitting of an existing school.

Among recent publications, some of them mainly focus on the improvement of the HVAC and lighting using MOO (Ferreira et al. 2012; Kim et al. 2016; Wei et al. 2015). Kim et al. (2016) developed an Integrated Daylighting and HVAC (IDHVAC) model using simulation-based optimization to predict building energy performance by artificial lighting regression models and ANN as shown in Table 2-4. Their model used the design of experiments method to generate the database that was utilized for ANN training. Integration of GA and IDHVAC system, which is based on the database that was generated using the EnergyPlus model, leads to minimizing TEC while satisfying occupants visual and thermal comfort, concurrently (Kim et al. 2016).

Minimizing the energy and cost for HVAC systems in existing commercial buildings is studied by Huang et al. in (2015). They proposed a Hybrid Model Predictive Control (HMPC) by combining a classical Model Predictive Control (MPC) with an ANN feedback linearization algorithm. The HMPC model contains a simplified physical model for control and an inverse ANN, which works independently as a nonlinear compensator for the HVAC process. They utilized both a forward ANN and an inverse model in the feedback loop. The merits of using an inverse ANN model is to determine the link between the virtual input and the actual input (Huang et al. 2015). Wei et al. (2015) proposed a data-driven method to optimize the TEC of the HVAC system in an Energy Resource Station (ERS) center, considered as a typical office facility.

Garnier et al. (2015) developed a predicative method for the management of multi-zone HVAC systems in non-residential buildings using EnergyPlus, GA, and a low-order ANN. Initially EnergyPlus is used for energy simulation modeling. Consequently, GA is developed to minimize the total consumption of electrical power while achieving acceptable thermal comfort requirements utilizing Predicted Mean Vote (PMV) indicator. In more detail, GA optimizes the operation time of all of the HVAC subsystems by computing the right time to turn the HVAC subsystems on and off while meeting thermal comfort requirements. They created six self-growing ANN-based models and implemented them as internal controller models.

The study by Neto and Fiorelli (2008) on comparing EnergyPlus simulation methods with ANN models has two important conclusions. Firstly, both models are suitable to estimate energy consumption, and secondly, EnergyPlus predictions have an error range of ±13% for 80% of the tested reference buildings. The results for the ANN models revealed a fair agreement between energy consumption predictions and Existing Situation (ES), with about 10% error considering different networks for working days and weekends. However, they claim that utilizing a more suitable ANN can improve the results (Neto and Fiorelli, 2008).

Ahmad et al. (2017) showed that the performance of the BPNN is marginally better than the performance of Random Forest (RF) for predicting the hourly HVAC electricity consumption. RF is an ensemble learning algorithm based on the decision tree methodology. The proposed BPNNs architecture had nine input parameters, i.e., outdoor air temperature, dew point temperature, relative humidity, wind speed, hours of the day, day of the week, month of the year, and social parameters (i.e., number of guests for the day, number of rooms booked) (Ahmad et al. 2017).

Reviewing the existing prediction models using ANN for energy consumption done by Amasyali and El-Gohary (2018a), leads to the following observations: (1) The majority of models (81%) focused on non-residential buildings, specifically educational and commercial buildings; (2) Almost half of the proposed models predicted TEC (47%), while 31% and 20% of the models predicted cooling and heating energy consumption, respectively. Interestingly, only 2% of the models predicted lighting energy consumption; (3) variety of features were selected by scholars, including external weather conditions, indoor environmental conditions, building attributes, related occupant behavior and occupancy, and time features. However, previous studies used ANNs to simulate or predict only few aspects of the buildings. Besides, there is limited research combining all types of features in a building simultaneously (Amasyali and El-Gohary 2018a; Wei et al. 2018). Furthermore, currently only a modest amount of literature is available on the energy consumption prediction through integrating ANN and BEM and none of them consider the whole building envelope, HVAC, and lighting simultaneously.

To the author's knowledge, the application of MLMs for whole building renovation of regarding TEC, LCC, and LCA is original, and cannot be found in the literature.

Table 2-4. Overview of some ANN literature.

Author	Method	ANN Method		Input				Output				Scope	Tool
				Env	HVAC	Li	Comments	TEC	LCC	LCA	Comments		
Afram, et al., 2017	ANN used to design the supervisory MPC for HVAC. The MPC generated the dynamic temperature set-point profiles and BT water	S O	BNMI for ANN; A simple feed forward MLP network	-	✓	-	HVAC system data for: ERV, AHU, BT, RFH and GSHP	✓	✓	-	Operating cost of the equipment and thermal comfort	Residential HVAC system	MATLAB, EnergyPlu, Measured data
Ahmad et al. 2017	Comparison between RF and ANN for high-resolution prediction	S	feed-forward BP ANN, RF	-	✓	-	Electricity consumption, outdoor air temperature, RH, time, social parameters	✓	-	-	Building energy consumption	Hotel in Madrid, Spain	Python, neurolab
Asadi et al., 2014	Evaluation of ANNs with the optimization power of GA. MOO to study the interaction between the conflicting objectives and assess their trade-offs.	S	RSA, LHS, feed-forward model	✓	✓	-	Building's characteristics and performance: EC, retrofit cost, and thermal discomfort hours, EW and R materials, W, solar collector and HVAC	✓	✓	-	EC, Retrofit cost, TPMVD	A school building **Retrofit**	MATLAB, TRNSYS, and GenOpt
Ayata et al., 2007	ANN for the prediction of both average and maximum indoor air velocities	S	Five hidden layers, SCG and LM	✓	-	-	Air velocity, Wind speed and direction for door openings, building width and length	-	-	-	Predict indoor average and maximum air velocities	New building designs in Turkey	FLUENT, MATLAB
Azari et al., 2016	Single objective and MOO trained by ANN (filled with the genes of the best chromosome)	S O	Five-layer ANNs, hyperbolic tangent sigmoid	✓	-	-	Insulation material, W type, W frame material, wall thermal resistance, and south and north WWR	✓	-	✓	Operational energy and environmental impacts	Low-rise office building envelope design	eQuest, ATHENA IE, Pascal
Bocheng et al., 2015	LM used to optimize the NN training. Then the prediction model based on the new algorithm was set up in terms of the main factors affecting the EC.	S O	LM to genetic NN. A three-layer BP network. GALM NN	-	-	-	Average temperature, Dew-point temperature, RH, electric consumption data	✓	-	-	Electric consumption	Public building short-term Prediction	MATLAB
Chen et al., 2010	NN used as the temperature identification structure to calculate the temperature of the near future accurately	O	Feed forward NN with one hidden layer and PSO	-	-	-	Observed temperature of building equipment in an intelligent building	✓	-	-	Effective calculation of temperature	University library electronic reading room	Sensor data
Ascione et al., 2017	The cost-optimal analysis by MOGA uses ANNs to predict building energy performance	S O	Feed forward MLP	-	✓	-	Annual PEC factors, DH, global cost for energy uses over building lifecycle, TC	✓	✓	-	PEC_h, PEC_c, DH, and energy retrofit	Feasible for any building **Retrofit**	EnergyPlus and MATLAB

Table 2-4. Overview of some ANN literature (Cont.).

Garnier et al. 2015	Predictive control of multi-zone HVAC management (six self-growing ANN)	S O	Low-order ANN	-	✓	-	MPC and total consumption of electrical power	✓	✓	-	Thermal comfort and EC	Non-residential building	EnergyPlu, GA, and MATLAB
Huang et al. 2015	Hybrid Model Predictive Control (MPC) for energy and cost savings	-	Combining MPC with a NN feedback linearization	-	-	-	Thermal dynamics of the building, overall thermal capacitance and heat gain from the occupants	✓	✓	-	MPC, temperature, energy and cost savings	An airport terminal building	Resistance capacitance thermal networks
Kim et al. 2016	Simulation-based optimization of an integrated meta-model for daylighting and HVAC	S O	Design of experiments model to generate the database for ANNs	-	✓	✓	Outdoor temperature, illuminance (blind slat angle, supply air set point, AHU status, water flow, and outdoor air mixing ratio)	-	✓	-	Total power consumption, constraints indoor thermal and visual comfort	Office building	EnergyPlus and MATLAB
Magnier and Haghigh at, 2010	A simulation-based ANN to characterize building behavior, and combines this ANN with NSGA-II. GAINN approach	S O	RSA, a multilayer feed forward ANN	✓	✓	-	HVAC system settings, thermostat programming, and passive solar design, W, WWR, RH, thermal mass	✓	-	-	Thermal comfort and EC	Residential house	TRNSYS and MATLAB
Neto and Fiorelli, 2008	Comparison between ANN and detailed energy simulation model	S	Feed-forward ANN	✓	✓	✓	Building EC profile and meteorological data (geometry, wall & W materials, Li, equipment and occupancy schedules)	✓	-	-	Predict EC (Li, Occupancy & equipment) and weather parameters	University admin building	EnergyPlus
Yang et al., 2005b	Adaptive ANN for unexpected pattern changes, and real-time on-line building prediction	-	LM and gradient descent (big data)	-	✓	-	Data about temperatures and chiller electric demand and the temperature and electric demand measurements enclosed within the W	✓	-	-	Predict the chiller electric demand	CANMET Energy Technology Center	MATLAB
Yu et al., 2015	MOGA –BP network model for rapidly prediction	S O	Back propagation (BP)	✓	-	-	Plans, floor area, orientation, stories, shape coefficient, WWR, Wall, R, W (HTC, HII)	✓	-	-	EC and indoor thermal comfort	Residential buildings design	MATLAB
Sharif and Hammad , 2019	Surrogate ANN for Selecting Near-Optimal Building Energy Renovation Methods	S O	NSGA-II and ANN	✓	✓	✓	R, EW, FT, W, WWR, HVAC, COS, HOS, Li, EWO	✓	✓	✓	TEC, LCC, and LCA pairwise	University buildings	Design-Builder and MATLAB

Nomenclature: Air Handling Unit (AHU); Best Network after Multiple Iterations (BNMI); Back Propagation (BP); Buffer Tank (BT); Particle Swarm Optimization Algorithm (PSO); Percentage of Annual Discomfort Hours (DH); Energy Consumption (EC); Energy Recovery Ventilator (ERV); Heat Transfer Coefficient (HTC); Heat Inertia Index (HII); Fixed Set-Point (FSP); Genetic Algorithm (GA); Ground Source Heat Pump (GSHP); Latin Hypercube Sampling (LHS); Levenberg-Marquardt Algorithm (LM); Life Cycle Environmental (LCE); Multi Criteria Analysis (MCA); Mean Squared Error (MSE); Model Predictive Control (MPC); Multi-Objective Genetic Algorithm (MOGA); Mean Absolute Percentage Error (MAPE); Multi-Layer Perceptron (MLP); Natural Ventilation (NV); Neural Network (NN); Predicted Mean Vote (PMV); Optimization (O); Primary Energy Consumption (PEC); Radiant Floor Heating (RFH); Relative Humidity (RH); Response Surface Approximation Model (RSA); Simulation (S); Scaled Conjugate Gradient (SCG); Thermal Comfort (TC); Thermal Predicted Mean Vote Discomfort (TPMVD); Window to Wall Ratios (WWR)

2.10.2 Deep Learning and Building Energy Predictions

Building's electricity consumption prediction covers long-term (more than a year), medium-term (week to a year), and short-term (an hour to a week), which is a complex task (Rana and Koprinska, 2016; Citroen et al. 2016). Citroen et al. (2015) and Li et al. (2015) developed models for long-term predicting. There are several studies on short-term and medium-term electricity prediction (Naganathan 2017). These studies utilize different ANN (Monteiro et al. 2016) and statistical methods, i.e., PSO algorithm (Bahrami et al., 2014), adaptive neuro-fuzzy logics (Osório et al., 2015), expert system, pattern recognition, space modeling (Al-Hamadi and Soliman 2004), smoothing, kernel-based support vector quantile regression (He et al., 2017), regression (Song et al., 2005; Papalexopoulos and Hesterberg 1990), and time series models using clustering (Espinoza et al. 2005).

DNNs have been proven to be very accurate in many tasks, e.g., video prediction (Mathieu et al. 2016), image generation (Salimans et al. 2016), and image classification (Simonyan and Zisserman 2014). Deep learning is defined as a subset of MLM, such as deep feed forward neural networks, Convolutional Neural Networks (CNNs), and RNNs. These algorithms have grown from fledgling research subjects into mature techniques in real-world use. Recently, deep learning has become a promising avenue of research for many complex topics in building engineering due to its capability to explore unlabeled datasets, extract the inner features, and utilize labeled data for fine-tuning (Yu et al. 2016). This potential improves classification accuracy and discrimination power in machine learning tasks for estimating building energy consumption (Amasyali and El-Gohary 2018; Mocanu et al. 2016).

DNNs are powerful automated extraction algorithms for feature extraction of complex data representation with the ability of observe, learn, analyze, and make decisions at high levels of abstraction (Najafabadi et al. 2015) and better accuracy compared with other traditional shallow MLMs (Mocanu et al., 2016). However, the implementation of DNN into whole building energy consumption analysis and prediction studies is limited (Mocanu et al. 2016; Naganathan 2017; Paterakis et al. 2017).

In DNN the definition of unsupervised, semi-supervised, and supervised learning models is sometimes blurred. Therefore, based on the focus of the study, a semi-supervised learning can be interpreted as either an unsupervised or supervised learning algorithm (Choliet, 2013). Although deep supervised MLMs have achieved recent progress, semi-supervised and unsupervised learning still remain uncertain topics. These algorithms are widely recognized as useful tools for learning representations of features and solving problems with limited labeled dataset. Based on the literature, unsupervised algorithms can be used in a semi-supervised scenario to solve problems with limited labeled dataset (Makhzani 2018).

Based on the research of Zhu et al. (2003), several studies have concluded recently utilizing semi-supervised DNNs in comparison with traditional MLMs, which are either fully unsupervised or fully supervised. In this case, there is a small set of labeled data from the input data in the latent space, which is often unlabeled (Gibson et al., 2013). One of the benefits of using semi-supervised DNNs is to utilize both unlabeled and labeled data with good performance in many applications (Goldberg et al., 2011; Zhu and Goldberg, 2009).

Despite the increase in the number of published research papers related to application of DNNs in building industry (especially in building energy efficiency) in the last five years, there is limited or no reported research focusing on the use of generative DNNs on the design of new building or renovation of existing buildings.

(a) Autoencoders

Autoencoders are a well-known category of neural network algorithms that perform unsupervised learning, where the model outputs are the reconstructions of the inputs (Figure 2-10). Recently, advanced techniques have been presented for analyzing different types of data as well as advanced training architectures (e.g., deep convolutional neural network, autoencoders, and Generative Adversarial Network (GAN)) (Lecun et al., 2015). However, there are few studies addressing the applications of various types of autoencoders in building energy (Fan et al., 2018).

An autoencoder contains an encoder network and a decoder network. The encoder converts the input data (denoted as X_i) into features (denoted as b_i in Figure 2-10), while the decoder attempts to reconstruct the input data (i.e., denoted as $\tilde{X}_i$) using the features (Figure 2-10). If the number of b_i is smaller than the number of nodes in the input and output layers (X_i and $\tilde{X}_i$) the autoencoder has under-complete (bottleneck layout) architecture; otherwise it has over-complete (i.e., higher dimensional than the input layer) architecture (Fan et al. 2018). The learning process in general autoencoders is unsupervised since there are no label features. The training goal in an autoencoder is to minimize the reconstruction residuals between X_i and $\tilde{X}_i$, which is usually calculated using cross-entropy losses or Mean Squared Error (MSE). Training constraints are typically indicated in the autoencoder layout to learn meaningful features (Vincent et al. 2010).

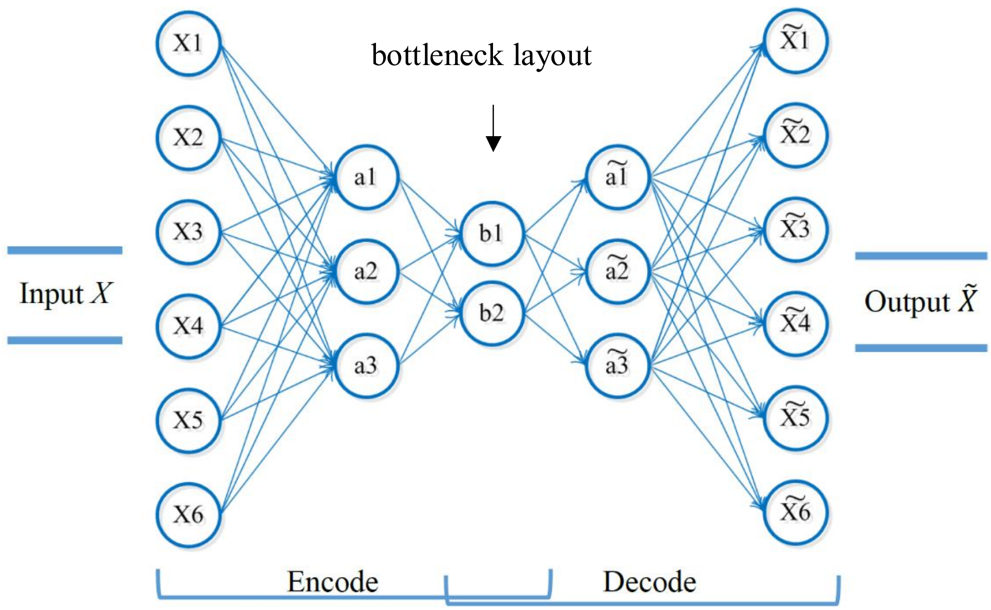


Figure 2-10. The general Autoencoder architecture.

A linear autoencoder with a hidden layer is similar to Principal Component Analysis (PCA). Usually, adding hidden layers improves the network reconstruction capability. However, autoencoders can be nonlinear and deep (Kelly, 2016). Autoencoders can be used for features extraction, which means extracting hidden but relevant information from the input data and transforming the extracted patterns into knowledge. Feature extraction is a data-driven approach in autoencoders that can be used to handle some challenging tasks in unsupervised and semi-supervised DNNs. For instance, feature learning algorithms for time-series problems (Längkvist et al. 2014) or anomaly detection in building energy data (Fan et al. 2018). Feature extraction is a combination of approaches, i.e., selecting, encoding, normalizing, extracting and reducing data to retain most useful information on the features in a high or low dimensional space before being reduced (Kunang et al. 2019; Yu 2012).

In previous studies, the feature learning capability of autoencoders utilizing both over-complete and under-complete layout has been investigated (Yong et al. 2019; Vincent et al. 2010). To guarantee the robustness and reliability of the training model, more data are required. However, this is not always the case.

Different types of autoencoder architectures cover a wide range of techniques, from a basic version to the feed-forward fully connected autoencoders. The latter group of autoencoders, which includes multiple fully connected layers of complex architectures, are more capable of capturing the dependency, e.g., spatial dependency in image data and temporal dependency in time series predictions (Honkela et al. 2011). Makhzani (2018) used stochastic gradient descent algorithm to optimize the model parameters in a generative autoencoder that uses the GAN framework for generative image modeling.

CNN utilizes convolution and pooling operations to capture structural dependencies, such as temporal and spatial dependencies. These hierarchical networks are developed as the primary tools for signal processing and image classification (Choliet, 2013). Convolutional autoencoders (CAEs), which are similar to CNN, have more reliable performance than feed-forward fully connected autoencoders. Furthermore, by limiting the connections of input data with neurons, CAEs can decrease the number of model parameters efficiently.

Li et al. (2017) combined extreme learning machine (ELM) with an extreme deep learning method, which is Stacked Autoencoders (SAEs), to improve the accuracy of the building energy consumption prediction. To gain accurate prediction outcomes, ELM is used as a predictor and the building energy consumption features are extracted utilizing SAE. Furthermore, to assess the performances of the developed method, four popular MLMs, i.e., SVR, BPNN, multiple linear regression (MLR), and generalized radial basis function neural network (GRBFNN) were computed and the outcomes were compared with the results of the developed method. Experimental outcomes proof that the developed model has the best performance in predicting the energy consumption of the building (Li et al. 2017).

(b) Variational Autoencoders

Autoencoders are designed to extract rich representation of data. However, autoencoders do not have a generative capability, i.e., they cannot be used to automatically generate new samples. Many recent studies have focused on latent variable models, such as VAE. VAE is capable of capturing interesting relationships within the dataset and extracting features of the data, which is representative of the most related information from the input data in the latent space (Vincent et al., 2010). VAEs are more advanced than conventional autoencoders because they combine Bayesian inference with DNNs. The general architecture of a VAEs is the same as an autoencoder;

however, in a VAE, two objectives are optimized rather than a single objective, which is the case in autoencoders (i.e., minimizing the reconstruction residuals between X_i and $\tilde{X}_i$). In a VAE, the parameters of a normal distribution (mean and variance) are estimated and, in addition to reconstruction loss, the Kullback-Leibler (KL) divergence between the estimated normal distribution and N (0, I) (normal distribution with zero mean and identity covariance) is minimized. At test time, by sampling from N (0, I), and feeding the sample into the decoder, new samples could be automatically generated (Chen et al. 2016; Vincent et al. 2010; Yang et al. 2011).

VAEs have a strong capacity to work as generative models (Gauthier 2014). They can be used in applications such as neural network pre-training, image generation, image denoising, and reinforcement learning (Gulrajani et al. 2016; Kingma et al. 2016; Kingma and Welling 2014; Makhzani 2018; Rezende et al. 2014). For instance, the denoising AE (dAE) model, which is utilized by Vincent et al. (2010), learns to regenerate empirical data X_i from noised inputs $\tilde{X}_i$. The activation functions executed in the hidden and output layers can be sigmoid, linear function or other functions, i.e., ReLU and hyperbolic tangent (Fan et al. 2018).

The accuracy of the VAE prediction model will be limited in two main cases, which are the incompleteness of the data and irrelevancy between input features and the results of the simulation. In the latter case, noisy information, which is not useful for VAE are used as inputs. Therefore, to improve the accuracy of the generative model and reduce the training computational time, it is critical to remove these types of data from the list of inputs (Yang et al. 2005b). Yang et al. (2005) removed all non-working hour data from the dataset. They found that the use of working-hour data improves the accuracy of prediction significantly. Makhzani et al. (2015) combined concatenated method and label data to reduce the classification error of their proposed generative adversarial autoencoder and improve the accuracy. A concatenation layer takes inputs that have the same dimension and concatenates them along the hidden layers as input to involve both unlabeled and labeled samples in the network. Such strategy is also employed by Kelly (2016).

Although these state-of-the-art, generative models are very flexible and successful, they have several limitations, e.g., they are unable to accurately model large scale and complex image datasets (i.e., LSUN and Imagenet) (Zhao et al. 2017). To the authors' knowledge, the application of VAEs for whole building renovation considering TEC and LCC cannot be found in the literature.

(c) Detailed description of VAE

The VAE takes a feature, as input, maps it to a latent vector space using an encoder network, and then decodes it back with the same dimensions as the original feature, using a decoder network. In this process, learning happens by reconstructing the output features to be the same as the original input features (Choliet 2013). VAE uses the statistical distribution of results, which forces the network to learn the continuous and highly structured dataset. The model turns input features into mean (μ) and variance (σ) value instead of compressing them into a fixed vector. The model utilizes these statistical values to randomly sample features and decodes these features back to the input features as shown in Figure 2-11. It is worth mentioning that the output has been generated by a statistical procedure, therefore the randomness of the generated values should be considered during the training process. Most importantly, due to the randomness of this process, each feature in the dataset should be decoded to a valid output that forces the model to encode meaningful representations, which increases the robustness of the model (Chen et al. 2016).

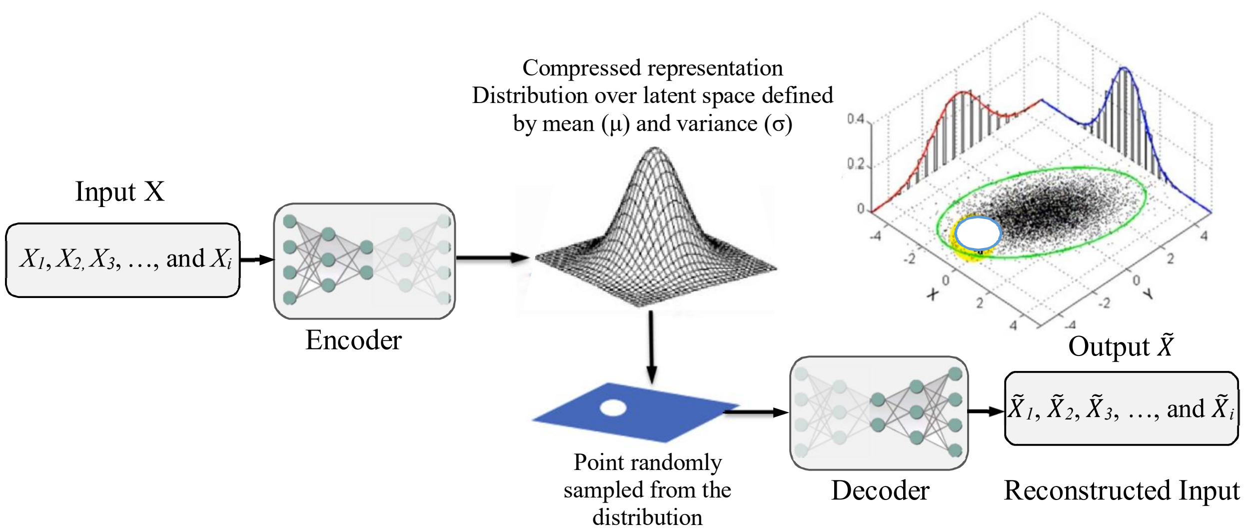


Figure 2-11. Detailed description of VAE (Adapted from Choliet, 2013).

(d) Generative Adversarial Network

Another popular type of generative neural network, i.e., the Generative Adversarial Network (GAN), is a deep MLM that is specially designed to simultaneously train a discriminator and a generator (Goodfellow et al. 2014). GANs are successfully used for various ML domains, e.g., image generation (Salimans et al. 2016) and video prediction (Mathieu et al. 2016). The generator network takes a random input from latent spaces of the dataset, and is trained to generate fake samples. The discriminator network is trained to differentiate between real samples and fake samples, which are created by the generator.

This generative MLM attempts to generate features utilizing random *noise* by implementing two adversarial networks that are trained concurrently (Mathieu et al. 2016). A typical GAN has mainly three networks that are generator, discriminator, and adversarial (Goodfellow et al. 2014).

(e) Detailed Description of Generative Adversarial Network

There are two adversarial networks running at the same time, and the training terminates if a stalemate has been achieved. These two networks are adversarial to each other; generator is trying to deceive the discriminator constantly and discriminator tries to not be deceived. Figure 2-12 explains the training loop for each epoch consists of the following steps: (1) Obtain random input samples in the latent space (e.g., feasible renovation scenarios), which are random *noises*; (2) Generate new samples with "generator" utilizing random *noises*; (3) Blend the generated samples with real ones and develop a group of samples (e.g., SBMO results); (4) Train "discriminator" implementing these various samples, with corresponding targets: either "real" (for the real sample) or "fake" (for the generated sample); (5) Obtain new random samples in the latent space; (6) Train GAN utilizing these random vectors, with targets that all say, "These are real samples." At this level the discriminator should not be trained; therefore, this updates the weights of the generator network attempting to get the discriminator to predict "These are real samples" for generated samples. Subsequently, the generator will be trained to fool the discriminator (Choliet, 2013).

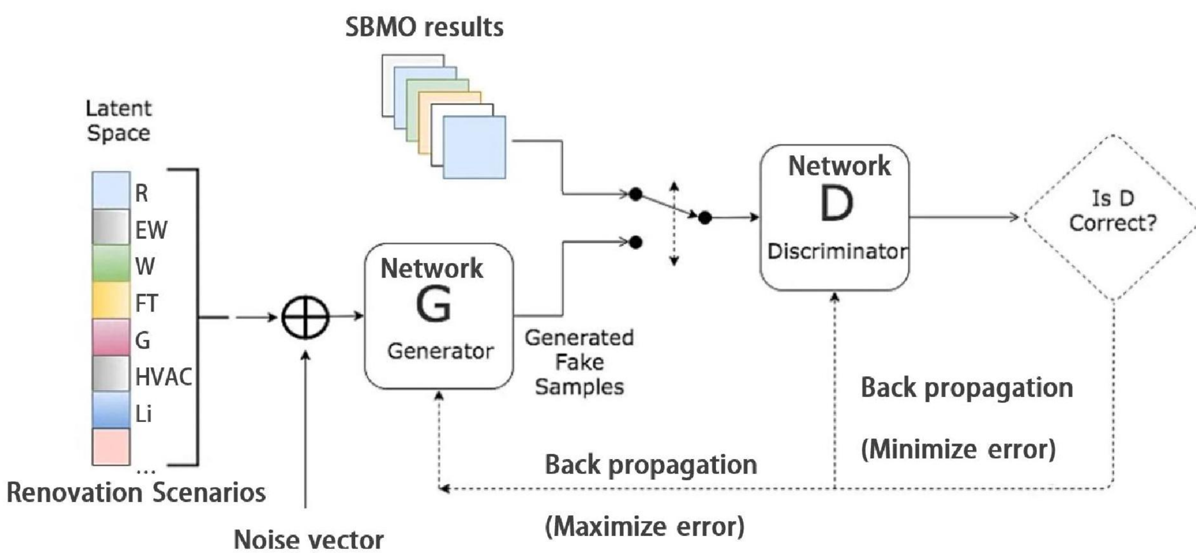


Figure 2-12. The training loop for GAN (Adapted from Shidanqing.net).

2.11 Summary

The construction sector is relevant to sustainability because of the tremendous amount of energy consumption and negative environmental impacts of construction products and also the benefits to society of the active role of this industry in achieving the aims of the sustainable development plans. Furthermore, buildings are responsible for about 30% of total energy usage (Wang and Srinivasan 2017). The potential for decreases in energy consumption and GHG emissions associated with buildings is remarkable (Tuominen et al., 2012). In this context, existing buildings have a very substantial role, which must be highlighted because of the potential for energy saving and the availability of regulatory incentives and regulations. Owners have faced increasing needs for minor repairs, as well as partial or major renovations of their buildings. However, they usually suffer from limited budgets or other constraints.

Several methods have been proposed by scholars to visualize, analyze, optimize, and predict the energy performance of buildings, implementing different mathematical, statistical and computational models (Abdallah 2014). These methods cover a wide range of techniques, from basic mathematics to the most complex neural networks, to improve building energy performance.

However, despite the significant contribution of research on optimizing energy consumption, there is limited research focusing on a comprehensive renovation of existing buildings to minimize TEC, LCC, and their environmental impact using LCA.

Building simulation is able to simulate energy consumption and LCC and apply different renovation scenarios based on the available building components and materials. However, despite its strength, simulation is not able to define optimal solutions from among the many possibilities of different scenarios. Therefore, integration of the building simulation and optimization algorithm gives an opportunity for decision makers and practitioners to improve the energy performance of buildings through selection of near-optimal scenarios, SBMO, and the fine-tuning of the desired renovation methods, and as a result, to accurately estimate the energy consumption of buildings. To the author's knowledge, full integration of simulation, and optimization especially for comprehensive building renovation, is still an open research problem.

Furthermore, for a big project current SBMO models often need hundreds or thousands of simulation evaluations. Therefore, the optimization becomes unfeasible because of the computation time and complexity of the dependent parameters. To this end, one feasible technique to solve this problem is to implement surrogate models to computationally imitate expensive real building simulation models with a more applicable model. Furthermore, several research studies have been conducted considering MLM for buildings as surrogate models. Also, a few studies addressing the integration of MLM and simulation or optimization have been conducted. However, full integration between them, especially for building renovation, is still an open research problem. Although these state-of-the-art generative models are very flexible and successful, there is limited research focusing on the use of generative DNNs on the design of new building or renovation of existing buildings. Furthermore, the application of VAEs for whole building renovation considering TEC and LCC cannot be found in the literature.

CHAPTER 3. OVERVIEW OF RESEARCH METHODOLOGY

3.1 Introduction

The proposed framework has four essential and interdependent parts, which are data management model, i.e., input data collection and preparation, database development, definition of the renovation strategies, and integration (Section 3.2), SBMO model development and validation (Section 3.3), data processing, i.e., data preprocessing, data preparation, and data normalization for each MLM separately (Section 3.4), and surrogate model development, i.e., load normalized data, MLMs development, training, testing, and validation (Section 3.5). Each process has several phases that are explained in detail. As shown in Figure 3-1, the first two parts (called Module 1) have six phases and are described in Chapter 4, while the second two parts are done for the surrogate ANNs (called Module 2) and generative VAEs (called Module 3) separately and are explained in Chapters 5 and 6, respectively.

3.2 Data Management (Part 1)

This part has three main phases. The first phase of the proposed framework is data collection and preparation. Extensive data is collected on existing buildings related to several factors including total energy consumption, outside temperature, building envelope components, HVAC and lighting systems. The data collected is then validated by other methods such as comparing with energy bills, through a semi-structured interview, site visit, and analyzing the plans and sections of the buildings.

The specific collected data are then added to the extensible database, which includes a wide range of different renovation methods of the buildings envelope, HVAC, and lighting. The extensible database also contains other information, i.e., LCC and environmental impacts related to each method. The outcome of the second phase contains all possible methods to achieve the renovation goals and saves them in the extensible database. It is worthy to mention that the proposed database also takes advantage of coupling with the BIM model. The third phase involves defining the renovation goals, methods, and tasks for each renovation scenario, which are embedded in the databases.

The goal of this phase is to develop renovation scenarios based on a set of methods. Each scenario consists of several renovation methods within the applicable strategy. The exact formation of renovation strategies differs case-by-case and depends on different factors, such as the size of the project, budget, results of the simulation of the case, severity of the building's problems, and other mandatory requirements. Another factor, which is vital to define a renovation strategy, is the owner's preferences.

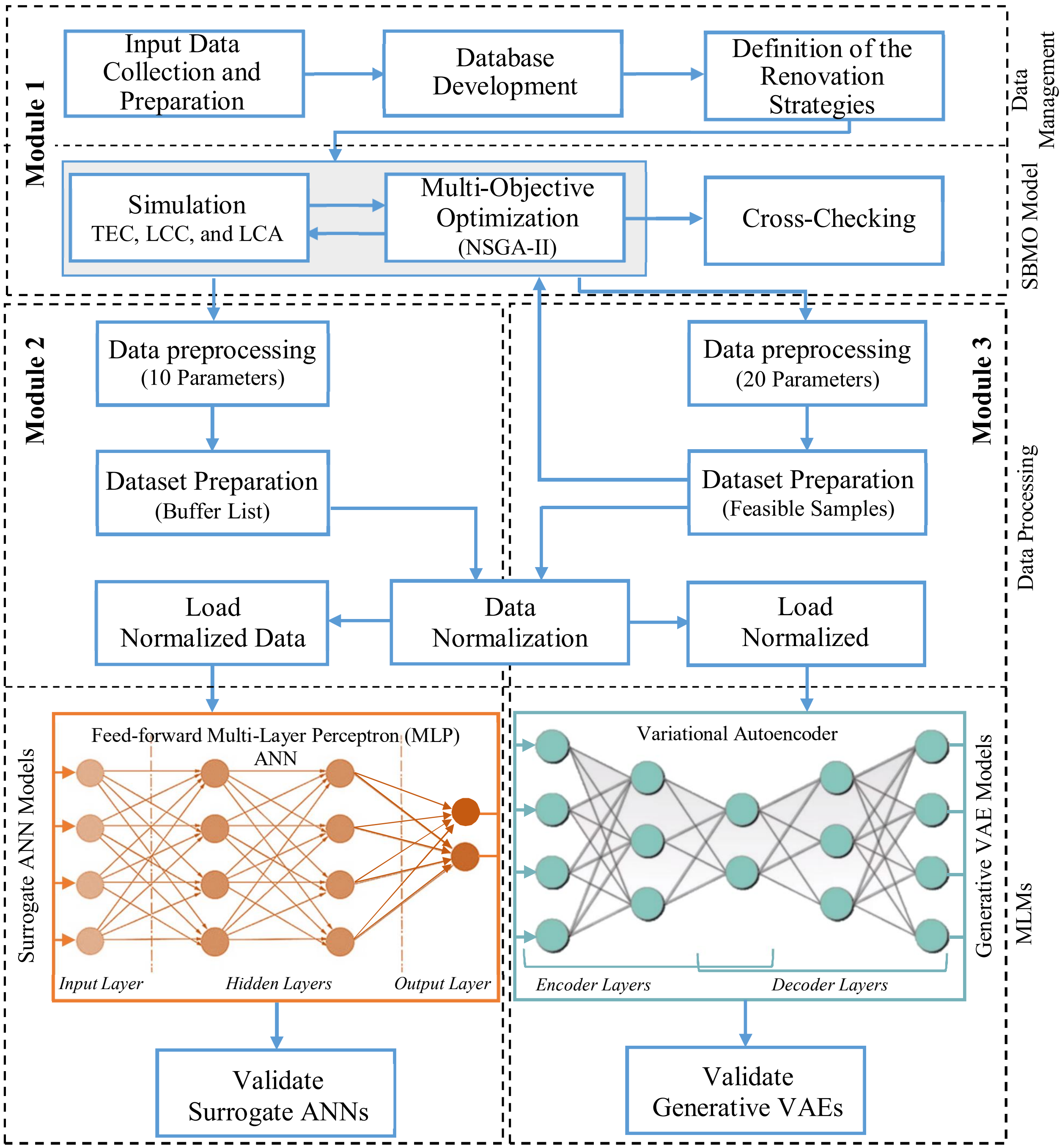


Figure 3-1. Structure of the proposed framework.

3.3 Simulation-Based Multi Objective Optimization Framework (Part 2)

The SBMO model development part has two main steps. In the first step, an energy simulation model is developed, which is one of the key parts of this methodology. A computer model of the building under consideration is developed in the energy simulation tool.

Different parameters of the building have been collected and can be generally categorized into five types: (1) Energy and cost variables (i.e., total building heating and cooling loads and electricity and gaz consumptions and utility bills from Hydro-Québec and Gaz Métropolitain); (2) weather conditions (e.g., temperature, outside dry-bulb temperature, radiant temperature, and relative humidity); (3) operating parameters (e.g., Cooling Operation Schedule (*COS*), Heating Operation Schedule (*HOS*), External Window Open (*EWO*), operative temperature, the temperatures and flow rates of chilled water and condenser water); (4) Building envelope characteristics (i.e., Roof Types (*R*), External Walls (*EW*), Glazing Types (*GT*), Window frame types (*W*), Window to Wall Ratio (*WWR*), and Airtightness (*A*)); (5) Building system parameters (i.e., detailed HVAC system (*HVAC*), system loads, infiltration, total fresh air, Domestic Hot Water (DHW), and Lighting systems (*Li*)). Then, other information is modeled, such as the functionality of each space, typical occupant activities and clothing, and appliance energy consumption, as would be expected in the real building. For verification, the simulation results should be compared with energy bills, in terms of energy consumption. These databases have been used to create a comprehensive BEM as a baseline model for investigating the performance of Existing Situation (ES) and calibration and comparison of results.

Consequently, the second step involves developing the optimization model, which is integrated with the simulation tool to shape the SBMO model. A specific category of Genetic Algorithms, named Multi-Objective Evolutionary Algorithm (MOEA), is selected. The MOEA enables the algorithm to optimize all objective functions simultaneously, based on Pareto dominance.

NSGA-II is chosen for this study. As explained in Section 2.7.4, NSGA-II is one of the most efficient genetic algorithms for multi-objective optimization, and is often used for multi-criteria optimization in different domains (Deb et al., 2002). The objective functions are calculated for each renovation method using the capability of the simulation tool. The optimization engine computes the objective functions, which minimize TEC, LCC, and LCA for each scenario, based on the selected values of the methods in each simulation run. To define decision variables in MOO, the objective functions and constraints are mathematically formulated (Eq. 3.1). The goal is to find the near-optimal building renovation scenario considering predefined constraints. The detailed NSGA-II model is explained in Chapter 4. The SBMO model considers the renovation methods as decision variables for the NSGA-II which selects the optimum value for each renovation method considering an acceptable range for the methods. The objective functions constraints are also defined for SBMO model. The optimization algorithm starts with generating the initial population of size N in the first generation. The simulation model calculates TEC, LCC, and LCA for each member (i.e., renovation scenario) of the population. Consequently, the selection, crossover, and mutation operations are applied for the entire population. This procedure is iteratively repeated for all members in all generations until the convergence happens or a predefined number of generations is reached. Finally, the results of the optimization are shaped into the Pareto front, which will be used to investigate the trade-off relationships among the different renovation scenarios, as well as to develop input data for the data processing step, as shown in Figure 3-2. The final goal is to simultaneously optimize all objective functions of TEC, LCC, and LCA.

$$\begin{aligned} &\text{Minimize } f(X) = \{f_1(X), f_2(X), f_3(X)\} \\ &\quad \text{Min } f_1(X) = \text{TEC}(X) \\ &\quad \text{Min } f_2(X) = \text{LCC}(X) \\ &\quad \text{Min } f_3(X) = \text{LCA}(X) \\ &X = \{x^{R}, x^{EW}, x^{W}, x^{GT}, x^{WWR}, x^{HVAC}, x^{COS}, x^{HOS}, x^{Li}, x^{EWO}\} \end{aligned} \qquad \text{Eq. 3.1}$$

where X is the vector of the decision variables (i.e., building parameters). The details about the decision variables are explained in Section 4.2.4. The SBMO model considers two categories of constraints when creating and evaluating the renovation scenarios: (1) renovation methods constraints; and (2) objective functions constraints. The renovation methods constrain specify, in general, which kind of renovation is applicable for the project considering the renovation budget limitations, owner's preferences, and desired energy certificate specifications. The constraints indicate the acceptable renovation methods. The objective functions constraints should be defined to guarantee that the proposed renovation scenario's TEC, LCC, and LCA do not exceed certain limits, as shown in Equation 3.2.

$$\text{TEC}_r < \text{TEC}_e$$

$LCC_r < LCC^e$ Eq. 3.2

$LCA_r < LCA_e$

where TEC_e is Total Energy Consumption of existing situation; TEC_r is Total Energy Consumption of selected renovation scenario; LCC_e is Life-Cycle Cost of existing situation; LCC_r is Life-Cycle Cost of selected renovation scenario; LCA_e is Life-Cycle Assessment of existing situation; LCA_r is Life-Cycle Assessment of selected renovation scenario.

The SBMO generates near-optimal scenarios for a particular strategy as shown in Figure 3-2. Among the near-optimal points, the ones that belong to two adjacent strategies can be then selected as the best scenarios. These points are located at the boundary of the two strategies, which are shown as white circles in Figure 3-2. Consequently, at this phase, the model provides a detailed action report that includes selected methods, TEC, LCC and LCA for selected scenarios.

The final step is cross-checking of the results. Once the SBMO is implemented and well tuned, validation of results is done to verify the accuracy of the SBMO model. The results of the environmental analysis tool and the SBMO model are compared. The LCA module has been developed to import the results of the SBMO model into ATHENA LCA tool for calculating the Operational Energy (OE) consumption, Embodied Energy (EE) of building components, construction, and demolition, to develop a comprehensive understanding of the environmental impacts of a building.

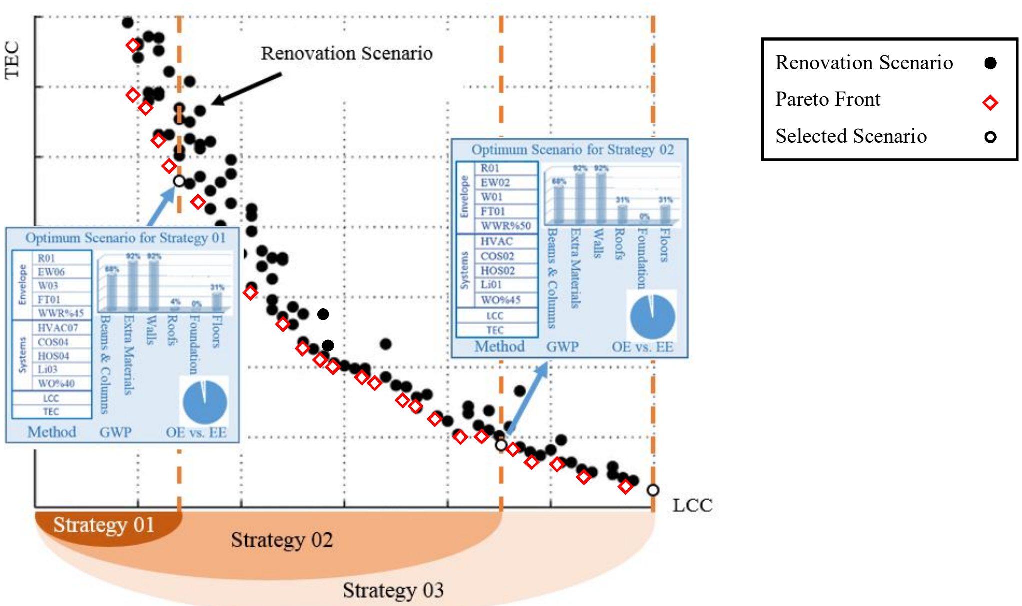


Figure 3-2. Schematic definition of the renovation strategies, scenarios, and methods.

3.4 Data Processing (Part 3)

This part has three main phases including data preprocessing, dataset preparation, and data normalization. This part is done for each MLM separately, to generate different datasets that are tailored for their specific needs.

The initial search space contains a huge number of different renovation scenarios (by the billions), which include many related factors. A small number of possible scenarios (about 5000 different renovation scenarios, including Pareto fronts) are generated from the SBMO model. However, calculating TEC, LCC, and environmental impacts for these generated scenarios is a time-consuming task for simulation tools. It is worth mentioning that training a surrogate model using inaccurate data can produce misleading results.

As explained in Section 2.10, the preprocessing of the input layer elements is vital, which is sometimes ignored in MLMs developments, or is considered as a transition phase. The initial datasets are collated from the previous phase, and noisy or repeated scenarios are identified with significant variations in the TEC, LCC, or LCA. These noisy or repeated scenarios should be removed from the final dataset through data transformation and integration. The preprocessing phase has many advantages, such as eliminating *noise*, minimizing the biased data, and creating a complete and clean dataset. In data preprocessing phase, the input and output parameters and the number of samples were defined for each MLM architecture. The number of the input parameters and layers are determined through a trial-and-error process.

For ANN models, the aim of the dataset preparation phase is to select a buffer of acceptable scenarios (called samples), in terms of TEC, LCC, and LCA using a sequential approach. Initially, the Pareto Front results are selected, labeled, and excluded from the main list. Consequently, new Pareto Front results are generated from non-optimal configurations and excluded from the main list, and added to the selected list of samples. This step is iteratively repeated until a sufficient number of solutions is selected and added to the list of samples. For ANNs the list of samples are the renovation scenarios provided by ten parameters including building renovation parameters (as described in Tables 5-2 and 5-3), which are considered as input of the ANNs, and two parameters representing TEC, LCC and LCA pairwise, which are considered as output of the ANNs.

For VAE models, the aim of the dataset preparation phase is to develop a comprehensive list of feasible scenarios. The SBMO results including all near-optimal and non-optimal renovation scenarios, are identified, labeled, and added to the main list of samples. Consequently, new results are generated using different configurations and added to the selected list of samples. These steps are iteratively repeated until a sufficient number of samples is selected. For VAEs, samples are the renovation scenarios provided by 22 parameters including 20 parameters representing building renovation parameters and two parameters representing TEC and LCC related to each specific scenario. The value of each parameter represents the properties of a particular building component (as described in the Appendices B1-7). A small dataset may not be able to capture a representative sample of the search space, while selecting too many samples will require a large computational cost to process (Amasyali and El-Gohary 2018).

When the datasets preparation is finished for each MLM and a sufficient number of samples have been added to their datasets, data normalization begins. The normalization process is conducted on both input data and target data. After normalizing the data, each feature must be related to a weight that indicates its importance. This important process minimizes the effects of magnitude and range of variations of the input variables throughout the training process and prevents the occurrence of the outweighing problem (Azari et al. 2016; Freeman and Skapura 1991). Data normalization unifies features, which can stop features with large ranges from dominating those with relatively smaller ranges.

3.5 Development of Machine Learning Models (Part 4)

The MLMs development has four main phases, which is defined for each model separately, i.e., load normalized data, MLMs development, training, testing, and validation, and finally deploying the models. Two different MLMs have been developed in this study, i.e., ANN and VAE. The most important phases in MLM development are selecting the network architecture, training, and validating the model's performance.

3.5.1 Surrogate ANN Models (Module 2)

The ANNs have been developed using the results of the previous parts. The surrogate ANNs have been developed for selecting near-optimal building energy renovation methods considering TEC, LCC and LCA pairwise. The proposed model will be used to predict TEC, LCC and LCA of the potential renovation scenarios of existing institutional buildings as shown in Figure 3-3. The ANNs will be used as surrogate models for emulating computationally expensive, real building optimization models. The effectiveness of the proposed method will be examined using Mean Squared Error (MSE).

3.5.2 Generative VAE Models (Module 3)

The second MLM in this study develops generative VAEs to generate different renovation scenarios for building envelope, HVAC, and lighting system considering TEC and LCC as shown in Figure 2-11. The developed semi-supervised VAEs learn the inner data structure by discovering unlabeled data and utilize labeled data for fine-tuning, better discrimination and accurate classification. Therefore, the use of unlabeled and labeled data for semi-supervised training can be considered as an advantage of this method over traditional ANN. The performance of the developed model is demonstrated using a simulated renovation dataset to prove its potential. The effectiveness of the proposed method is examined using two validation methods, i.e., MSE (internal validation) and validation of results using DesignBuilder as BEM (external validation).

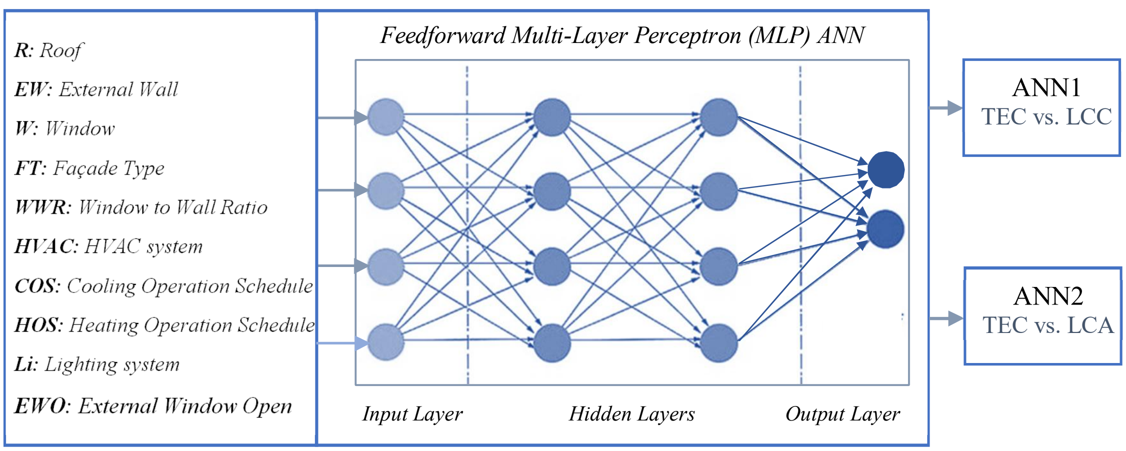


Figure 3-3. Artificial Neural Network architecture.

3.6 Summary

This chapter presented an overview of the proposed framework. This research consists of four main components that are necessary to realize the proposed methodology: (1) developing a framework for data collection and preparation to define the renovation strategies; (2) proposing SBMO model to define near-optimal renovation scenarios based on the available methods; (3) applying data processing methods to reduce the effects of magnitude and range of variations of the input variables throughout the MLMs training process and remove the inconsistencies of different attributes; and (4) developing two surrogate MLMs by learning from the generated SBMO datasets and reducing the computing time while achieving acceptable accuracy.

Initially SBMO model has been developed for renovation of existing buildings envelope, HVAC, and lighting considering TEC, LCC, and LCA. SBMO model uses NSGA-II optimization and simulation tools simultaneously to create feasible renovation scenarios including Pareto Front results (as explained in Chapter 4). Consequently, two MLMs have been developed using the results of SBMO. ANNs have been used to predict TEC vs. LCC (ANN1) and TEC vs. LCA (ANN2) for different building energy renovation scenarios (as explained in Chapter 5). VAEs have been used to generate feasible renovation scenarios considering TEC and LCC (VAE1), TEC (VAE2), and LCC (VAE3) (as explained in Chapter 6). The proposed MLMs will be used to: (1) predict the energy performance, LCC and LCA of the potential renovation scenarios for existing institutional buildings using surrogate ANNs, and (2) develop a DNN to generate different renovation scenarios for building envelope, HVAC, and lighting system considering TEC and LCC. The main advantage of these models is to improve the computing time while achieving acceptable accuracy.

CHAPTER 4. SIMULATION-BASED MULTI-OBJECTIVE BUILDING RENOVATION OPTIMIZATION CONSIDERING TEC, LCC, AND LCA

4.1 Introduction

As mentioned in Section 2.1, it is necessary to reduce the energy consumption of buildings by improving the design of new buildings or renovating existing buildings. Heat losses or gains through building envelopes affect the energy used and the indoor conditions. Renovating building envelopes and energy consuming systems to lessen energy losses is usually expensive and has a long payback period. Despite the significant contribution of research on optimizing energy consumption, there is limited research focusing on the renovation of existing buildings to minimize their LCC and environmental impact using LCA. This chapter aims to find the optimal scenario for the renovation of buildings considering TEC and LCA while providing an efficient method to deal with the limited renovation budget considering LCC. Different scenarios can be compared in a building renovation strategy to improve energy efficiency. Each scenario considers several methods including the improvement of the building envelopes, HVAC and lighting systems. However, some of these scenarios could be inconsistent and should be eliminated. Another consideration in this research is the appropriate coupling of renovation scenarios. For example, the HVAC system must be redesigned when renovating the building envelope to account for the reduced energy demand and to avoid undesirable side effects. An efficient GA method, coupled with a simulation tool, is used for simultaneously minimizing the energy consumption, LCC, and environmental impact of a building. A case study is developed to demonstrate the feasibility of the proposed method.

Chapter 4 is organized into sections that include the proposed methodology (Section 4.2), implementation and case study (Section 4.3), and finally, summary and conclusions (Section 4.4).

4.2 Proposed Methodology

The model is developed in four main phases as shown in Figure 4-1: (1) model input data collection; (2) databases development; (3) definition of the renovation strategies; and (4) simulation-based multi-objective optimization. The first phase aims to define the model input data collection methods. Consequently, the common methods that shape each scenario should be investigated and added to the available databases. Having these databases related to the BIM tool helps the designer to select sustainable renovation strategies for buildings in the BIM environment easily and efficiently. The databases are used to store different data for three main categories, which are building envelope, building HVAC and lighting systems, and economic and environmental data. These steps are presented in the first and second phases of Figure 4-1. Subsequently, the renovation team defines an energy performance goal, which is used for developing the building renovation strategies (Phase 3). It is worthwhile to mention that each strategy consists of different scenarios for renovation considering different building methods. The major task of Phase 4 is to produce near-optimal solutions considering energy performance, LCC and, LCA concurrently. The SBMO model is implemented to calculate the Pareto front. Then, the environmental analysis tool is implemented to validate the results of the LCA optimization. Finally, the results of the Pareto front form the content for the recommendation and results report. The development procedure is explained in detail through the following four phases.

4.2.1 Model Input Data Collection (Phase 1)

Phase 1 has two steps: (1) provide the model input data, and (2) develop BIM model. This model will be used to save input data related to building components from the project Material Take-Off (MTO) table and other sources of data.

To calculate environmental impacts of the components of the building, energy consumption needs to be measured or calculated. In existing buildings, energy bills can be considered as a reliable reference to show the amount of the energy consumption. Energy audits or commissioning are also excellent resources for this purpose. The TEC of building equipment is calculated based on the characteristics of the equipment and its operational schedule. Furthermore, other related data about the building characteristics should be gathered to create a comprehensive understanding of the ES. These data are used to assess the current status of the building and to create a baseline model for calibration and comparison of results. A sample of the input data that summarizes the building features is shown in Table 4-4, which will be explained in the case study.

The simulation software, which is linked to the model, simulates the energy consumption of each building equipment in detail. Data from energy bills and other reliable databases are used to validate the results. Building characteristics are imported into the energy model from the BIM Tool. This model contains thermophysical properties of the building envelope, data from the HVAC system and lighting, and other necessary information about the building.

Module 1

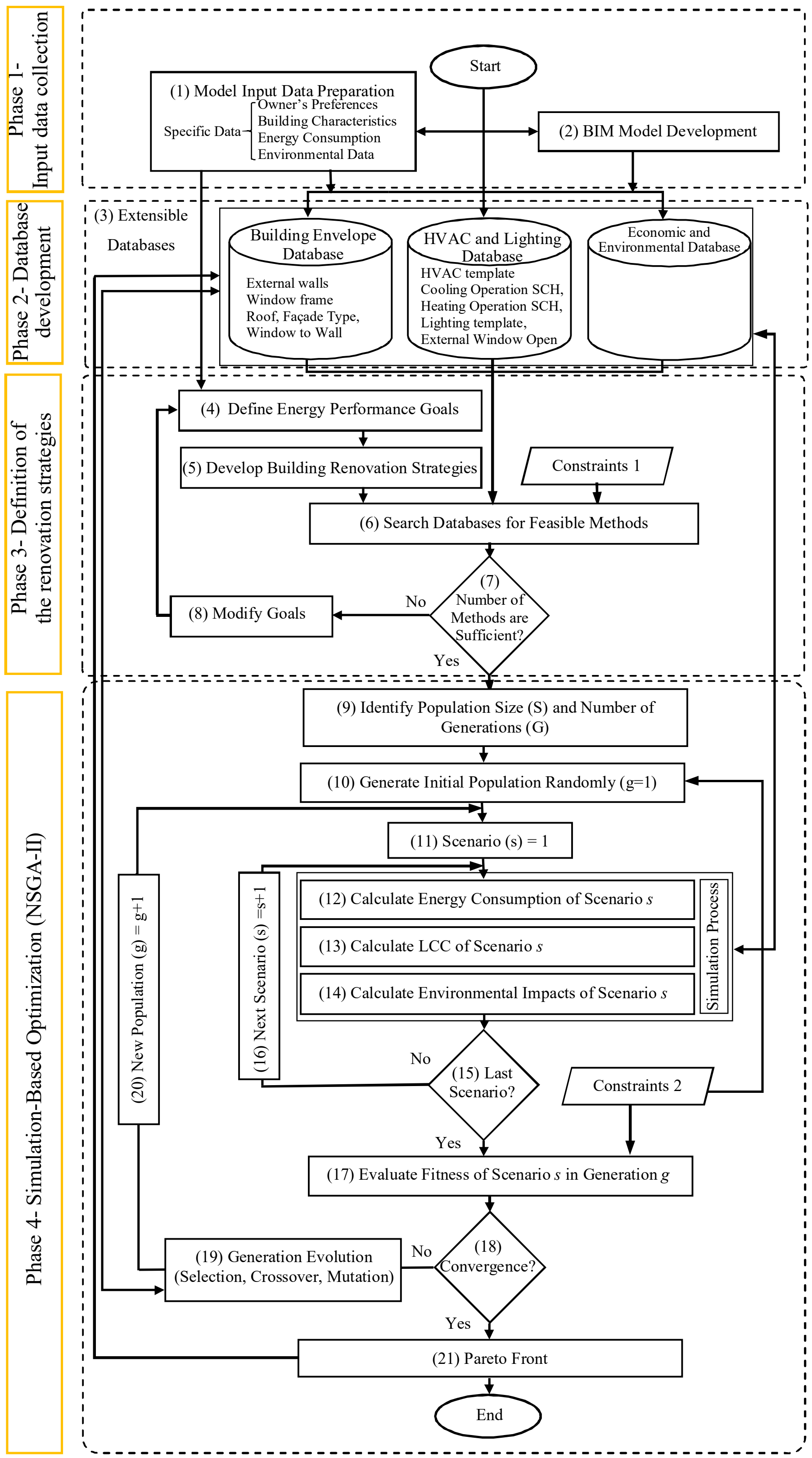


Figure 4-1. Model development phases.

Data related to the LCC and LCA of building materials and components are also added to the model from available generic databases. Figure 4-2 shows the building components considered in this study (green boxes).

The primary role of the BIM tool is to visualize the model results as well as the initial situation of the building. The BIM model of the building under consideration for renovation should be enriched with associated data for components commonly used in the building. Furthermore, the BIM tool will be used to provide the platform and to integrate the databases with the model at different steps.

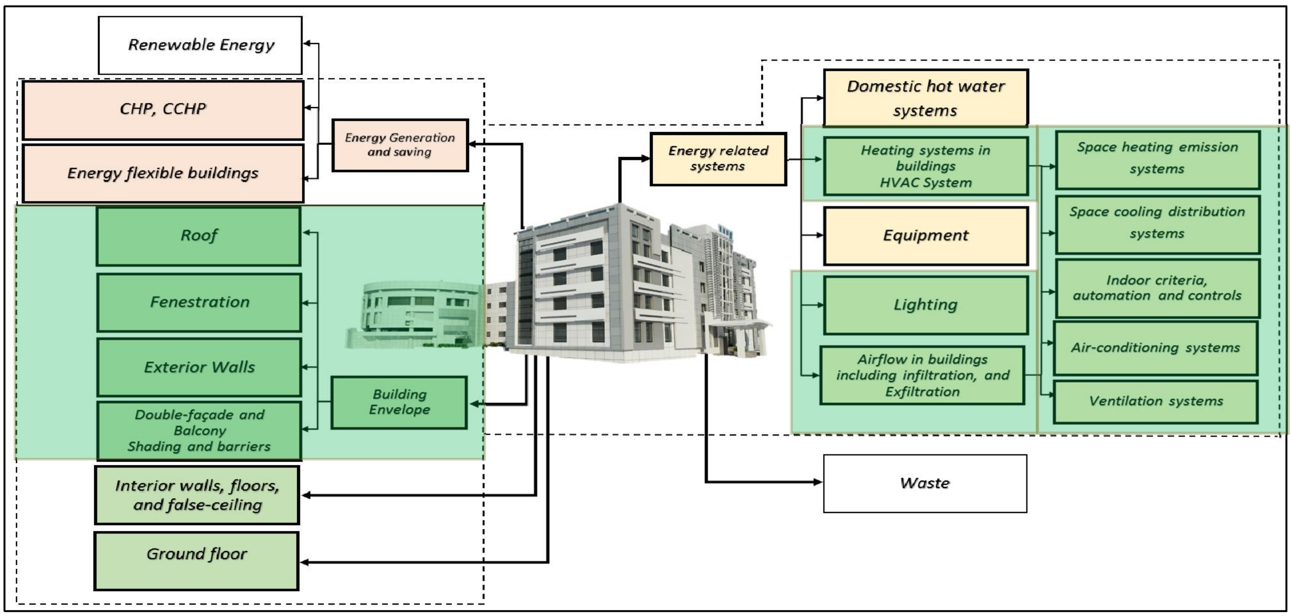


Figure 4-2. Building components considered in the research (Green boxes).

4.2.2 Database Development and Integration (Phase 2)

Phase 2 has only step (3), which is developing the extensible databases, including building components for the renovation project. The model's relational databases are developed to combine and relate different building components, renovation techniques, and other useful data. Each combination of the methods creates a renovation scenario. There are several critical factors, which guarantee a consistent information system. These factors are integration between databases, programming languages, and applicable tools (Loucopoulos et al., 1992). The required information is linked to the predefined library of the BIM tool. Each method contains a variety of data, such as the materials used, providers' data, allocated ID, cost, energy and environmental-related data. The economic and environmental database has different references, such as USGBC (USGBC, 2016), Canadian Green Building Council (CaGBC) websites (CaGBC, 2016), LCA tools inventory databases (e.g., ATHENA (Bowick et al., 2014), SimaPro (Goedkoop et al., 2016), and DesignBuilder (DesignBuilder, 2016)), IFC Revit database, literature, and providers' web pages.

4.2.3 Define Renovation Strategies (Phase 3)

A detailed explanation of how to define renovation strategies is not the main goal of this study. However, reviewing its theoretical concepts provides us with a general understanding of how strategies are categorized. This is important because this study delves further into how to combine methods and create renovation scenarios using SBMO. Needless to say, this phase plays a major role in SBMO's success. In this phase, the most important tasks are to define the scope of the renovation project and allocate the appropriate methods for each strategy.

To define the general renovation strategies, this phase concentrates on developing a model to combine all data gathered from previous steps and integrate them to find, in general, which kind of renovation is applicable for the project considering the renovation budget limitations, owner's preferences, and certificate specifications (Constraints 1). This phase has five steps: (4) define energy performance goals. (5) Develop building renovation strategies. In the first step, all collected data are evaluated quantitatively or qualitatively, and then the strategy of the renovation is finalized through group work between the decision-maker, facility management, and the owners who have agreed on the goal. It is essential to consider the owner's preferences early in the renovation design and plan interdisciplinary collaboration between all participants in the project (Galiotto et al. 2015). In this study, the decision-making process is considered as a collaboration between the decision-makers and the facility management, who is the representative of the owner. The outcomes of these steps clarify the general scope of the renovation, whether it is a major renovation or a minor repair. Table 4-1 provides an example of the classification of renovation strategies. (6) Search the databases to find feasible methods to create renovation tasks and methods tables for building envelope and systems (e.g., Tables 4-2 and 4-3). Each scenario consists of different methods of the building envelope and building energy systems. The goal is to allocate appropriate methods to predefined renovation strategies. The classification of renovation methods depends on different factors. (7) Assessing that there are enough renovation methods available for each strategy, this step is iteratively repeated until all feasible methods are allocated. (8) If the goals have not been achieved the goals should be modified.

To achieve the goal of the renovation project, three renovation strategies are developed. These strategies start from minor and conclude with a major renovation. The concept of each strategy is accumulative as explained in Section 2.4.1.

Minor renovation strategy (S01)

This strategy is proposed to address only minor repair maintenance in case of limited renovation budget or if the building is a heritage building. *Add-in* and *wrap-it* methods are proposed for this strategy. The goal of this strategy is to repair or upgrade defective parts from the inside. Renovation in this stage usually does not add new elements. Adjustments in control strategies for HVAC and lighting are also considered in this strategy. Furthermore, full integration between mechanical and natural ventilation must be considered.

Medium renovation strategy (S02)

This strategy has more intervention than S01. In this strategy, minor replacements for defective elements and old parts are applicable. Add-in/ Wrap-it/ Replace methods can be applied in this strategy. Defective façade elements or outdated parts are upgraded from the inside, repaired, removed and/or replaced with new ones. The building can also be wrapped in a second layer. The decision-maker has more flexibility to replace elements with new ones. Needless to say, this strategy is more expensive, and the results are more promising in terms of energy efficiency. Moreover, replacing the HVAC and lighting equipment with minor effect on building characteristics could be suggested considering the cost of renovation. Monitoring systems for HVAC and lighting are proposed in this strategy to monitor the situation of the building after renovation. Additionally, building automation and control could be proposed in this strategy.

Major renovation strategy (S03)

This strategy is the most comprehensive. With this strategy old façade elements or outdated elements are upgraded. The renovation can be extended to the load-bearing structure. New structures can be added on to the existing building, cover parts or entire internal and external courtyards and atria; the function of some parts may be changed. A major renovation of HVAC and lighting is applicable in this strategy.

4.2.4 Define Renovation Tasks and Methods

As noted earlier, the renovation methods in this study relate to the building envelope, HVAC system or lighting system, and are assigned to each strategy. Different methods related to the following variables have been considered in this part of the research, i.e., R, *EW*, *FT*, *GT*, *W*, *WWR* (in the range of 30-70%), *HVAC*, *COS, HOS*, and *Li*. Furthermore, three continuous variables are defined for determining ventilation methods: The *EWO* in the range of 0-70%, Mechanical Ventilation Rate (*MVR*) with 10 options, and Airtightness (*A*) with 4 options for each zone, as described in Table 4-1.

This research proposes the different choices and stresses their role, application, and limitations as building envelope methods. Also, some typical and innovative envelope-related renovation methods including the type of window, glazing materials, roof and exterior wall components are considered in this study (e.g., PCM, photochromic glazing, and Building Integrated Photo Voltaic (BIPV)) as shown in Table 4-2. Furthermore, many types of HVAC systems can be used in buildings.

ASHRAE Design Guide recommends several systems, each of which can save up to 50% of energy consumption for office buildings (ASHRAE Design Guide, 2014). Based on the literature review and expert opinions, several methods and systems are identified as the most commonly used in the energy renovation of buildings: Electric radiators, air to water heat pumps, split with no fresh air, hot water boilers, and exhaust heat recovery systems are commonly selected by the decision-makers. Building systems considered are in two ways: first, renovation of HVAC systems and secondly, operational setting-related methods, such as heating and cooling operation schedules. Percentage *EWO* also included, measuring ventilation rate. Additionally, Mechanical Ventilation Rate (*MVR*) and airtightness (*A*) parameters are proposed for minor renovation strategies.

Finally, different lighting methods are considered in the model. Furthermore, different lighting operation schedules address the control strategies (Table 4-3). Renovation methods are categorized in Table 4-1, and the particular renovation tasks alongside the renovation methods for buildings envelope and HVAC/lighting systems are explained in Tables 4-2 and 4-3, respectively. Table 4-2 and 4-3 show different renovation tasks and associated methods that are classified according to the appropriate strategy from minor to major. Due to the cumulative concept of renovation strategies, for a major renovation, the proposed model considers all methods that are considered to be minor to major. For example, a medium renovation strategy for fenestration in Table 4-2 contains all tasks from S01 and S02 strategies and comprises 13 methods: *G01, G02, G05, G06, G07, FT01, FT02, FT05, FT06, Li01, W05, WWR*, and *EWO*.

The role of natural daylight is not the main focus of this study; however, as described in Table 4-2, several variables of the renovation methods of the building envelope (i.e., *W, FT*, and *WWR*) have indirect correlation with natural daylight within the optimization. In addition, three operation schedules (*Li01*) are considered for lighting as renovation methods (Table 4-1). Furthermore, different renovation methods are considered for glazing, which have effects on the daylighting (i.e., *G05, G06*, and *G07*).

Table 4-1. Renovation methods.

ID	Renovation methods (# of Options)	ID	Renovation methods (# of Options)
R	**Roof Types (16)**	HVAC	**HVAC (29)**
R01	Insulation (2)	HVAC01	Air to Water Heat Pump (ASHP) (2)
R02	Flat roof - 19 mm asphalt (3)	HVAC02	Fan Coil Units (4-Pipe) (4)
R03	Combined semi-exposed Uninsulated (3)	HVAC03	Packaged Thermal Air Conditioner, PTAC (2)
R04	Combined flat roof (3)	HVAC04	Packaged Thermal Heat Pump, PTHP(1)
R05	Combined semi-exposed (3)	HVAC05	Radiator heating (3)
R06	Photovoltaic (1)	HVAC06	Split (2)
R07	Innovative roofs (1)	HVAC07	Radiators Electric, Nat. Vent. (1)
EW	**External wall (22)**		
EW01	Brick air, concrete block (2)	HVAC08	VAV, Air-cooled Chiller (6)
EW02	Brick cavity with insulation (3)	HVAC09	VAV, Dual Duct (2)
EW03	Cavity wall (E&W) Part L (2)	HVAC10	VAV, Water-cooled Chiller (2)
EW04	Lightweight curtain wall (2)		
EW05	Semi-exposed wall (6)	HVAC20	Ventilation system with heat recovery (HR) (1)
EW06	Wall- Energy code standard (3)	RMV	Repair Mechanical Ventilation (2)
EW07	Wall- State-of-the-art (1)		
EW08	Advanced Insulation (2)		
EW09	Innovative walls (1)	HOS, COS	**Heating/ Cooling Operation Schedule (7)**
FT	**Façade types (24)**	H/C OS1	ON 24/7 (1)
FT01	100% fitted glazing (1)	H/C OS2	Max mode (3)
FT02	40% Vertical Glazing (1)	H/C OS3	Two season schedules (1)
FT03	Fixed windows (5)	H/C OS4	7:00 - 23:00 Mon – Fri (1)
FT04	Curtain wall, 85% glazed (1)	H/C OS5	6:00 - 18:00 Mon – Fri (1)
FT05	Horizontal strip, % glazed (6)		
FT06	Preferred height 1.5m (10)	Li	**Lighting (11)**
G	**Glazing Types (103)**	Li01	Operation Schedule (3)
G01	Single glazing (25)	Li02	Canadian energy code (1)
G02	Double glazing (30)	Li03	LED (2)
G03	Triple glazing (25)	Li04	Fluorescent (3)
G04	BIPV (1)	Li05	High-pressure Mercury (1)
G05	Smart glazing systems (PCM) (4)	Li06	High-pressure sodium (1)
G06	Fixed Shading (15)		
G07	Shading adjustable (3)		**Ventilation/ Area control**
W	**Window frame types (6)**	EWO%	External window open (0-70%)
W01	Aluminum window frame (2)	MVR	Mechanical Ventilation Rate (0-10, Increment: 0.2)
W02	Wooden window frame (2)	A	Airtightness (0-4, Increment: 1)
W03	UPVC window frame (1)	WWR%	Window to Wall ratio (30-70%)
W04	BIPV (1)		

ASHP:	Air to Water Heat Pump	Max:	Maximum
BIPV:	Building Integrated Photo Voltaic	Nat. Vent.:	Natural Ventilation
DOAS:	Dedicated Outdoor Air System	PTAC:	Packaged Terminal Air Conditioner
FPID:	Fan-Powered Induction Unit	PTHP:	Packaged Thermal Heat Pump
HR:	Heat Recovery	UPVC:	Unplasticized polyvinyl chloride
LED:	Light-Emitting Diode	VAV:	Variable air volume

Table 4-2. Renovation tasks and methods for building envelope.

		Renovation tasks	Renovation methods	Type of Intervention
Roof	S01	Add insulation, unheated roof	**R01**- Insulation between rafters, lining or interior insulation	Add-in, Wrap-it
		Insulation entirely above deck, heated attic roof	**R01**- Insulation on attic floor or on roof	Add-in
	S02	Additional insulation on roof slab, waterproofing Internal insulation	**R01**- Insulation entirely above deck, waterproofing	Add-in
	S03	Increase roof surface reflectance and emittance	**R02**- Flat roof - 19 mm asphalt	Add-in
			R03- Combined semi-exposed roof	Add-in
			R04- Combined flat roof	Add-in
			R05- Combined semi-exposed roof	Add-in
		Photovoltaic	**R06**- Photovoltaic	Add-in, Add-on
		Additional floor	**R02**- Additional flat roof	Add-in, Add-on
		Green roof	**R07**- Green roof	Replace, Wrap-it
		Use innovative techniques	**R07**- Roof pond system	Replace, Cover-it
External wall	S01	Provide continuous air barrier	**A**- Airtightness (cavity insulation)	Add-in
		Increase thermal mass	**A**- Airtightness (internal insulation)	Add-in
		Cavity insulation	**EW01**- Brick air concrete block or (thermolite block insulation), **EW02**- Brick cavity with insulation, **EW03**- Cavity wall, **EW05**- semi-exposed wall	Add-in, Add-on Replace
	S02	Exterior Insulation and Finishing Systems (EIFS)	**EW06**- Wall- Energy code standard (LW Concrete block, LW super insulated, ICF), **EW07**- Wall- State-of-the-art (SIPS, Precast enclosure wall/ precast concrete sandwich panels, EIFS)	Wrap-it, Add-on, Replace
		Use thermal storage, Trombe walls, interior mass		Wrap-it
	S03	Use innovative techniques	**EW09**- BIPV wall	Wrap-it, Add-on
			EW08- Advanced Insulation (SHG, Dynamic insulation)	Wrap-it, Add-on
		Second Façade/ Single glazing	**EW04**- LW curtain wall, **FT04**- Curtain wall (Second Façade/ Single glazing, Ventilated façade)	Wrap-it, Add-on Replace
		Additional space/ Second façade integrated/ Ventilated façade	**EW09**- Second Façade/ Double glazing, **EW09**- Additional space/ Second façade integrated	Wrap-it, Add-on, Replace, Cover-it

Table 4-2. Renovation tasks and methods for building envelope (Cont.).

Fenestration	S01	Use glazing with low solar heat gain coefficient (SHGC)	**G01, G02**- Upgrade window (Single glazing, double glazing) **FT01**- 100% fitted glazing, **FT02**- 40% Vertical glazing	Add-in
		Maximize the benefits of daylighting	**Li01**- Operation Schedule	NA
		Operable windows with screens so that air conditioning and heating are not necessary during transition periods	**Li01**- Operation Schedule	NA
			FT05- Horizontal strip glazing	Add-on, Replace
			FT06- Preferred height 1.5m	Add-on, Replace
	S02	Use skylights and north-facing clerestories to daylight interior zones	**G05**- Smart glazing systems (Transparent insulation, PCM)	Add-on
		Shading fixed	**EWO**- Operation Schedule, **G06**- Fixed shading	Add-on, Cover-it
		Enlarged windows	**WWR**- Window to Wall (Improve the window frame)	Add-in, Replace
		For buildings with operable windows, renovate building layout for effective cross-ventilation	**WWR**- Window to Wall **G07**- Shading adjustable	Add-on Replace, Cover-it
		Shade building surfaces	**W05**- Secondary single glazing	Add-on, Cover-it
	S03	Shading adjustable	**G07**- Shading adjustable (Diffusing Shades, Electrochromic switchable, slatted blinds, PV/T hybrid solar window)	Add-in, Replace, Wrap-it
		Replace windows with double glazing	**G02**- Secondary double glazing **G02**- Replaced Windows with double glazing	Cover-it, Wrap-it Replace
		Replace windows triple glazing	**G03**- Replaced Window with triple glazing or Quadruple LoE Film, **G07**- Replace with Ventilated double-glazed window	Replace
		Minimize windows East and West, Maximize North and South	**FT01**- 100% fitted glazing, **FT02**- Vertical glazing, **FT03**- Fixed windows, **FT05**- Horizontal strip glazing, **FT06**- Preferred height	Add-on, Replace, Cover-it
		Upgrade windows, use innovative components	**W04, G04**- BIPV, **G05**- Smart glazing systems (Advanced glazing windows, PCM, Thermochromic, Electrochromic windows)	Replace, Wrap-it Add-in, Replace

EIFS:	Exterior Insulation and Finishing Systems	PV/T hybrid:	Photovoltaic thermal hybrid
ICF:	Insulated Concrete Forms	SHGC:	Solar Heat Gain Coefficient
LW:	Lightweight	SHG:	Solar Heat Gain Insulation
NA:	Not applicable	SIPS	Structural Insulated Panel Systems

Table 4-3. Control and renovation tasks and methods for HVAC and lighting systems.

<table>
<tr><th></th><th></th><th>Renovation tasks</th><th>Renovation methods</th></tr>
<tr><td rowspan="7">Ventilation</td><td rowspan="3">S01</td><td>Shut off outdoor air and night time out door air during unoccupied periods</td><td>EWO- Control strategy</td></tr>
<tr><td>Use time-of-day scheduling, temperature setback, and setup, pre-occupancy purge</td><td>H/COS- Operation Schedule</td></tr>
<tr><td>Seal all duct joints and seams (Ducts)</td><td>MVR- Mechanical ventilation</td></tr>
<tr><td rowspan="2">S02</td><td>Use demand-controlled ventilation</td><td>RMV- Repair Mechanical ventilation, Natural ventilation</td></tr>
<tr><td>Use air economizer</td><td>MVR- Mechanical ventilation</td></tr>
<tr><td rowspan="2">S03</td><td>Minimize duct and fitting losses (Ducts)</td><td>MVR- Mechanical ventilation</td></tr>
<tr><td>Change constant speed Vs. Variable speed fans</td><td>RMV- Repair Mechanical ventilation</td></tr>
<tr><td rowspan="6">HVAC</td><td rowspan="2">S01</td><td>Use control strategies that reduce energy use</td><td>H/COS- Operation Schedule</td></tr>
<tr><td>Insulate ductwork</td><td>RMV- Repair Mechanical ventilation</td></tr>
<tr><td rowspan="2">S02</td><td>Use high-efficiency fans
Test, adjust and balance the air distribution system
Use energy recovery to precondition outdoor air
Select efficient energy recovery equipment</td><td>HVAC20- Ventilation system with HR
HVAC02- Fan Coil Units (4-Pipe) with District Heating + Cooling
HVAC03- ASHP, Convectors, Nat Vent, PTAC Electric Heating, PTAC HW Heating,
HVAC04- PTHP</td></tr>
<tr><td>No ductwork outside the building envelope
Divide building into thermal zones</td><td>MVR- Mechanical ventilation</td></tr>
<tr><td rowspan="2">S03</td><td>Improve equipment efficiency

Enhance efficiency of HVAC systems</td><td>HVAC02- Fan Coil Units (4-Pipe), Air-cooled Chiller, DOAS, Water-Cooled Chiller, Water-side economizer,
HVAC03- ASHP, Convectors, Nat Vent, PTAC Electric Heating, PTAC HW Heating,
HVAC04- PTHP
HVAC05- Radiator heating, Boiler HW (Mech vent Supply + Extract, Mixed mode Nat Vent, Local comfort cooling,
HVAC07- Radiators Electric</td></tr>
<tr><td>Integrate systems, innovative and green systems</td><td>HVAC06- Split
HVAC01- ASHP Hybrid with Gas Boiler, Nat Vent.
HVAC08- VAV, Air-cooled Chiller, Fan-assisted Reheat (Parallel PIU), HR, Outdoor air reset, mixed mode, Outdoor air reset, Steam humidifier, Air-side HR),
HVAC09- VAV, Dual Duct,
HVAC10- VAV, Water-cooled Chiller</td></tr>
</table>

Table 4-3. Control and renovation tasks and methods for HVAC and lighting systems (Cont.).

		Renovation tasks	Renovation methods
Lighting	S01	Use automatic controls to turn off lighting when not in use	**Li01**- Operation Schedule
		Use separate controls for lighting in areas near windows	**Li02**- Canadian energy code
	S02	Use efficient electric lighting system	**Li03**- LED with linear control,
		Do not use incandescent lighting unless it will be infrequently used	**Li04**- Fluorescent, High-frequency control, LINEAR dimming daylighting control, T5, **Li04**- Fluorescent, High-frequency control, with On/Off dimming daylighting control, T8,
	S03	More efficient exterior lighting	**Li05**- High-pressure Mercury **Li06**- High-pressure sodium

ASHP:	Air to Water Heat Pump	VAV:	Variable air volume
DOAS:	Dedicated Outdoor Air System	LED:	Light-Emitting Diode
FPID:	Fan-Powered Induction Unit	Max:	Maximum
HR:	Heat Recovery	PTAC:	Packaged Terminal Air Conditioner
Nat Vent:	Natural Ventilation	PTHP:	Packaged Thermal Heat Pump

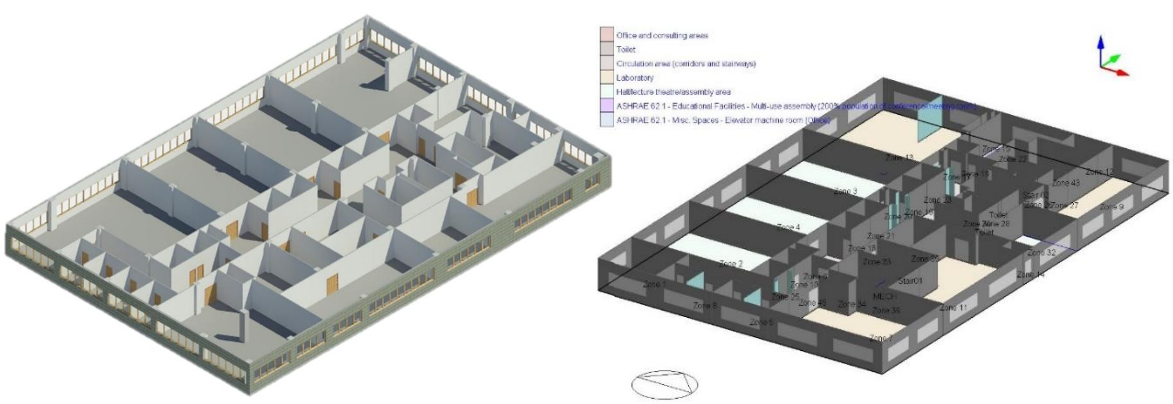
4.2.5 SBMO for Energy Performance, LCC, and LCA (Phase 4)

The BIM tool is used to export data to the SBMO. The SBMO uses the NSGA-II optimization method. As explained in Section 2.7.4, NSGA-II is one of the most efficient genetic algorithms for multi-objective optimization and is often used for multi-criteria optimization in different domains. NSGA-II is implemented by developing the initial population of size *N* in the first generation (Deb et al., 2002). Phase 4 has 14 steps: (9) the decision-maker sets the population size *(P)* and the number of generations (*G*). (10) Then, the initial population is generated randomly. (11) SBMO uses an energy simulation tool to calculate the energy consumption, LCC, and LCA for each potential solution representing a combination of renovation scenarios. The input parameters to the optimization engine are divided into two main categories: building envelope and building systems. The optimization engine computes the objective functions, which are (12) energy consumption, (13) LCC, and (14) environmental impact for each scenario based on the selected values of the methods in each simulation run. (15) The system repeats the calculations using the input scenarios of different buildings' envelopes, components, and materials. (16) The integration of the simulation model and an optimization algorithm is performed through a systematic approach, which allows exploitation of the best features of these tools simultaneously. (17) The next step is to evaluate the fitness values of the scenarios in the generation. Some constraints are also applied to specify the boundaries of TEC and LCC (Constraints 2). (18) Convergence condition is evaluated in this step. (19) Consequently, the selection, crossover, and mutation operations are applied on the entire population. (20) This procedure is iteratively repeated for all members in all generations until the convergence happens or a predefined number of generations is reached. (21) The results of the optimizations are shaped into the Pareto front, which will be used to inform decision-makers of different renovation scenarios, as well as the trade-off relationships among the various scenarios.

4.3 Implementation and Case Study

Many organizations (e.g., universities) own a large variety of aging buildings. A recent report revealed that about 40% of university buildings in Quebec are in poor condition (CBC News, 2016). In this case study, the effect of building envelope and systems renovation is investigated in one floor of a building at Concordia University (Montreal, Canada). It has an approximate gross floor area of 11,000 m^2 out of which 1,708 m^2 (a typical floor) has been studied. The input data were provided using the building 2D plans and sections, facility management documents and a site visit to identify and validate the data, such as the functions and services of the spaces in the floor, building envelope components and materials, types and sizes of HVAC and lighting systems, and the operational schedules. The building is considered a multipurpose university building. It is modeled in Revit 2017 to create the BIM model with Level of Detail 300, as shown in Figure 4-3(a). The developed model information is converted to the green building Extensible Markup Language (gbXML*)* schema to facilitate the transfer of building data stored in BIM to the energy analysis tool to interactively analyze its environmental impact and MTO table. The gbXML file is imported to DesignBuilder software (DesignBuilder, 2016) as shown in Figure 4-3(b). The zoning is used to define the function for each part to be able to apply the specific renovation scenarios for each zone (i.e., laboratory, office and consulting area). It is worthwhile to mention that the function of a zone has a significant impact on the selection of the renovation scenario. If, based on the renovation design, a new function is defined for a zone, many features of that zone should be modified. For instance, the window size for an office room should be changed if its function is changed to a storage room. The allocation of building activities is explained in Table 4-4.

Numerous types of software were used in this study, such as Autodesk Revit Architecture© (v.2017) and DesignBulder (V 5.02.). ATHENA (v. 5.2.0116) is used for the comparison of the results.



(a) BIM model (b) DesignBuilder model

Figure 4-3. Case study model.

4.3.1 BIM Model Implementation

The gbXML schema, which is an open schema, enables the transfer of detailed description of building data stored in BIM to energy simulation software (Kumar, 2008). This schema can use Green Building Studio web-based service to exchange data between some common BIM tools (e.g., ArchiCAD, Revit, and Architectural Desktop) and energy analysis software (e.g., DesignBuilder, HAP, and e-QUEST) (DOE-2, 2007). gbXML is developed based on the Extensible Markup Language (XML) format and has a simplified schema for energy analysis. However, preparing an analytical model and importing data via gbXML format is time consuming for complex projects. The gbXML file can carry building environmental data, but the gbXML does not recognize the relationships among captured data (Jalaei and Jrade, 2014).

To have an accurate energy analysis of the case study, its BIM model must be transformed into a BEM. First, all the spaces must be converted into *rooms*. *Rooms* designate thermal z*ones* in DesignBuilder. By definition, a thermal zone is a space bounded by its roof, walls, and floor, and is the initial unit for calculating heat loads. Bounding elements (i.e., roofs, walls, and floors) describe the extent of a *room*. After defining *rooms* for analyzing the building's energy, bounding elements are transformed to 2D surfaces demonstrating their actual geometry. It is vital to define the position of the adjacent rooms in the analytical model. After preparing the energy analytical model, the BIM tool can directly transfer the modified model of the building to DesignBuilder using the gbXML format. The last floor of the building was studied including 39 thermal zones in seven different categories (i.e., office and consulting area, laboratory, hall/lecture theater/assembly area, multi-use assembly (conference and meeting), washroom, circulation area, and mechanical room). Furthermore, several parameters are added or modified in the model to obtain more accurate results.

As noted in Section 2.7.5, the accuracy of the BIM model is important to guarantee achieving reliable results, so a number of changes have been made and some parts of the model are rebuilt using the capabilities of DesignBuilder.

4.3.2 Energy Analysis of the Existing Building

In order to find the near-optimal strategy for the renovation of the building, the mandatory data were added to the model. Table 4-4 shows a part of the input data, such as the building envelope materials, windows, operational schedule, allocation of building activities, building systems, temperature set points, and *DHW*, which are added to the energy simulation tool.

Table 4-4. Sample input data of the building characteristics.

Description	Characteristics
Roof Surfaces	Flat roof U-value = 0.25 W/m^{2}K.
Exterior Walls	Brick/ block exterior finishing
Windows	WWR: 30% clear 6 mm glass, double glazing in some parts, Frame: Steel and Aluminum
Airtightness	0.3 ACH constant rate, ON 24/7
Operation Schedule	7:00- 23:00 Mon-Fri
Space Allocation	Study spaces (classroom and atelier), office, mechanical and electrical room, restrooms, storage, and corridors.
Activity	Educational Facilities (multi-use), Occupancy density: 1.0764 (people/m^2), Winter clothing: 1.2 (clo), Summer clothing: 0.5 (clo)
HVAC System	Fan coil units (4-Pipe), Air-cooled chiller, Boilers and chillers: on 24/7, Air systems shut off: 11:00 -7:00 a.m.
Temperature Setting	22°C cooling, 28°C cooling setback, 20°C heating, and 15°C heating setback
Heating	Natural Gas, Heating system seasonal CoP: 0.85, maximum supply air temperature: 45 °C
Cooling	Electricity from grid, Cooling system seasonal CoP: 2.8-3.2, minimum supply air temperature: 12 °C
DHW	Electricity from grid, Dedicated hot water boiler, Delivery temperature: 65 °C, main supply temperature: 10 °C, CoP: 0.85, Consumption rate: 10-20 l/m^2-day

The energy consumption results for the ES are calculated. Table 4-5 shows the heating results based on the outside temperature for the city of Montreal, for all visible thermal zones. The controlled temperature is 20.09˚C, radiant temperature is 15.84˚C, operative temperature is 17.97˚C and the outside dry-bulb temperature is -23.20˚C. Zone sensible heating is 79.08 kW, and heat losses dominated by the mechanical ventilation loss are -19.34 kW. The heat balance data in Table 4-5 show the breakdown of the heat losses. Figure 4-4 shows the daily cooling results for the hottest summer design weather conditions in Montreal. The energy tool calculates half-hourly temperatures and heat flows from each zone. Additionally, the results demonstrate a comprehensive overview of the heat flows, systems load, relative humidity, and total fresh air comfort conditions in each zone. The total site energy consumption estimates of the building components using the simulation tool is about 651,485 kWh, which is equal to 381 kWh/m$^{2;}$ while the actual energy consumption, based on the energy bills, was measured to be 611,479 kWh for the years 2014-2015, which reflects a 6.1% difference in the values. Comparing the results of the calculation with the energy bills shows that the results of the energy model are accurate and within the acceptable level of discrepancy.

In fact, for the ES, the energy consumption per square meter is distributed according to the energy bill for the entire building (with an area of 11,511 m^2), but the simulation software calculates energy consumption for the case study only (1,708 m^2). In addition, there are some physical inconsistencies between the actual building and the simulated model (e.g., the exact location of the building and adjacent open spaces). Additionally, the detailed HVAC system, which is designed for the case study is slightly different from actual conditions (e.g., the conditioned floor area (CFA) and heat losses per square meter are different).

Table 4-5. Daily energy calculation results (Heating).

Temperature	Air Temperature (°C)	20.09
	Radiant Temperature (°C)	15.84
	Operative Temperature (°C)	17.97
	Outside Dry-Bulb Temperature (°C)	-23.20
Heat Balance	Glazing (kW)	-13.62
	Walls (kW)	-7.58
	Roofs (kW)	-19.65
	Floors (ext) (kW)	-18.88
	External Infiltration (kW)	-19.34
	Zone Sensible Heating (kW)	79.08

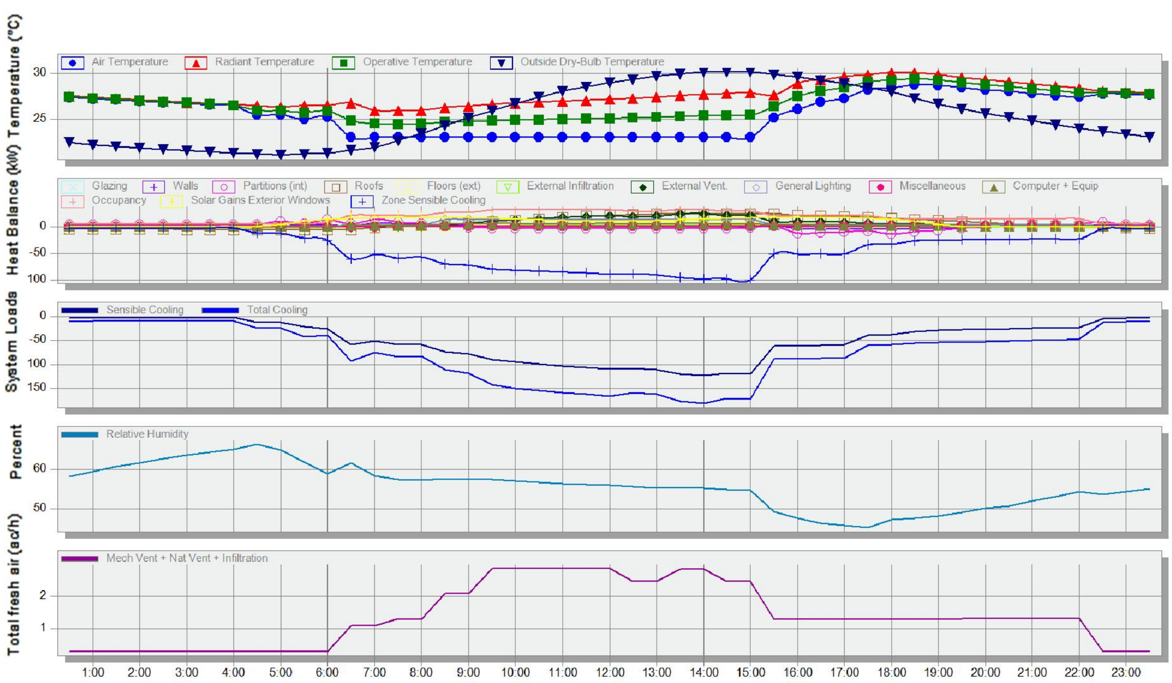


Figure 4-4. Energy calculation results (Cooling).

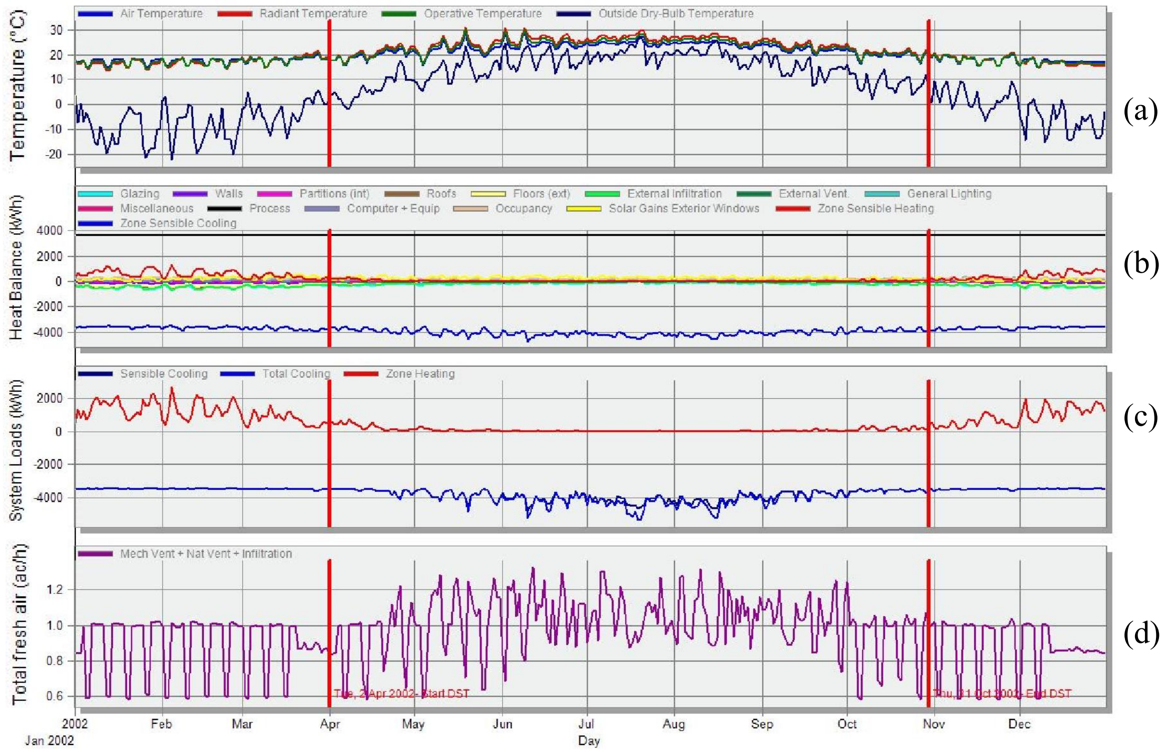


Figure 4-5. Annual energy simulation results (Temperature and Heat Gains).

Figure 4-5 shows the results of the annual Building Energy Performance Simulation (BEPS) of the existing building for temperature and heat gain. The higher number of time steps per hour, defined based on the preference of EnergyPlus, improves the accuracy. However, this increases the computational time. In this study, the defined time steps are ten minutes, because the model has a detailed HVAC simulation, which is consistent with EnergyPlus recommendations (DesignBuilder, 2016). The validation of the simulation models was checked using three procedures: (1) verify that the data are imported correctly into the model, ensuring that the changes at different parts have the anticipated effect; (2) summer and winter design weeks are simulated separately to generate hourly results. The analysis of the hourly results confirms the precise operation of the building and equipment, mechanical and natural ventilation, and fresh air; (3) annual simulation is generated based on monthly results and data distribution is controlled for the main zones. The results of the simulation show that the heating system is sufficiently sized to make the load at design conditions as the air temperature (blue line) never drops below the set point during the occupancy period and also never drops below the setback temperature of 15 ˚C (Figure 4-5(a)). The model also shows that the air temperature increased to around 26 ˚C in the afternoon over several weeks, so the building is probably overheated, therefore some changes to the existing design or controls are required (Figure 4-5(a)). The heat balance graph (Figure 4-5(b)) shows that the heating system has fluctuations especially in winter, which is confirmed by controlling the Zone Heating graph (red graph) in (Figure 4-5(c)). Therefore, the system needs modification or repair to have more efficient outcomes (Figure 4-5(c)). Investigating the fluctuation in the total fresh air graph (Figure 4-5(d)) explains that the variance in the infiltration rate seems significant and should be considered. Although the infiltration rate is set to a constant value and it is based on the reference temperature, changes in the variations in the indoor temperature should be studied.

As mentioned in Section 3.2, the data collected were then validated by other methods such as a semi-structured interview, site visit, and analyzing the plans and sections of the building. The result of the TEC for ES, which is calculated by the BEM, is validated through comparison with energy bills, and ATHENA LCA simulation tool as described in Tables 4-6 and 4-9. This difference is considered acceptable.

Table 4-6. Cross-checking of the results.

TEC of Existing Situation (ES) (kWh/m2)		Differences (%)
Energy Bills (Metering)	358	-
DesignBuilder (Energy Simulation Tool)	381	6.1
ATHENA (LCA Simulation Tool)	391	9.2

4.3.3 Development of the Renovation Strategies

Strategies are based on a set of renovation scenarios. As explained in Section 4.2.3, each scenario consists of several methods within the applicable strategy. The formation of renovation strategies depends on different factors, such as the size of the project, results from the energy simulation of the case, and the severity of the building's problems, and renovation budget. In addition, the constraints of renovation scenarios provide the boundaries of the acceptable range of each method. The methods are also influenced by several factors, such as the availability of components in the market, the applicability of the method, and other requirements (i.e., the energy certification requirements, mandatory building renovation codes, and technical standards and regulations). Another factor vital for defining a renovation strategy, is the owner's preferences. For example, in the renovation, if the shape and size of certain windows are specified by the owner, these items should be considered in the model (constraints 1). In this study, the requirements of facility management, which are mainly about the HVAC system and windows, are considered as the owner's preferences. Selected renovation methods are from a wide range of predefined methods, and are assigned to different zones that are located next to the exterior of the building. An example of the definition of renovation strategies is given in Table 4-7. Various options can be assigned to each strategy; however, a major renovation strategy usually involves additional medium and minor renovation methods. Based on the condition of the building and previously mentioned assessments, a major renovation strategy has been selected for this case study.

Table 4-7. Example of the definition of renovation strategies.

	Design Variable	Minor (S01)			Medium (S02)			Major (S03)		
		Opt.	Min	Max	Opt.	Min	Max	Opt.	Min	Max
Building Envelop	Roof (R)	-	-	-	10	-	-	17	-	-
	External Wall (EW)	5	-	-	15	-	-	33	-	-
	Window frame (W)	4	-	-	4	-	-	22	-	-
	Façade Type (FT)	15	-	-	22	-	-	75	-	-
	Glazing template (G)	75	-	-	15	-	-	-	-	-
	Window to Wall (WWR)	-	30%	70%	-	30%	70%	-	30%	70%
Building Systems	HVAC template- (HVAC)	-	-	-	15	-	-	25	-	-
	Mechanical Ventilation rate (MVR)	-	0%	10%	-	-	-	-	-	-
	Cooling Operation Schedule (COS)	10	-	-	7	-	-	7	-	-
	Heating Operation Schedule (HOS)	10	-	-	7	-	-	7	-	-
	Airtightness (A)	-	0%	4%	-	-	-	-	-	-
	Lighting template (Li)	5	-	-	7	-	-	11	-	-
	External Window Open (WO)	-	0%	70%	-	0%	70%	-	0%	70%

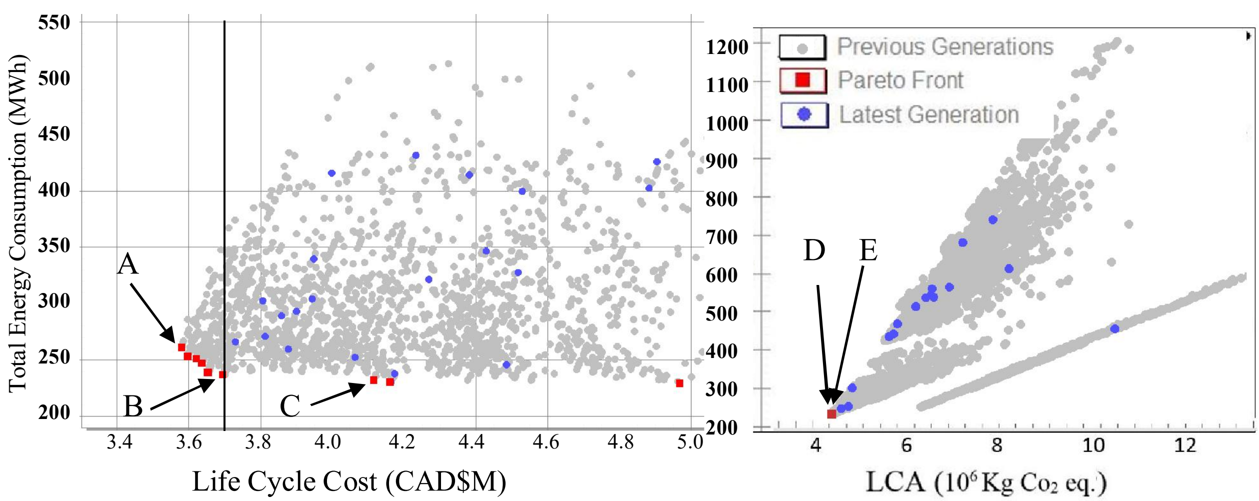
Opt.(option): The number of selected methods for each design variable.

4.3.4 SBMO for Energy Performance, LCC, and LCA

In this section, the results of the SBMO are presented. The calculations were carried out on a computer with Intel® Core™ i7-3770 CPU@ 3.40 GHz processor and 8.00 GB RAM. Each optimization, on average, took 170 hours. Using SBMO provides the capability of testing renovation scenarios within their specified ranges to find out which combination of methods results in the near-optimal solutions; therefore, the optimization usually requires running a significant number of simulations. The setting considered for the optimization algorithm in this research is 100 generations with a population size of 25 according to the DesignBuilder recommended setting (DesignBuilder, 2016). Due to the limitations of the software, multi-objective optimizations of TEC, LCC, and LCA are generated in pairs. In the first case, the TEC and LCC are considered as the two objective functions. In the second case, minimizing the TEC and the equivalent CO_2 emissions in the building's life cycle is studied.

The model identified the near-optimal renovation scenarios for the case study building for all the specified renovation scenarios, as shown in Figure 4-6 (a) and (b). The results include many combinations of the building's envelope, HVAC, and lighting renovation methods considering different TEC that range from 229 MWh to 513 MWh, various LCC that range from CAD$3.6M to CAD$5.3M and LCA CO_2 equivalent from 3.9×10^6 Kg CO_2 eq. to 20×10^6 Kg CO_2 eq for a period of 50 years.

Figure 4-6 (a) shows the generated near-optimal solution of TEC and LCC for a major renovation strategy as explained in Section 4.3.4. In this figure, the Pareto front includes 22 near-optimal solutions. As can be observed, a decrease in the TEC can only be achieved by increasing the LCC. For instance, scenario A in Figure 4-6(a) has lower LCC of CAD$3.58 M, and it provides a reduction in the TEC (390,370 kWh/year) while in scenario C reduction in the TEC is higher (421,143 kWh/year) with higher LCC that is CAD$4.16 M for the period of the study. Furthermore, scenario B, which is a moderate scenario offers more reduction in the TEC (414,695 kWh/year) with only CAD$115,000 increase in the LCC in comparison with scenario A. Therefore, scenario B is selected and analyzed.



(a) Total Energy Consumption vs. LCC (b) Total Energy Consumption vs. LCA

Figure 4-6. Two sets of optimizations results.

Figure 4-6 (b) depicts the Pareto front result of TEC and LCA for the major renovation strategy. It shows that a reduction in LCA can only be attained by decreasing the TEC. In this figure, two optimal scenarios that favor each objective function are revealed. However, the differences between these two scenarios are insignificant. Scenarios D and E have optimal environmental impacts (about 3.9×10^6Kg CO_2eq,) and low TEC (about 229,700 kWh). These two scenarios have very similar methods, the only differences are in EWO rates (34% vs. 8%) and the percentages of the glazed area in Façade types (10% vs. 20%).

The proposed results clarify the ability of the developed SBMO to create a wide range of near-optimal solutions that offer optimal trade-offs among the three optimization objectives. Therefore, decision-makers can explore results to find an optimal solution with an optimal balance among the objective functions while fulfilling predefined constraints. For instance, Figure 4-6(a) can be utilized to identify optimal solutions considering different TEC and LCC constraints. If the decision maker in this case study has an LCC constraint for CAD$3.7M to renovate the building for 50 years, it can be represented by a perpendicular line to the LCC axis, as shown in Figure 4-6(a). According to this specified constraint, Scenario B can be selected as the optimal solution that minimizes the LCC and TEC, simultaneously. Furthermore, the owner of the building can also be advised that an increase in the renovation budget from CAD$3.7M to CAD$5M does not have a significant effect on the reduction of TEC. The same investigation can be used to find out the least renovation scenario to achieve a specified environmental impact or required TEC. Figure 4-6(b) shows that the optimal solution for LCA is achieved only by reducing TEC to about 230,000 kWh/year. The action report that contains detailed information of all proposed building renovation methods for identified optimal scenarios A, B, C, D and E is described in Table 4-8. A closer observation of the generated optimal results for Scenarios A and B in Table 4-8 and comparing these results with the ES of the building (Table 4-4) reveal that in this renovation project; (1) *W, FT, WWR, HVAC* and *Li* should be modified, while only the insulation of the exterior walls should be improved and there is no need to change the roof. (2) TEC improvement of 24,325 kWh/year can be achieved (from scenarios A to B) by selecting different *EW* insulation, *FT, Li (*T5 to LED with linear control) and choosing different individual methods for *COS* and *HOS.* Comparison of scenarios A, B and D also shows that there are many similarities in proposed renovation methods such as *W, HVAC, Li,* and *WO.*

Scenarios D and E achieve the least LCA and TEC by recommending all possible methods that simultaneously cause the greatest reduction of negative environmental impacts and energy consumption simultaneously. The model selected LED light from the databases that consume the least amount of electricity to minimize the building electricity consumption and reduce the GHG emissions, as described in Table 4-8. The model also selects a special *HVAC* system (Split without fresh air) with similar methods for *COS* and *HOS*, as described in Table 4-8, which further reduces TEC in the building. Furthermore, the generated action report produced for scenario D recommends all applicable renovation methods for Scenario B, with some exceptions (i.e., *R, HVAC,* and *HOS* methods). Although they do not necessarily provide a similar TEC, differences are not significant.

Table 4-8. Detailed list of components implemented in the selected renovation scenarios.

(a)

	Method	TEC vs. LCC		
		Scenario A	Scenario B	Scenario C
Building Envelope	R	Project flat roof U-value = 0.25 W/m2K	Project flat roof U-value = 0.25 W/m2K	Combined semi-exposed Roof U-value = 0.25 W/m2K
	EW	Semi-exposed wall Typical reference LW (LW metallic Cladding 0.01 m+ XPS 0.09 m+ Gypsum Plastering 0.01 m)	Wall - State-of-the-art - MW (Brickwork Outer 0.11m+ XPS 0.12m+ Concrete 0.1m+ Gypsum Plastering 0.01 m)	Wall - State-of-the-art - MW (Brickwork Outer 0.11m+ XPS 0.12m+ Concrete (M) 0.1m+ Gypsum Plastering 0.01 m)
	W	Project BIPV Wall	Project BIPV Wall	Project BIPV Wall
	FT	Fixed windows - H:1m, W: 0.5	Preferred height 1.5m, 10% glazed	Fixed windows - H:1 m, W: 1 m
	WWR (%)	42	42	38
Building Systems	HVAC	Radiators Electric, Natural Ventilation	Radiators Electric, Natural Ventilation	Radiators Electric, Natural Ventilation
	COS	Max Outdoor temp for Nat Vent: Always 100	6:00 - 18:00 Mon – Fri	Mixed mode temperature control
	HOS	Max Outdoor temp for Nat Vent: Always 100	On 24/7	Max Indoor temp for Nat Vent: Always 100
	Li	T5 (16 mm diam) Fluorescent, triphosphor, high-frequency control	LED with linear control	LED with linear control
	EWO (%)	50	66	54
TEC (kWh)		261,115	236,790	230,342
LCC (CAD)		3,579,913	3,695,244	4,161,893

(b)

Method	TEC vs. LCA	
	Scenario D	Scenario E
R	Roof, Metal Building, R-19+10 (3.3+1.8), U-0.041 (0.232)	Roof, Metal Building, R-19+10 (3.3+1.8), U-0.041 (0.232)
EW	Wall - State-of-the-art - MW (Brickwork Outer 0.11m+ XPS 0.12m+ Concrete (M) 0.1m+ Gypsum Plastering 0.01 m)	Wall - State-of-the-art - MW (Brickwork Outer 0.11m+ XPS 0.12m+ Concrete (M) 0.1m+ Gypsum Plastering 0.01 m)
W	Project BIPV Wall	Project BIPV Wall
FT	Preferred height 1.5m, 10% glazed	Preferred height 1.5m, 20% glazed
WWR (%)	56	52
HVAC	Split no fresh air	Split no fresh air
COS	6:00 - 18:00 Mon – Fri	6:00 - 18:00 Mon – Fri
HOS	6:00 - 18:00 Mon – Fri	6:00 - 18:00 Mon – Fri
Li	LED with linear control	LED with linear control
EWO (%)	34	8
TEC (kWh)	229,694	229,777
LCA (Kg CO_2eq)	3,921,015	3,916,236

XPS: XPS Extruded Polystyrene- CO_2 Blowing
LW: Lightweight
MW: Medium weight

4.3.5 Evaluation of Environmental Impacts Using ATHENA and Cross-checking

Separate LCA was conducted to analyze the Pareto front results of the SBMO model. The analysis was conducted by inputting the results into the ATHENA via an Excel file. In this section, the OE consumption and EE of building components, construction, and demolition of Scenario B and ES are computed in ATHENA and compared with the results of DesignBuilder. There is a difference between these tools, due to differences in methods, databases, and reporting formats. SBMO model uses DesignBuilder to calculate LCA based on bulk carbon data obtained from the Bath ICE and other data sources. The embodied carbon related to several building services such as HVAC and lighting is not considered in the final results. Furthermore, DesignBuilder reports embodied carbon and equivalent carbon separately; the latter considers the effects of other greenhouse gases as equivalent carbon. Furthermore, DesignBuilder calculates only operational energy (DesignBuilder, 2016). On the other hand, ATHENA calculates embodied and operational energy (Athena Impact Estimator, 2017). It should be noted that both DesignBuilder and ATHENA do not capture all aspects of renovation projects. For example, although the comparison of the ES and the renovation scenario with respect to OE, EE, and LCA is possible, it still has some limitations. For instance, the impact of the components that have been removed in the renovation process is not included in the calculation. The result of the LCA comparison between ATHENA and DesignBuilder is given in Tables 4-9 and 4-10, and Figures 4-7 and 4-8. Table 4-9 compares the TEC and GWP for Scenario B and ES. Figure 4-7(a) compares the total primary energy and fossil fuel for Scenario B. As illustrated in Figure 4-7(b and c), it is obvious that in Scenario B the EE consumption with a total of 719,418 kWh is higher than OE consumption (257,995 kWh) and that the embodied GWP (E-GWP), with a total of 162,233 kg CO_2 eq, is higher than operating GWP (O-GWP), with a total of 40,151 kg CO_2 eq for one year. Figure 4-8 shows a comparison between ATHENA and DesignBuilder for ES.

A careful comparison of ATHENA and DesignBuilder results shows that the OE consumption is valid with a 2.7% difference in the values for ES, while in Scenario B, OE difference is higher (8.9%) for ATHENA because this scenario selects more efficient HVAC method, simplification of the HVAC in ATHENA, and differences in calculation methods. EE comparison is not possible because DesignBuilder only calculates OE. As shown in ATHENA part of Table 4-9, the 669,160 kWh of the OE consumed in the ES that has fallen to 257,994 kWh for Scenario B (Figure 4-7(b)), mainly due to the new HVAC, EW, W, COS, HOS and lighting methods. The EE for ES is 722,083 kWh and it decreased to 719,419 kWh for Scenario B (Table 4-9).

Table 4-9 compares the ATHENA and DesignBuilder results for operational and embodied GWP for ES and Scenario B. Differences between equivalent CO_2 amount from DesignBuilder and E-GWP amount from ATHENA, which are comparable concepts, are negligible in both ES (2.3% higher for ATHENA) and Scenario B (4.2% higher for DesignBuilder). However, operational GWP comparison is not possible due to the limitations of DesignBuilder. Comparison between E-GWP for ES and Scenario B for ATHENA (Table 4-9) shows a slight decrease in Scenario B. A significant reduction in O-GWP from ES (114,456 kg CO_2 eq per year) to Scenario B (40,150 kg CO_2 eq per year) can be observed. There are two reasons for this: First, utilizing different renovation methods. Second, the majority of the components and materials used in Scenario B are in direct contact with the outdoor environment. It is worthy to mention that ATHENA library supports only a limited number of green materials and components that can be considered as a constraint of the software.

For detail LCA using ATHENA, it should be noted that this project involves the renovation of a building envelope and systems, so the foundation category has no effect on the results. As shown in Figure 4-7(a), project extra materials, walls, beams and columns consume primary energy more than other assembly groups (504,989 kWh). Roof and floor use are 214,431 kWh of total primary energy (per year). On the other hand, when it comes to GWP, beams and columns creates the highest amount of GWP, averaging about 66,101 (Kg CO_2 eq), followed by the walls, with 45,882 (Kg CO_2 eq) (Table 4-10 and Figure 4-8(a)). Figure 4-7(c) compares the operational and embodied GWP for selected Scenario (B) in ATHENA. 40,150 kg CO_2 eq (per year) of the GWP in this building is for operating (O-GWP) while 162,233 kg CO_2 eq (per year) is for embodied (E-GWP) (Table 4-10). In the ultimate interpretation among the selected components, beams and columns and walls have the most effect on the environment in comparison with other assembly groups.

Table 4-9. Environmental impact sample report of the ES and selected scenario.

		DesignBuilder		ATHENA		Differences
TEC kWh	Existing situation	OE	651,485	OE	669,160	2.7%
		EE	NA	EE	722,083	NA
	Scenario B	OE	236,790	OE	257,994	8.9% (HVAC)
		EE	NA	EE	719,419	NA
GWP kg CO_2 eq	Existing situation	O-GWP	NA	O-GWP	114,456	NA
		Equivalent CO_2	164,428	E-GWP	168,302	2.3%
		Embodied Carbon	101,281	NA	NA	NA
	Scenario B	O-GWP	NA	O-GWP	40,150	NA
		Equivalent CO_2	169,110	E-GWP	162,233	4.2%
		Embodied Carbon	102,504	NA	NA	NA

Table 4-10. Comparison of the results of ATHENA.

Environmental impact factor	**Global Warming Potential** kg CO_2 eq		**Smog Potential** kg O_3 eq	
Assembly Group	ES	Scenario B	ES	Scenario B
Beams and Columns	66,101	66,101	7,537	7,537
Floors	42,487	42,487	3,975	3,975
Project Extra Materials	-12,463	-16,787	5,215	4,646
Roofs	24,550	24,550	2,247	2,211
Walls	47,628	45,882	5,352	3,880
Total	168,303	162,233	24,325	22,249

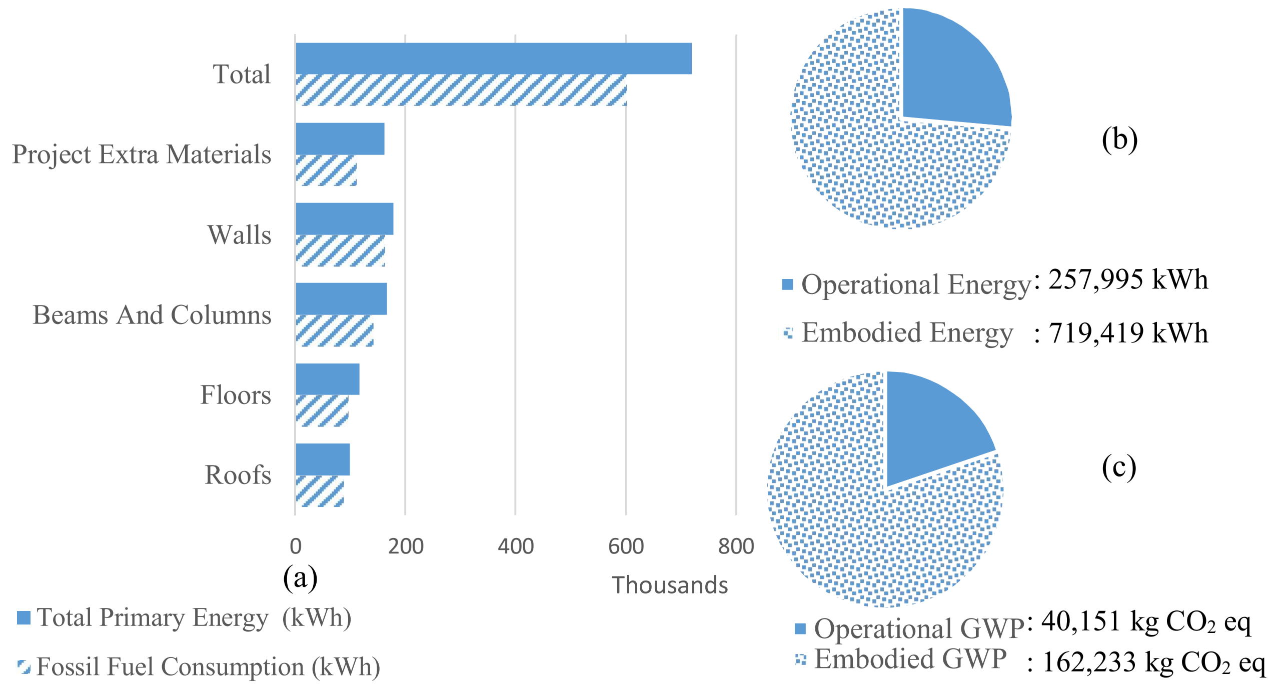


Figure 4-7. Total Primary Energy and Fossil Fuel Consumption, (b) Operational vs. Embodied GWP (Top pie chart) and (c) Energy consumption (Bottom pie chart), Scenario B.

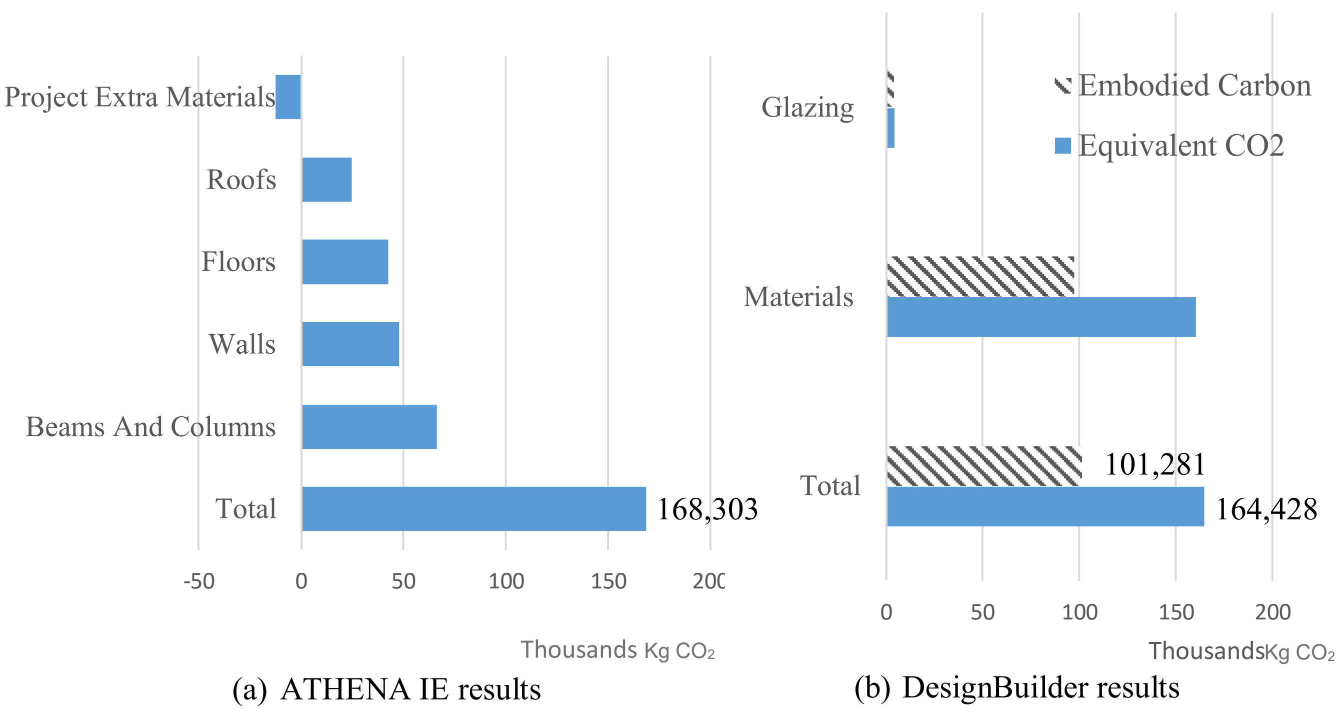


Figure 4-8. ES comparison of (a) Global Warming Potential LCA Measure (exported from ATHENA), (b) Embodied Carbon and Inventory (exported from energy simulation tool).

4.4 Summary and Conclusions

Quantifying the environmental impacts and simulating the energy consumption of building's envelope and systems at the renovation phase are very critical for decision-makers for the selection of the best renovation scenarios that would lead to a more energy-efficient building. This part of the research presented a SBMO that is capable of optimizing the building renovation scenarios to minimize the TEC, LCC and the environmental impacts of existing buildings. The proposed SBMO framework takes advantage of BIM coupled with simulation. There are different strategies for building renovation that focus on energy efficiency. Different renovation scenarios can be compared to find the near-optimal scenario based on the renovation strategy. Each scenario is created from the combination of several methods within the applicable strategy. The methods include the factors related to the building envelope, HVAC, and lighting system. However, the inconsistent scenarios should be removed. For example, when double-glazed windows are implemented, the building becomes more airtight, so the infiltration rate is decreased considerably. Therefore, the HVAC system should be rescheduled or renovated to reflect the new energy demand and to avoid unwanted side effects. The methodology includes developing a model that simulates the process of renovating buildings by using the renovation data in energy analysis software to analyze TEC, LCC, and LCA and identifies the potential renovation scenarios that can be implemented based on the selected renovation method. Furthermore, an LCA tool is used to evaluate the environmental sustainability of the final decisions.

This part of the research consists of two main components that are necessary to realize the proposed methodology: (1) developing a framework for data collection and preparation to define the renovation strategies; (2) applying SBMO model to define near-optimal renovation scenarios based on the available methods.

A case study of one floor of an existing building was studied to assess the implementation of the developed model. LCA and TEC have strong linear correlation in comparison with the LCC and TEC. It is worthy to mention that the optimization in the first case has a larger number of Pareto solutions because energy consumption and LCC are conflicting objectives (Sharif and Hammad, 2017). Comparing the ratio of LCC per TEC for the Pareto solutions clarifies their efficiency. This comparison demonstrates that there is a better potential in reducing TEC in Scenario B than in Scenario A since with a slight increase in LCC, significant decrease in TEC is attained.

Furthermore, the energy saving improvement from scenario A to B is 24,325 kWh/year, which is significant.

This chapter's results show that existing building envelopes and system renovations offer important opportunities for improving energy performance, LCC, and reducing negative environmental impacts. This approach can be considered as one of the key strategies for achieving sustainable development goals in the environment, at a relatively low cost, compared with the demolition and reconstruction of new buildings.

CHAPTER 5. DEVELOPING SURROGATE ANN FOR SELECTING NEAR-OPTIMAL BUILDING ENERGY RENOVATION METHODS CONSIDERING TEC, LCC AND LCA

5.1 Introduction

Common traditional methods such as trial-and-error processes or rules of thumbs techniques cannot guarantee near-optimal renovation solutions. To this end, optimization procedures, such as evolutionary algorithms, can be implemented. However, building optimization, including multiple objectives, is usually a time-consuming process (Kim et al. 2016). Nevertheless, to achieve reliable results, the energy performance of each renovation scenario should be calculated by implementing whole building energy simulation tools that consider the specific characteristics of the case building over the study period (Sharif and Hammad 2019; Wei et al. 2018; Kim et al. 2016; Wei et al. 2015).

The SBMO model, which is proposed in Section 4.2 of this study, often needs hundreds or thousands of simulation evaluations. For a big project (e.g., providing whole building simulation and optimization), the optimization can become unfeasible because of the computation time and complexity of the dependent parameters. Therefore, one feasible technique to solve this problem is to implement surrogate models to computationally imitate expensive real building simulation models with an appropriately representative model.

The second part of the research focuses on developing new and robust ML techniques and coupling them with the proposed SBMO model to explore vast and complex data generated from the first part of the research. The proposed method will potentially offer new venues to understand and predict energy consumption, LCC, and LCA for different renovation scenarios, and select the near-optimal scenario.

Chapter 5 is organized into sections that include the research method (Section 5.2), implementation of the ANN models and case study (Section 5.3), and finally, summary and conclusions (Section 5.4).

5.2 Proposed Methodology

The methodology in this study is proposed to assist decision-makers with respect to renovation methods for which there exist some constraints, and to help them in considering three main objective functions, namely TEC, LCC, and LCA.

Acceptable renovation methods or ranges are defined based on the results of Section 4.2 for building envelope, HVAC systems and lighting systems. They are determined based on the developed approach at Phase 3 of SBMO model considering other parameters, such as owner's and facility management's preferences, building codes or other limiting factors (i.e., limited renovation budget or some predefined methods) for the building under discussion.

As explained in Section 4.1, the inconsistency of some renovation methods adds more complexity to the model; therefore, these methods must compete, and weak or non-related solutions should be eliminated. For example, increasing the glazing area of the building (*WWR*) to reduce the energy consumption for the lighting system (using more daylight) can result in increased energy consumption for heating and cooling and increase TEC, which might not be necessarily valuable for reducing the negative environmental impact of the building. To this end, it is very important to have a powerful model for accurately assessing the effects of each proposed method of each renovation scenario. Although the SBMO model is capable of doing small tasks, or for some parts of the project, it requires a huge computational time and cost to evaluate the whole building, which is sometimes not feasible. Furthermore, the complexity of the objective functions, which is discussed in Section 4.4, adds complications to the problem.

This Chapter focuses on ANN to achieve renovation scenarios that minimize TEC, LCC, and environmental impacts. Different ANNs were used to model the relationship between the near-optimal renovation scenarios of the building's envelope, HVAC, and lighting, and their TEC, LCC, and LCA as shown in Figure 5-1. The following paragraphs initially provide a brief introduction of the SBMO and then explains the research methodology.

Firstly, extensive data is collected on existing buildings related to several factors including TEC, outside temperature, building envelope components, HVAC and lighting systems. Then an energy model of the existing building is created in DesignBuilder and validated through the comparison with energy bills. Consequently, the SBMO model that combines TEC, LCC, and LCA, which is proposed in Chapter 4 (Sharif and Hammad, 2018), is used to propose the near-optimal renovation scenarios. Subsequently, a representative dataset of renovation scenarios is created using the results of SBMO. This dataset is used to train and validate different ANN models. It is worthy to mention that the complexity of the ANN models has a significant effect on the training time and performance of the model. Furthermore, to evaluate the efficiency of the proposed model, a comparison between the SBMO and the final results of the ANNs is performed to clarify the performance of the surrogate model.

The proposed model integrates the optimization power of SBMO with modeling capabilities of ANN. The main advantage of this integration is to improve the computing time while achieving acceptable accuracy.

As mentioned in Section 3.1, the proposed framework has three essential and interdependent parts, which are SBMO model development, data processing, and surrogate model development. Each part has several phases that are explained in detail. The proposed method combines the following seven phases as shown in Figure 5-1: (1) SBMO for building renovation considering TEC, LCC, and LCA for some parts of the building, which was the result of a previous study (Sharif and Hammad, 2018); (2) data preprocessing including database development and integration; (3) dataset preparation using the buffer list; (4) data normalization; (5) loading normalized data; (6) ANNs development; and (7) training and testing of proposed ANNs, which will be used as a prediction model.

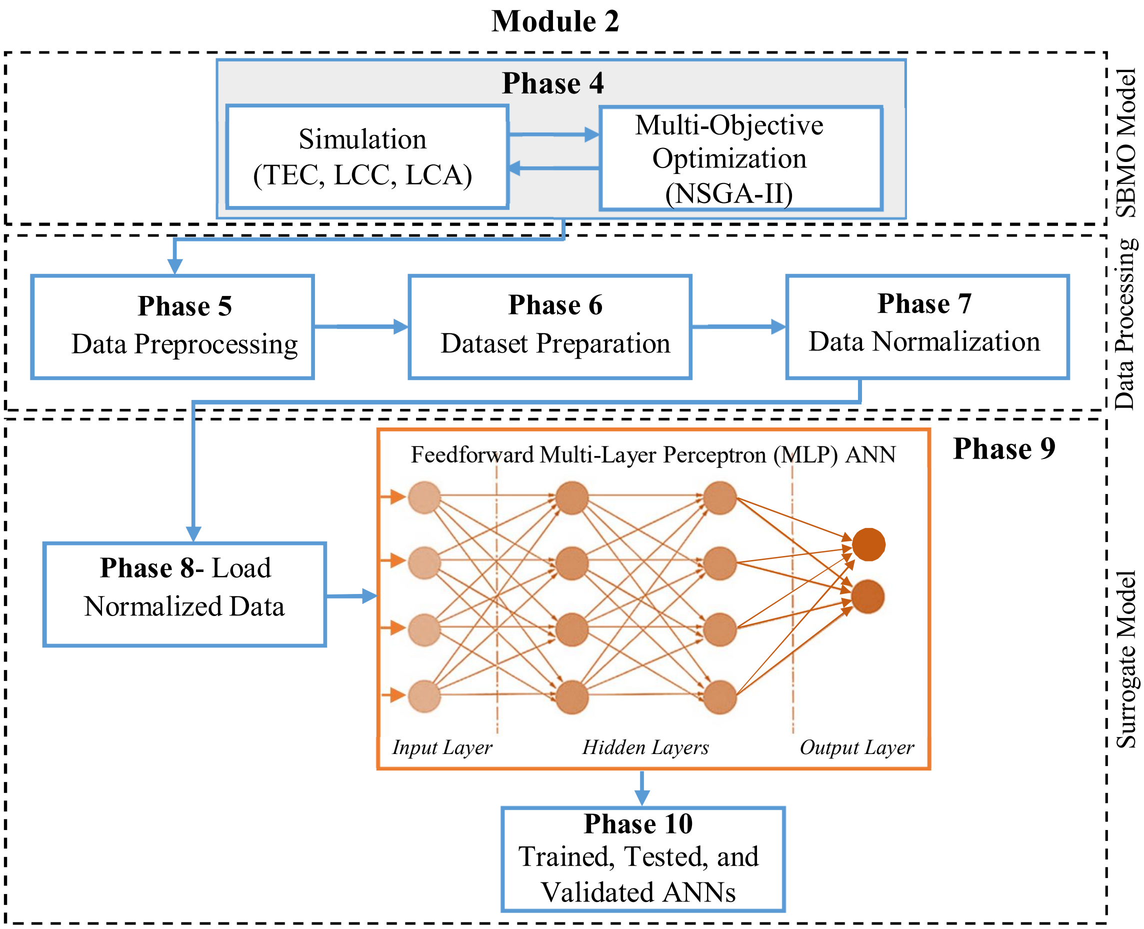


Figure 5-1. Architecture of the proposed model.

5.2.1 Modeling in Simulation Tool (SBMO model) (Phase 4)

As explained in Section 4.3, a computer model of the building under consideration is developed in the BEM. Special care should be taken in the model development. The simulation model contains information about related external factors, such as weather data and geographic location, and internal critical factors, such as building envelope components and materials, detailed HVAC system and lighting system, as well as an operational schedule for heating and cooling to investigate the performance of the ES. Finally, other information is modeled, such as the functionality of each space, typical occupant activities and clothing, and appliance energy consumption, as would be expected in the real building. For validation, the simulation results should be compared with energy bills, in terms of energy consumption. Although other factors such as building occupancy, equipment, and DHW have been modeled on the BEM, they remain constant for SBMO optimization. Acceptable renovation methods or ranges are defined based on the results of a previous study (Sharif and Hammad, 2018) for the building envelope, HVAC systems and lighting systems. Each renovation scenario considers several methods, including the improvement of the building envelopes, HVAC and lighting systems, and has individual labels, including TEC and LCC, or TEC and LCA.

Consequently, the second part of Phase 4 involves developing the optimization model, which is integrated with the simulation tool to shape the SBMO model. The NSGA-II is chosen for this part of the study. The objective functions are calculated for each renovation method using the capability of the BEM. The optimization engine computes the objective functions, which minimize TEC, LCC, and LCA for each scenario, based on the selected values of the methods in each simulation run.

As explained in Section 3.3, the SBMO generates near-optimal scenarios for a particular strategy. The results of the optimization are shaped into the Pareto front, which will be used to investigate the trade-off relationships among the different renovation scenarios, as well as to develop input data for Phase 5 of the data preprocessing (as shown in Figure 5-1). The final goal of this phase is to simultaneously optimize all objective functions of TEC, LCC, and LCA.

To lessen the computational burden, one part of the building (i.e., one floor) that is representative of the whole building has been simulated and optimized using the SBMO model (using the results of the Section 4.3.4). The initial search space contains a huge number of different renovation scenarios (by the billions), which include many related factors. A small number of possible scenarios (about 5,000 different renovation scenarios, including Pareto front) is generated from the SBMO model. However, calculating TEC, LCC, and environmental impacts for these generated scenarios is a time-consuming task for simulation tools. It is worth mentioning that training a surrogate model using inaccurate data can produce misleading results.

5.2.2 Data Preprocessing (Phase 5)

Data preprocessing includes dataset development and integration. The preprocessing of the input layer data is vital, which is sometimes ignored in ANN developments. The preprocessing step is needed to eliminate missing or repeated values, and inconsistencies for different features through data transformation and integration (Yu, 2012). As explained in Section 2.10, the preprocessing phase has many advantages, such as minimizing biased data, and creating a complete and clean dataset. In this study, repetitive and noisy (invalid) renovation scenarios have been removed from the dataset.

5.2.3 Dataset Preparation Using a Buffer (Phase 6)

Phase 6 is for selecting a buffer of acceptable scenarios (within a predefined range), in terms of TEC, LCC, and LCA using a sequential approach. Initially, the Pareto Front results are identified, labeled, and excluded from the main list. Consequently, new Pareto Front results are generated from non-optimal configurations and excluded from the main list, and added to the selected list of solutions. This step is iteratively repeated until a sufficient number of solutions is selected. A schematic definition of the buffer (blue area) of acceptable renovation scenarios considering two constraints (maximum acceptable value) for TEC and LCC is shown in Figure 5-2.

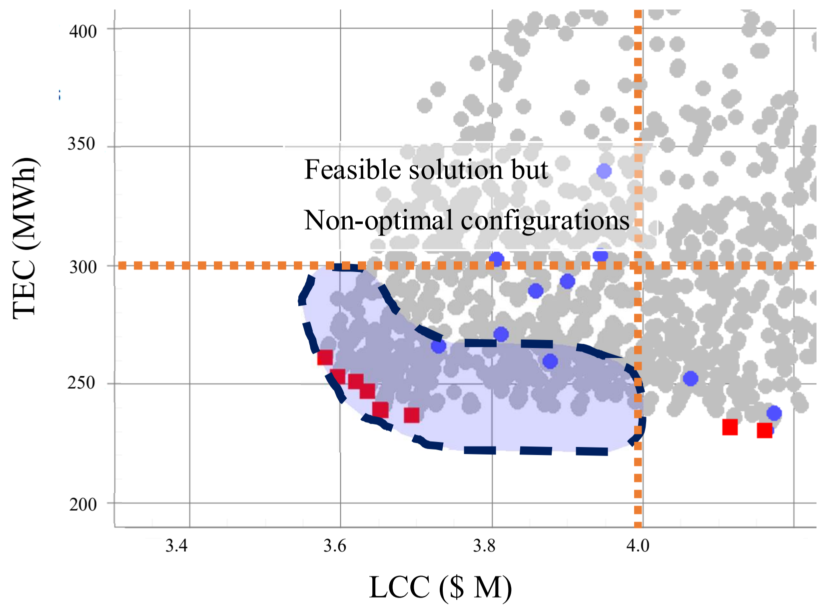


Figure 5-2. A schematic definition of the proposed buffer.

Several studies have concluded that for a network with N number of variables, a sample size of 2×N or more is sufficient to correctly sample the search space (Conraud-bianchi 2008; Magnier and Haghighat 2010b). It should be noted that a smaller sample dataset can reduce the representation of the search space, while selecting too many samples will increase computation cost (Conraud-bianchi 2008).

5.2.4 Data Normalization (Phase 7)

In Phase 7, both the renovation methods (that are considered as input features) and the objective functions resulting from proposed scenarios (target features) are normalized using a linear transformation approach. The magnitude of the input values should be scaled to avoid the overflow error in the input value (Freeman and Skapura 1991). Furthermore, some of the features do not have units (e.g., R, EW, and W) or have percentages (e.g., WWR and EWO) or have their own units (e.g., TEC, LCC, and LCA).

Data normalization unifies features that may significantly alter the feature values, thereby affecting the quality and accuracy of the dataset and avoiding dependency on the selection of feature units. Also, data normalization can stop features with large ranges from compensating for those with relatively smaller ranges (e.g., LCC with a value range of millions can outweighs EWO with a maximum value of 70%). The contribution of different renovation methods as input features, to TEC, LCC, and LCA values, as target features, may differ substantially. A code is assigned to each method that specifies its name. Furthermore, the Number of Replications (NoR) of a method in different renovation scenarios indicates its importance, which must be considered to prevent the occurrence of the outweighing problem. Otherwise, it may force the network into depending on specific methods and outweighing the others. Although excellent outputs can be shown, the ANN's performance is tied to that particular dataset, which may result in the incapability of the ANN to perform well with new data. Therefore, the ANN cannot be generalized. After normalizing the data, each feature must be related to a weight that indicates its importance. As explained in Section 3.4, the normalization phase is very critical to increase the range of deviance and reduce the effect of the magnitude of the input data throughout the ML training process. Min-max normalization (Eq. 4.1), which is used in this research, has the ability to maintain the intrinsic interaction between the initial data because it executes a linear normalization. To achieve better training performance, all input and output data are transformed using min-max normalization (Yu, 2012). For a parameter x the normalized value x', is obtained as:

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})}(x'_{man} - x'_{\mathrm{min}}) + x'_{min} \qquad \text{Eq. 4.1}$$

where x_{min} and x_{max} are the minimal and maximal value of the variable x, and x'_{min} and x'_{max} are the minimal and maximal values of the variable x after normalization, which can be transformed to a range between -1 and +1.

5.2.5 Surrogate Model Training and Testing (Phases 8-10)

Surrogate model development has three phases: (1) Load normalized data (Phase 8), (2) ANN models' development (Phase 9), and (3) Training, validation, and testing (Phase 10). The goal of Phase 8 is to divide and load input data into two subcategories, which are training and testing data, to find the optimum modeling of an ANN including weights and biases. Therefore, a random selection approach is utilized that selects 70% of the normalized data to train the ANN and optimize weights and biases, and the remaining 30% of the data is used for testing and validation. Subsequently, the definition of the ANN architecture is implemented in the Phase 9 of ANN methodology. The aim is to define the number of layers and the number of neurons within each layer and select a suitable training algorithm. Two different ANNs have been developed, i.e., ANN1 (TEC vs. LCC) and ANN2 (TEC vs. LCA) as shown in Figure 3-3.

Each MLP ANN is defined with different neurons in the input, hidden, and output layers. The number of neurons in the input layer is equal to the number of input variables. The most commonly used activation functions in the optimization of ANNs are hyperbolic tangent sigmoid, linear transfer functions, and Logistic sigmoid (Azari et al. 2016; Yang et al. 2005b). The final phase for surrogate modeling (Phase 10) in ANN is training, validation, and testing of the network. Therefore, the Mean Squared Errors (MSEs) for both training and testing datasets should be calculated to evaluate the performance of the ANN. Weights and biases values for each neuron should be adjusted and optimized to minimize the MSEs for the training and test datasets concurrently (Azari et al. 2016). MSE values describe the network's performance and are calculated based on the average of the summation of the differences between the network predictions and the targets (Eq. 4.2):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - X_{i,target}\right)^2 \qquad \text{Eq. 4.2}$$

where N is the number of data, X_i, and $X_{i,target}$ are the network output and target values for training and test processes, for the i^{th} experiment, respectively.

5.3 Implementation and Case Study

The following section describes the implementation of ANN based on the results of SBMO on the last floor (containing the roof) of a multipurpose university building at Concordia University. The input data were provided by developing the BIM using Revit. 2D plans and sections, documents including building envelope and roof components and materials, were adjusted in the BIM model as shown in Figure 4-3(a and b). Further information about the case study building is available in Section 4.3.

DesignBuilder is used in analyzing whole building energy performance calculations. It is a user-friendly tool and it has the capability of optimizing building performance (DesignBuilder, 2016). ANNs are created in MATLAB® using the results of the DesignBuilder as input parameters and weighting factors for networks' training and testing. As explained in Section 4.3.4, the SBMO model of building energy performance considering TEC, LCC, and LCA is developed to create networks' inputs to properly select the accurate values for decision variables (i.e., to identify the near-optimal renovation scenarios).

MATLAB® has substantial computational capability, which allows data processing, meta-modeling, optimization, and simulation. The MATLAB® environment is used for developing the related functions, which are employed later on for ANNs. Based on the recommendation of MATLAB, the range of (-1, 1) was used to normalize all inputs and outputs before training, to improve the efficiency of the network. The complexity of an ANN model is determined by the number of hidden layers. To minimize the training dataset error, the number of hidden layer neurons should be increased, which, as a result, will compromise the generalization ability of the ANN. The back-propagation method is used for the ANN training, associated with the Levenberg-Marquardt (LM) algorithm. Two different transfer functions are used, which are the hyperbolic tangent sigmoid, used in the initial and hidden layers, and linear functions, used in the output layer. Figure 5-3 shows the implementation steps and the tools used to achieve the results.

5.3.1 Energy SBMO Model

As mentioned in Section 4.3, the case building is located in Montreal, Canada. The local weather data were used in the simulations. Extensive data were collected on the existing building related to several factors including TEC, outside temperature, existing building envelope components, i.e., external walls, roof, properties of windows (frame and glazing), their locations, and orientations. A gbXML format of BIM model is transferred into the energy model automatically. Also, the detailed HVAC system and lighting systems, allocation of building activities, and DHW were adjusted in the BEM. Several parameters were added or modified, and different "zones" were defined in the model to obtain more accurate results as shown in Figure 4-3(a). Sample input data of the building characteristics are shown in Table 4-4. Simulations are performed for the cold-climate city of Montreal (Climate Zone 5). In this climate zone, the energy consumption in buildings is mainly used for heating.

The specific collected data are then added to the extensible database, which includes a wide range of different renovation methods of the buildings envelope, HVAC, and lighting. The extensible database also contains other information, i.e., LCC and environmental impacts related to each method. The next step involves defining the renovation goals, methods, and tasks for each renovation scenario based on available methods, which are embedded in the databases. The goal is to develop renovation scenarios based on a set of methods. Each scenario consists of several renovation methods within the applicable strategy.

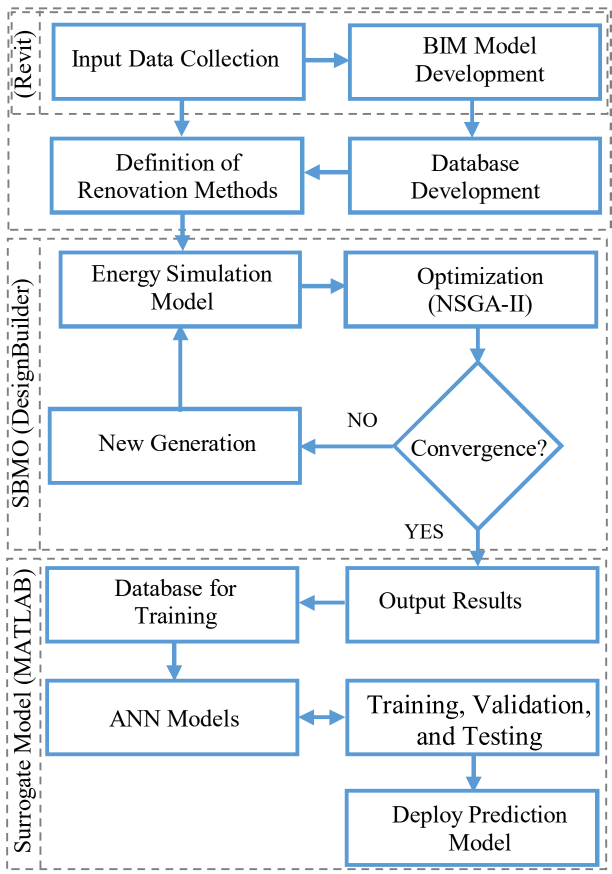


Figure 5-3. Implementation steps.

As mentioned in Section 4.3, two separate optimizations are performed using the NSGA-II algorithm, which is integrated in the simulation tool. Simulation is carried out for each renovation scenario generated by the NSGA-II optimization process, and TEC, LCC, and LCA values obtained from the simulations are calculated pairwise. An example of the selected near-optimal renovation scenarios is presented in Table 4-8. In this study the results of SBMO are used to generate the lists of acceptable renovation scenarios (Sharif and Hammad, 2018).

Subsequently, in preprocessing phase, datasets are collected, and noisy or repeated scenarios are identified with significant variations in the TEC, LCC, or LCA. These noisy (e.g., invalid scenarios) or repeated scenarios should be removed from the final dataset through data transformation and integration. The output of the SBMO model is summarized in two different Excel files containing 4,720 results. It is worthwhile to mention that the contribution of different renovation methods to the TEC, LCC and LCA may differ significantly, which is defined by the Number of Replications (NoR) of that method in different renovation scenarios (Tables 5-1 and 5-2). Consequently, in Phase 6, the results of previous phases were filtered to remove the infeasible scenarios using the buffering approach that is explained in Section 5.2.3. Among the different renovation scenarios, only 463 were selected due to their acceptable results in terms of TEC, LCC, and LCA. The next phase is the normalization of data (Phase 7), which can prevent the occurrence of the outweighing problem between large-scale results (e.g., LCC and LCA) and those with relatively small ranges (e.g., *WWR* and *EWO*). Therefore, a code is assigned to each method that specifies its name and its importance while avoiding the occurrence of the outweighing problem.

Table 5-1. Building systems renovation codes and Number of Replications (NoR).

ID	HVAC- Heating, Ventilation and Air-Conditioning (25)	Code	NoR
HVAC01	Air to Water Heat Pump (ASHP) Hybrid with Gas Boiler, NV	15350	53
HVAC01	Air to Water Heat Pump (ASHP), Convectors, NV	15400	191
HVAC02	Fan Coil Unit (4-Pipe) with District Heating + Cooling	15450	175
HVAC02	Fan Coil Unit (4-Pipe), Air cooled Chiller	15500	5
HVAC02	Fan Coil Unit (4-Pipe), Air cooled Chiller, DOAS	15550	24
HVAC02	Fan Coil Unit (4-Pipe), Water cooled Chiller, Water-side economiser	15600	72
HVAC03	PTAC Electric Heating	15650	174
HVAC03	PTAC HW Heating	15700	57
HVAC04	PTHP	15750	28
HVAC05	Radiator heating, Boiler HW, Mech vent Supply + Extract	15800	84
HVAC05	Radiator heating, Boiler HW, Mixed mode NV, Local comfort cooling	15850	8
HVAC05	Radiator heating, Boiler HW, NV	15900	78
HVAC07	Radiators Electric, NV	15950	2992
HVAC06	Split + Separate Mechanical Ventilation	16000	71
HVAC06	Split no fresh air	16050	19
HVAC08	VAV, Air-cooled Chiller, Fan-assisted Reheat (Parallel PIU)	16100	149
HVAC08	VAV, Air-cooled Chiller, HR, Outdoor air reset	16150	14
HVAC08	VAV, Air-cooled Chiller, HR, Outdoor air reset + mixed mode	16200	32
HVAC08	VAV, Air-cooled Chiller, Outdoor air reset	16250	45
HVAC08	VAV, Air-cooled Chiller, Reheat	16300	75
HVAC08	VAV, Air-cooled Chiller, Steam humidifer, Air-side HR, Outdoor air	16350	18
HVAC09	VAV, Dual duct, Air-cooled Chiller	16400	16
HVAC09	VAV, Dual duct, Water-cooled Chiller	16450	225
HVAC10	VAV, Water-cooled Chiller, Air-side HR, Outdoor air reset	16500	5
HVAC10	VAV, Water-cooled Chiller, Full Humidity Control	16550	9

ID	HOS- Heating Operation Schedule (7)	Code	NoR
HOS04	7:00 - 23:00 Mon - Fri	2050250	1030
HOS05	6:00 - 18:00 Mon - Fri	2050750	575
HOS02	Max Indoor temp for NV: Always 100	2051250	1583
HOS02	Max Outdoor temp for NV: Always 100	2051750	795
HOS02	Mixed mode temperature control	2052250	182
HOS01	On 24/7	2052750	167
HOS03	Two season schedule (Northern Hemisphere)	2053250	287

ID	COS- Cooling Operation Schedule (7)	Code	NoR
COS04	7:00 - 23:00 Mon - Fri	450900	263
COS05	6:00 - 18:00 Mon - Fri	451500	2844
COS02	Max Indoor temp for NV: Always 100	452100	230
COS02	Max Outdoor temp for NV: Always 100	452700	258
COS02	Mixed mode temperature control	453300	636
COS01	On 24/7	453900	148
COS03	Two season schedule (Northern Hemisphere)	454500	140

ID	Li- Lighting (8)	Code	NoR
Li02	Canadian energy code	90000	378
Li04	Fluorescent, compact (CFL)	91500	97
Li05	High-pressure Mercury	93000	238
Li06	High-pressure sodium	94500	99
Li03	LED with linear control	96000	491
Li03	LED	97500	2992
Li04	T5 (16mm) Fluorescent, HF, LINEAR daylighting	99000	67
Li04	T5 (16mm) Fluorescent, HF	100500	257

Table 5-2. Building envelope renovation codes and Number of Replications (NoR).

ID	EW- External wall (22)	Code	NoR
EW04	Lightweight curtain wall (insulated to 1995 regs)	100	92
EW04	Lightweight curtain wall insulated to 2000 regs	140	150
EW09	Innovative wall	180	57
EW08	Advanced Insulation	220	14
EW03	Cavity wall (E&W) Part L	260	34
EW08	Advanced Insulation	300	8
EW01	Brick air, concrete block-Uninsulated - MW	340	28
EW03	Cavity wall (E&W) Part L	380	63
EW05	Semi-exposed wall Energy code - HW	420	21
EW05	Semi-exposed wall Energy code - LW	460	142
EW05	Semi-exposed wall Energy code - MW	500	71
EW05	Semi-exposed wall Typical reference - HW	540	49
EW05	Semi-exposed wall Typical reference - LW	580	90
EW05	Semi-exposed wall Typical reference - MW	620	155
EW06	Wall - Energy code standard - HW	660	243
EW06	Wall - Energy code standard - LW	700	53
EW06	Wall - Energy code standard - MW	740	197
EW07	Wall - State-of-the-art - MW	780	2669
EW02	Brick cavity with insulation - HW	820	335
EW02	Brick cavity with insulation -LW	860	19
EW02	Brick cavity with insulation -MW	900	69
EW01	Brick air, concrete block	940	60

ID	R- Roof (16)	Code	NoR
R02	Combined flat roof - Energy code - HW	5000	83
R02	Combined flat roof - Energy code -LW	5250	63
R02	Combined flat roof - Energy code -MW	5500	184
R03	Combined flat roof - 19 mm asphalt - HW	5750	265
R03	Combined flat roof - 19 mm asphalt -LW	6000	22
R03	Combined flat roof - 19 mm asphalt - MW	6250	91
R04	Combined flat roof - Typical reference - HW	6500	32
R04	Combined flat roof - Typical reference - LW	6750	29
R04	Combined flat roof - Typical reference -MW	7000	72
R05	Combined semi-exposed roof - Energy code - HW	7250	17
R05	Combined semi-exposed roof - Energy code - MW	7500	20
R00	Project flat roof	7750	3114
R07	Innovative	8000	299
R01	R-19+10 (3.3+1.8), U-0.041 (0.232)	8250	184
R01	R-19+19 (3.3+3.3), U-0.046 (0.261)	8500	62
R05	Combined semi-exposed roof - Energy code - LW	8750	82

ID	FT- Facade type (22)	Code	NoR
FT01	100% fitted glazing	1350	36
FT02	40% Vertical Glazing ASHRAE 90.1 Appx G	1400	72
FT04	Curtain wall, 85% glazed	1450	36
FT03	Fixed height 1.5m, 30% glazed	1500	42
FT03	Fixed height 1m, 20% glazed	1550	62
FT03	Fixed windows - height:1.0m, width:0.5	1600	3093
FT03	Fixed windows - height:1.0m, width:1.0	1650	113
FT03	Fixed windows - height:1.5m, width:1.0	1700	128
FT05	Horizontal strip, 50% glazed	1750	33
FT05	Horizontal strip, 60% glazed	1800	108
FT05	Horizontal strip, 70% glazed	1850	76
FT05	Horizontal strip, 80% glazed	1900	69
FT05	Horizontal strip, 90% glazed	1950	133
FT05	Horizontal strip, 100% glazed	2000	93
FT06	Preferred height 1.5m, 10% glazed	2050	305
FT06	Preferred height 1.5m, 20% glazed	2100	38
FT06	Preferred height 1.5m, 30% glazed	2150	35
FT06	Preferred height 1.5m, 40% glazed	2200	34
FT06	Preferred height 1.5m, 50% glazed	2250	33
FT06	Preferred height 1.5m, 60% glazed	2300	25
FT06	Preferred height 1.5m, 70% glazed	2350	18
FT06	Preferred height 1.5m, 80% glazed	2400	21
FT06	Preferred height 1.5m, 90% glazed	2450	4
FT06	Preferred height 1.5m, 100% glazed	2500	10

ID	W- Window frame types (6)	Code	NoR
W01	Aluminium window frame (no break)	1105000	57
W01	Aluminium window frame (with thermal break)	1106000	143
W02	Painted Wooden window frame	1107000	167
W04	BIPV	1108000	3453
W03	UPVC window frame	1109000	329
W02	Wooden window frame	1110000	470

5.3.2 Architecture of ANN Models

Two datasets of 463 renovation scenarios, including ten renovation methods (results of SBMO) and the values of two objective functions for each scenario (i.e., TEC, LCC, and LCA pairwise), were used for ANN training and testing. There is no general rule for choosing the number of hidden layer neurons. It is essential to develop ANNs that are able to predict TEC, LCC, and LCA of a renovation scenario with reliable accuracy. However, an increase in the number of neurons in hidden layers may result in overfitting/overtraining problem. In this case the generalization accuracy of ANNs may be impaired because of fitting some *noise* in the dataset. Concurrently, another problem that also effects the ANNs performance is the underfitting, which occurs in shallow ANNs with too few neurons in hidden layers. Underfitting can result in large errors in the ANN (Ahmad et al. 2017).

In this study, initially five-layer ANNs were defined with ten neurons in the input layer, three neurons in the hidden layers, and two neurons in the output layer. Then a cross-validation method was used to reach the optimal values. It was found that in this model, the higher number of layers and neurons significantly improves the accuracy of the ANN. Finally, a five-layer ANN was defined with 10-5-6-4-2 neurons in input, hidden (three layers), and output layers. The number of neurons in the input layer is equal to the number of input variables, i.e., *R, EW, W, FT, WWR, HVAC, COS, HOS, Li*, and *EWO* as illustrated in Figure 3-3. The numbers of hidden neurons in the respective layers are defined based on the try and error approach to achieve the best MSE on the test data. The most commonly used *Tansig* activation function was used for the hidden and output layers to measure outputs of each neuron within the normalization range of −1 to +1. ANNs were trained, implementing the Levenberg–Marquardt and Bayesian regularization algorithms. Convergence for the training is achieved if MSE is stabilized over certain iterations or if the maximum number of epochs is reached (e.g., 900) as shown in Figure 5-4.

5.3.3 Results and Discussion of ANN Models

A sample of 138 renovation scenarios, different from the previous cases, was used to test each network. A random selection approach was utilized that selected 70% of the normalized data to train the ANN and optimize weights and biases, and the remaining 30% of the data is used for the validation and testing process. ANN outputs were assessed with the equivalent SBMO outputs. It is worthwhile to mention that both ANNs were trained and tested using the same datasets. In this research, only the results of the ANN1, which is considering TEC and LCC are discussed. The same procedure was implemented for TEC and LCA (ANN2), and the results are given in Table 5-3.

Regression correlation coefficients, between the network outputs and the corresponding SBMO model outputs, were found to be very close to 1 for the two outputs studied, thus demonstrating a very good correlation between outputs and target values, Figure 5-5(a and b). The normalized LCC and TEC results for SBMO and the predicted values of the ANN training (325 points) and testing (138 points) outputs were compared in Figures 5-6 and 5-7, respectively. Each point in the scatter plot in Figures 5-6 and 5-7 corresponds to a renovation scenario obtained from SBMO, and each line corresponds to ANN prediction model results at the tips of the line. The predicted values for each ANN models enjoy high levels of accuracy, since the amounts of underestimated or overestimated values predicted by the network are negligible. A careful observation of SBMO points shows that the majority of them are near the tips of the ANN prediction line. Therefore, it indicates that prediction results are in very good agreement with the SBMO.

Table 5-3. Statistical details of the ANN model training and testing.

Response	TEC vs. LCC	TEC vs. LCA
Training dataset	325	325
Testing dataset	138	138
Dataset (Total)	463	463
Number of epochs	900	900
Training MSE	0.016	0.056
Test MSE	0.088	0.124

5.3.4 Performance Evaluation of the Proposed ANN Model

In this section, performance results of the ANN prediction model for TEC and LCC vs. LCA are reported. The training is considered to have 900 epochs. However, the MSE stabilized after a certain number of iterations. The training goal was achieved after 170 epochs as illustrated in Figure 5-4. The results predicted by the ANNs (LCC and TEC) presented in Figure 5-5 (a and b) show high accuracy because the MSE of the predicted TEC vs. LCC is 0.016, while MSE of the predicted TEC vs. LCA is 0.056, respectively as shown in Table 5-3. Consequently, the fact that the ANNs provide suitable approximations with an acceptable deviation has been proven.

5.3.5 Computational Time Considerations of the Proposed ANN Model

Simulations were performed for the SBMO model with the total time of 170 hours to generate about 5000 renovation scenarios using an Intel® Core™ i7-3770 CPU@ 3.40 GHz processor and 8.00 GB RAM. The total computation time for the training, testing, and validation of the ANN model was about 150 seconds using the same computer.

It is worthy to mention that each simulation takes about 180 seconds using the SBMO model.

The applicability of the ANNs were tested by different sets of renovation scenarios. It was found that the ANNs can provide accurate results in less than 1 second. The ANNs were developed as surrogate models for emulating computationally expensive, real building simulation models. It is clear that using energy simulation tools results in a prohibitive computational time. The computational time saving associated with the proposed surrogate models is significant.

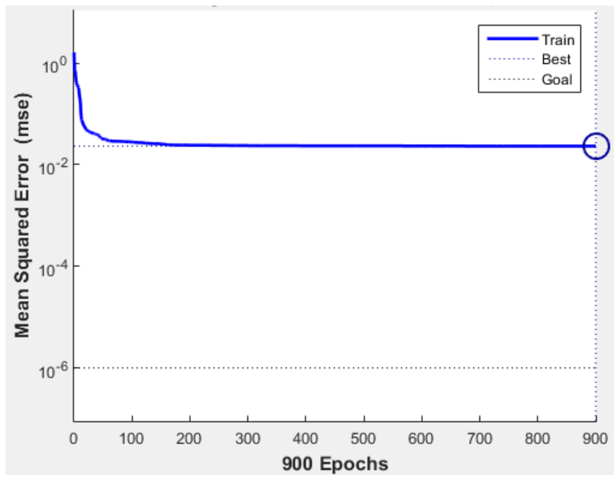
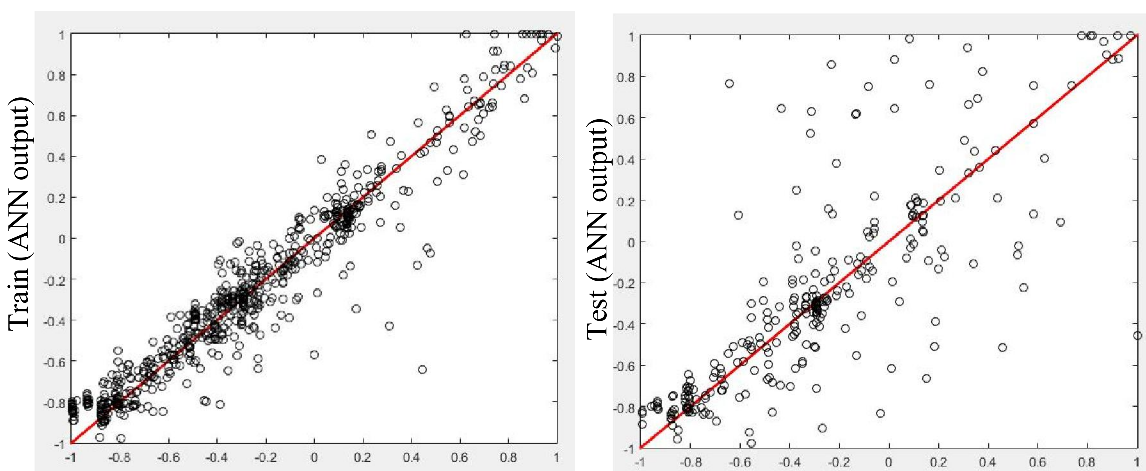
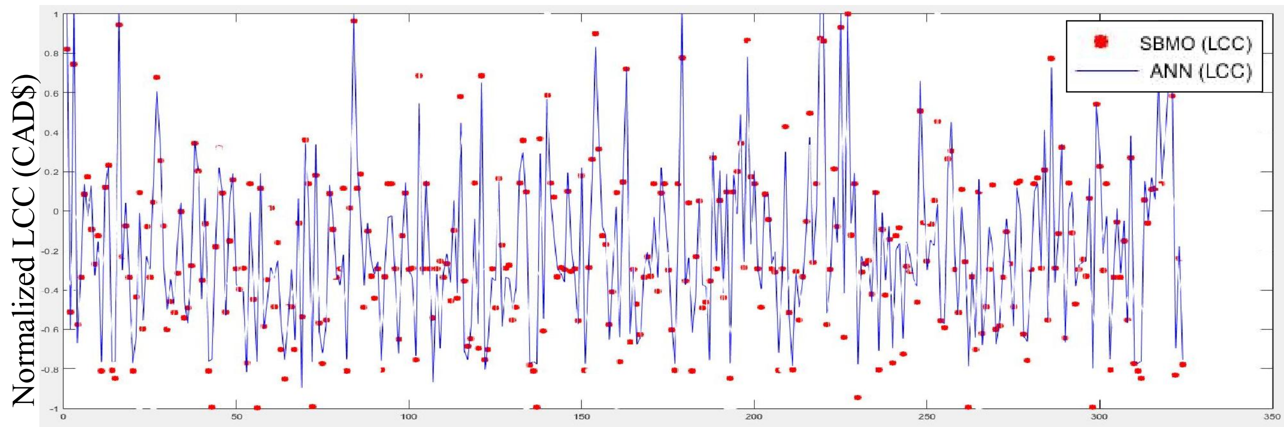


Figure 5-4. The performance of ANN training (TEC vs. LCC).



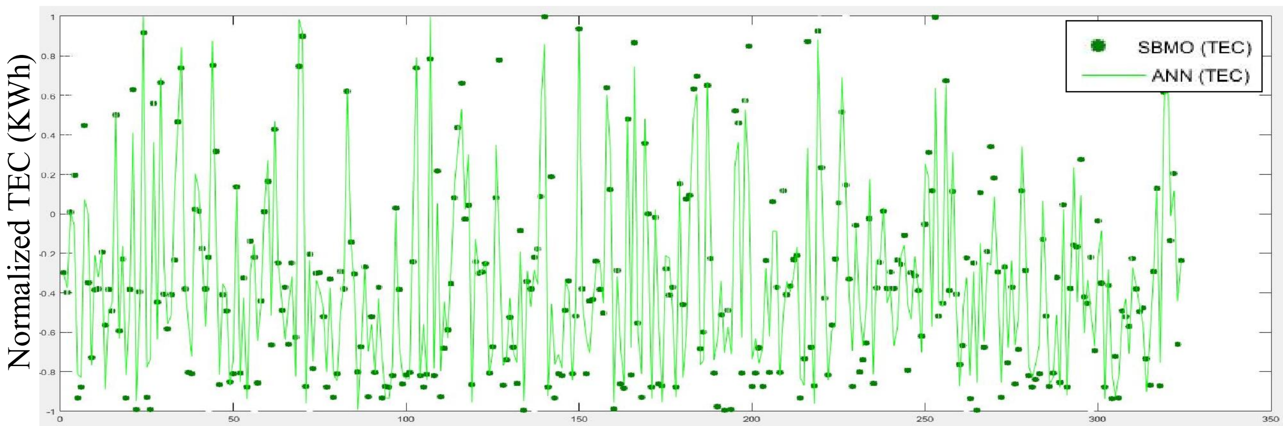
(a) Train (SBMO output) (b) Test (SBMO output)

Figure 5-5. Regression plots of ANNs vs. SBMO outputs.



Renovation Scenarios

(a) Scatter plot of LCC using SBMO and ANN



Renovation Scenarios

(b) Scatter plot of TEC using SBMO and ANN

Figure 5-6. Scatter plots of training output.

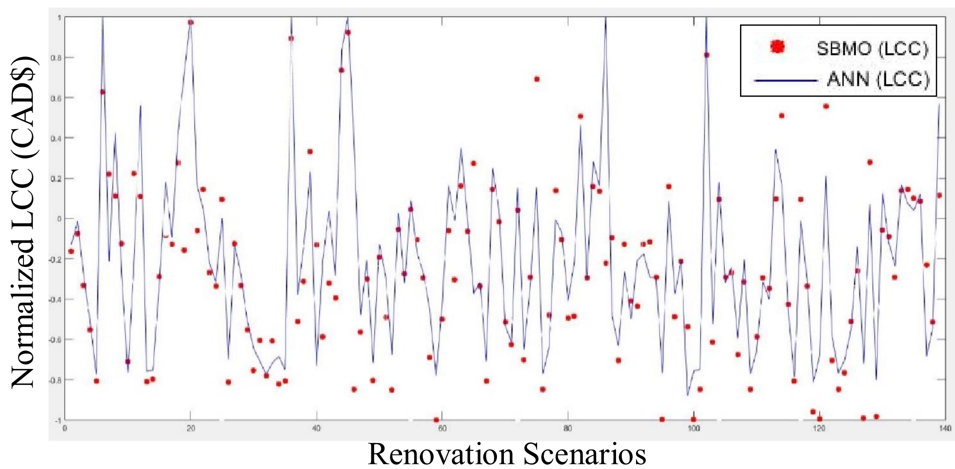
5.4 Summary and Conclusions

This Chapter focuses on developing new and robust ANNs for use as surrogate models for simulation by using data generated from the SBMO model developed in our previous research (Sharif and Hammad, 2018).

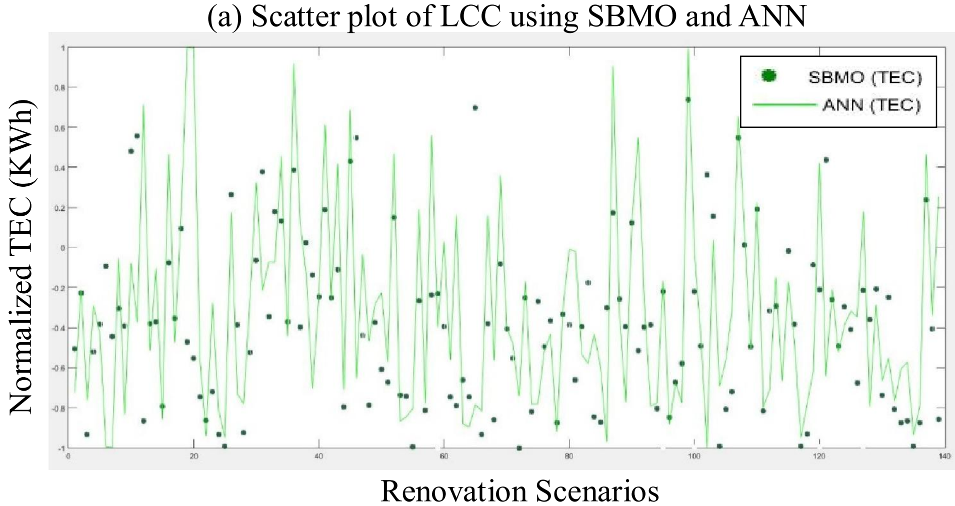
In the first phase, the optimization process, coupled with the energy simulation tool, forecasts the building TEC, LCC, and LCA pairwise. Then, two different ANNs were developed to predict and model TEC, LCC, and LCA of renovating combinations of elements of an existing building (i.e., *R, EW, W, FT, WWR, HVAC, COS, HOS, Li*, and *EWO*).

The outcome of this study shows that the proposed ANN models can efficiently predict the TEC, LCC, and LCA for the whole building renovation scenarios considering the building envelope, HVAC, and lighting systems. The proposed ANNs can work as a surrogate BEM to predict TEC, LCC, and LCA; thereby significantly decreasing computational time and effort while achieving acceptable accuracy. Furthermore, the proposed surrogate ANNs are user-friendly in comparison with detailed BEMs, which can be considered as advantages.

The case study was implemented based on the results of the SBMO. Different ANNs are generated in MATLAB® by using the outcomes of DesignBuilder energy simulations for network training and testing. The regressions between the ANN predictions and target SBMO outputs plots show an acceptable agreement between the predictions and the SBMO, with regression coefficients close to 1. The ANNs provide satisfactory approximation to the SBMO, with the MSE for TEC vs. LCC and TEC vs. LCA of 0.016 and 0.056, respectively.



(a) Scatter plot of LCC using SBMO and ANN



(b) Scatter plot of TEC using SBMO and ANN

Figure 5-7. Scatter plots of testing outputs.

CHAPTER 6. GENERATION OF WHOLE BUILDING RENOVATION SCENARIOS USING VARIATIONAL AUTOENCODERS

6.1 Introduction

Few studies have been conducted addressing the coupling of MLM and SBMO. Furthermore, despite the recent development in DNNs, semi-supervised and unsupervised machine learning studies still have a large potential for improvement. Hence, this Chapter aims to address this research gap by proposing a novel generative model to predict potential renovation scenarios considering TEC and LCC of existing institutional buildings using a DNN. The proposed DNN is capable to generate renovation scenarios based on semi-supervised Variational Autoencoders (VAEs). The proposed VAEs extract deep features from a whole building renovation dataset and generate renovation scenarios considering TEC and LCC of the existing institutional buildings. The proposed model also has the generalization ability due to its potential to reuse the dataset from a specific case in similar situations.

Chapter 6 is organized as follows. The research methodology is explained in Section 6.2, which contains data description, data processing, and MLM development. The implementation and case study are explained in Section 6.3. The results and discussion about the performance evaluation are explained in Section 6.4. Finally, we conclude this chapter by conclusions, limitations of this study (Section 6.5).

6.2 Proposed Methodology

The proposed model can handle three main scenarios as shown in Figure 6-1: (1) with a certain combination of TEC and LCC for renovation, it provides feasible scenarios with renovation details (VAE-1), (2) with a certain LCC for renovation, it provides feasible scenarios with renovation details (VAE-2), and (3) with a targeted improvement in the TEC, the model provides feasible scenarios with renovation details (VAE-3).

A three-step methodology is developed, which has three modules as shown in Figure 6-2: (1) SBMO for whole building renovation considering TEC and LCC, which is proposed by the authors (Sharif and Hammad 2018), (2) data processing, and (3) developing surrogate VAEs by learning from the generated SBMO dataset.

In Module 1, a dataset which includes TEC and LCC of different renovation methods of building envelope, HVAC, and lighting was generated using a SBMO (Phase 4). The proposed VAE analyzes the big dataset, including 20 parameters on building characteristics, which are categorized in ten main groups, i.e., Roof Types (R) [U_{roof} and C_{roof}], External Walls (EW) [U_{wall}, T_{wall}, and C_{wall}], Window Frame Types (W) [U_{window}, R^{l}_{window}, C^{m}_{window}, and C_{window}], Glazing Type (GT) [$U_{glazing}$, $L^{t}_{glazing}$, and $SHGC_{glazing}$], Window to Wall Ratio (WWR) [WWR], HVAC systems (HVAC) [E^{aux}_{hvac} and C_{hvac}], Cooling Operation Schedule (COS) [COS], Heating Operation Schedule (HOS) [HOS], Lighting systems (Li) [$NPD_{lighting}$ and $C_{lighting}$], and External Window Open (EWO) [EWO]. For simplicity reason, these 20 input parameters are shown as ten nodes in Figures 6-2, 6-4, 6-5, 6-6, 6-7, and 6-8. Dataset description is shown in Figure 6-3 and the complete list of parameters is shown in Appendix A.

In Module 2, there are three phases. Data processing includes data preprocessing of the input layer data (Phase 5), dataset preparation (i.e., dataset development and integration (Phase 6)), and data normalization (Phase 7). Yu (2012) explained that preprocessing phase (Phase 5) has advantages including excluding missing or repeated values, and inconsistencies in the dataset, minimizing biased data, and creating a complete and clean dataset.

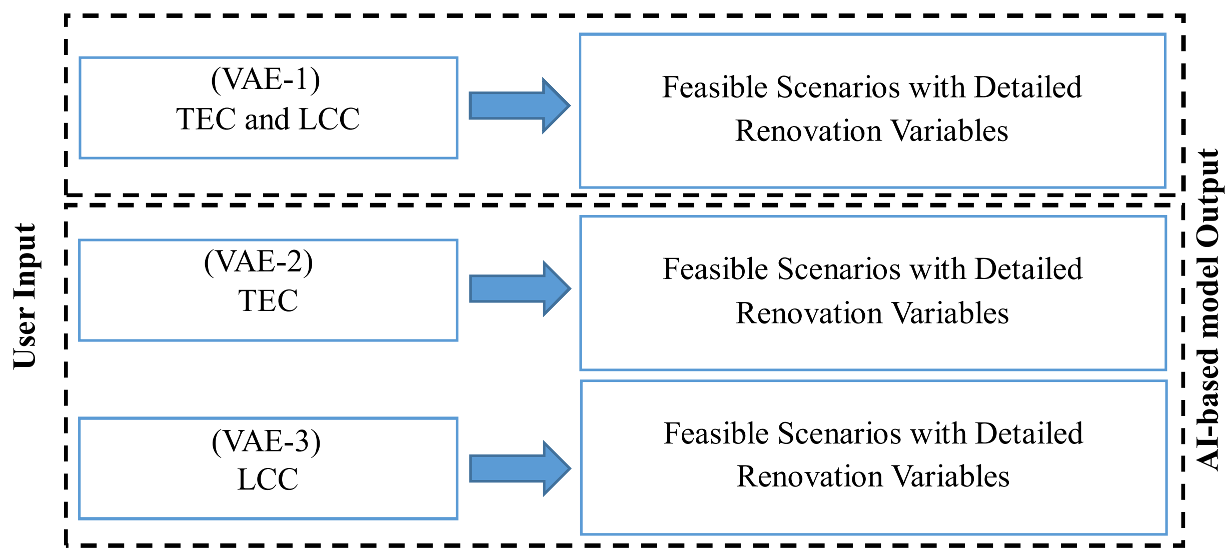


Figure 6-1. Input and output of the proposed model.

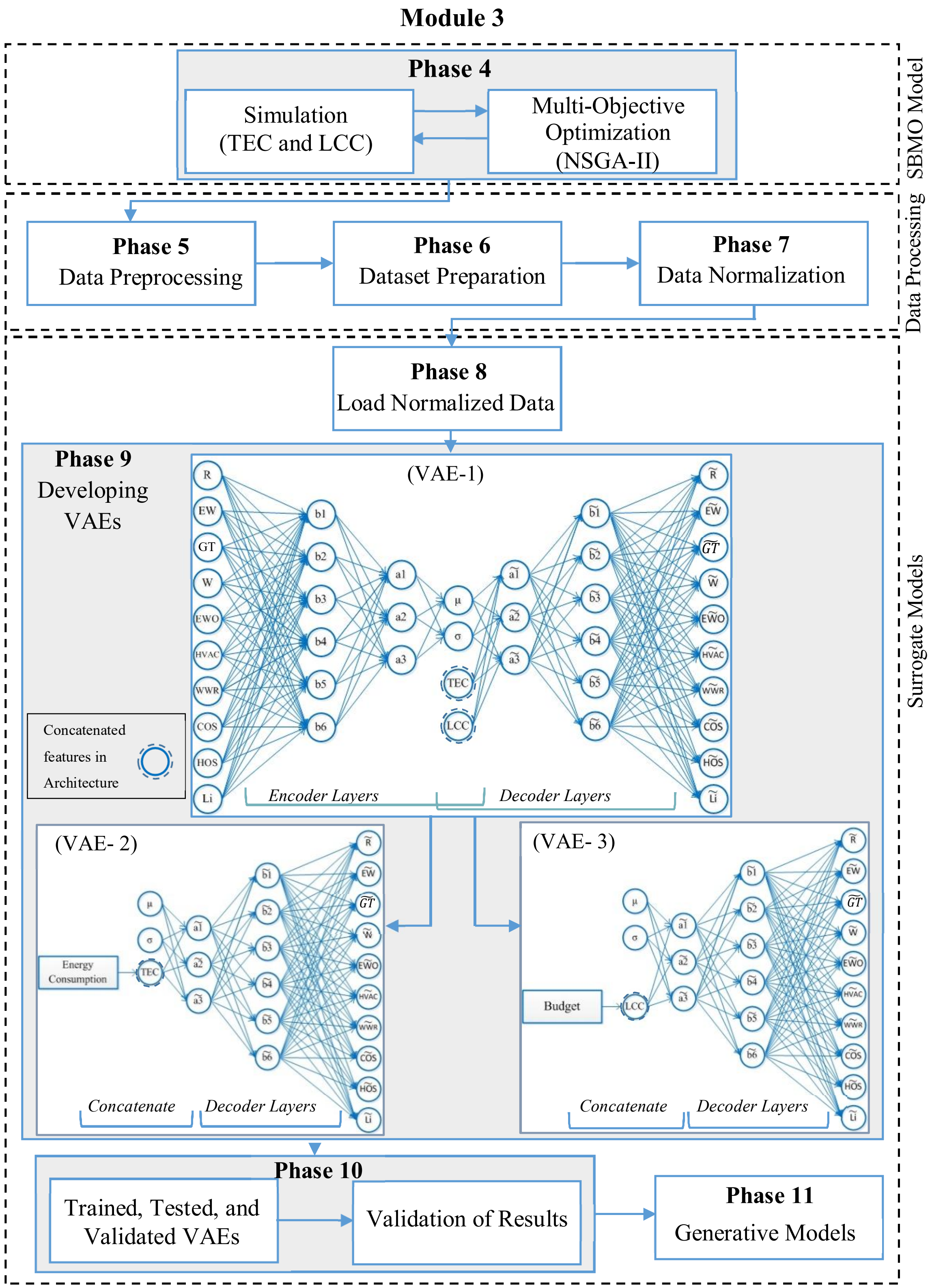


Figure 6-2. Proposed methodology.

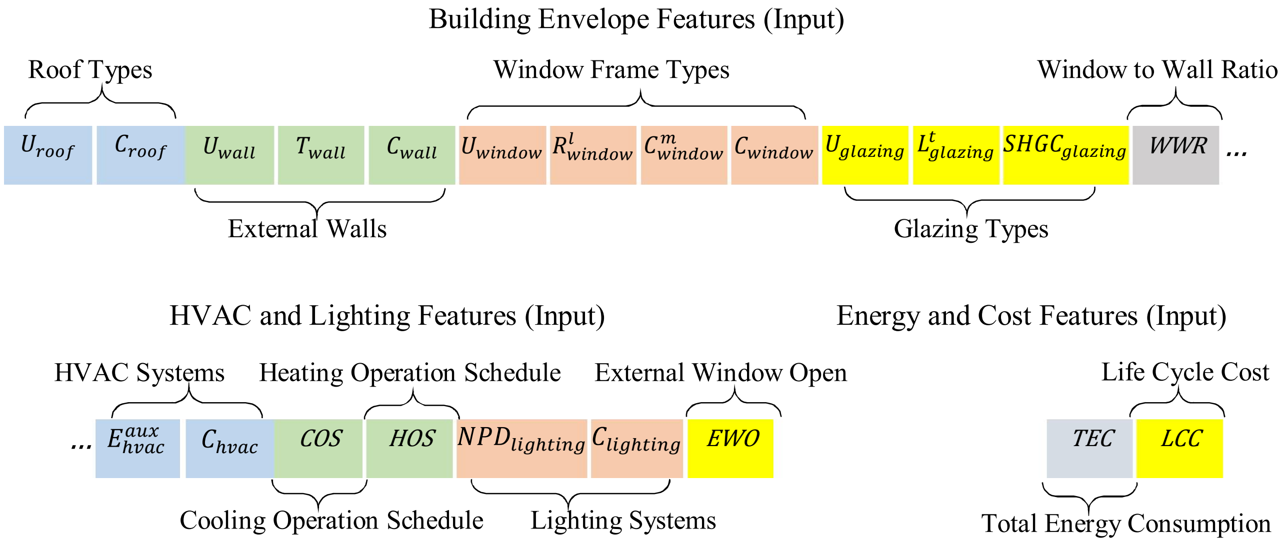


Figure 6-3. Dataset description.

In Phase 6, the SBMO results including all optimal and non-optimal renovation scenarios, are identified, labeled, and added to the main list of samples. Consequently, new results are generated using different configurations and added to the selected list of samples. The first three phases (4, 5, and 6) are iteratively repeated until a sufficient number of samples is selected. Samples are the renovation scenarios provided by 22 parameters including 20 parameters representing building renovation parameters and two parameters representing TEC and LCC related to each specific scenario. The value of each parameter represents the properties of a particular building component (as described in the Appendices B1-7). A small dataset may not be able to capture a representative sample of the search space, while selecting too many samples will require a large computational cost to process (Amasyali and El-Gohary 2018). When the dataset preparation (Phase 6) is finished and a sufficient number of samples have been added to the dataset, data normalization (Phase 7) begins.

In Phase 7, input features are normalized using a linear transformation approach. The input values should be normalized to avoid the overflow error in the input dataset (Freeman and Skapura 1991). In order to prevent this error, the min-max normalization method (Eq. 4.1) is used in this study (as explained in Section 5.2.4). Phase 7 improves the quality and accuracy of the dataset and prevents dependency on the selection of feature units (as described in Section 3.4).

In Module 3, there are four phases. The goal of Phase 8 is to load normalized data into VAEs. In Phase 9, different VAEs are developed. The proposed semi-supervised dimensionality reduction VAE consists of an encoder and a decoder neural network that tries to capture interesting relationships within the dataset and extract features from data (Phase 9). As mentioned in Section 2.10, feature extraction in VAE identifies the most relevant information from the input data in the latent space (Singaravel et al. 2017). An example of a feature extraction can be TEC and LCC of a renovation scenario, which is generated based on the interactions between different renovation methods of building envelopes, HVAC systems, and lighting systems. A schematic architecture of a dimensionality reduction VAE is shown in Figure 6-4.

In the first step of Phase 10, the developed VAEs are trained, tested, and validated on this generated dataset. The next step in Phase 10 involves the validation of the results, which verifies the accuracy of the model by comparing the results of VAEs with the results of the SBMO model. One feasible way of training the network to extract a compact representation (bottleneck layout) of the data is to have an input layer with more dimensions than the code layer (Kelly, 2016). In this case, the process of VAE has two steps: first, encode the input dataset to a compact vector representation that is the code layer (in dimensionality reduction method) then decode to regenerate the input (first step in Phase 10). The deep generative VAE proposed in this study uses Bayesian regularization backpropagation method for training (MacKay, 1992). Cross-validation of data during the training process is not required as Bayesian regularization backpropagation method uses regularization through Bayesian inference (MacKay, 1992). Once the training, testing, and validation are implemented and well tuned, validation of results is done to verify the accuracy of the generative model (second step in Phase 10). In the second step of Phase 10, the results of VAEs and the SBMO model are compared. Finally, in Phase 11, VAEs can be utilized as generative models.

6.2.1 Description of VAE Architectures

Three steps are considered to develop the VAE architectures in this research (Table 6-1): (1) Developing a traditional unsupervised VAE and training, testing, and validating the network, (2) developing an VAE to extract features and training, testing, and validating the network, and adding concatenate layer to improve the learning of the VAE as a semi-supervised model (VAE-1), and finally (3) removing the encoder network and use the decoder network as a semi-supervised prediction model (VAEs 2 and 3). In this study, VAEs are developed utilizing the input features of our previous study (Sharif and Hammad 2019). The numbers of hidden neurons in the respective layers are defined based on the trial-and-error approach to achieve the best evaluation metrics (explained in Section 6.2.2) on the test data. The best architecture is found with three hidden layers for both the encoder (i.e., b_i, a_i, and *level 2 features*) and decoder (i.e., *level 2 features*, $\tilde{a}_i$, and $\tilde{b}_i$) as will be explained in Section 6.3. The number of nodes in a_i, b_i, $\tilde{a}_i$, and $\tilde{b}_i$ layers are schematic in Figures 6-2, 6-4, 6-5, 6-6, 6-7, and 6-8. The VAE network is trained layer-by-layer by stochastic gradient descent (explained in Section 2.7.4). The model with the lowest MSE (Eq. 5.1) is selected for the final configuration.

Table 6-1. Input and output parameters in proposed VAEs.

No	Type of VAE	Input	Output
0	Unsupervised (Unconstrained Generation)	*R*, *EW*, *GT*, *W*, *EWO*, *HVAC* *WWR*, *COS*, *HOS*, and *Li*	$\tilde{R}$, $\widetilde{EW}$, $\widetilde{GT}$, $\tilde{W}$, $\widetilde{EWO}$ $\widetilde{HVAC}$, $\widetilde{WWR}$, $\widetilde{COS}$, $\widetilde{HOS}$, and $\widetilde{Li}$
1	Semi-supervised	*R*, *EW*, *GT*, *W*, *EWO*, *HVAC* *WWR*, *COS*, *HOS*, and *Li* *TEC and LCC*	
2	Semi-supervised	*R*, *EW*, *GT*, *W*, *EWO*, *HVAC* *WWR*, *COS*, *HOS*, and *Li* *TEC*	
3	Semi-supervised	*R*, *EW*, *GT*, *W*, *EWO*, *HVAC* *WWR*, *COS*, *HOS*, and *Li* *LCC*	

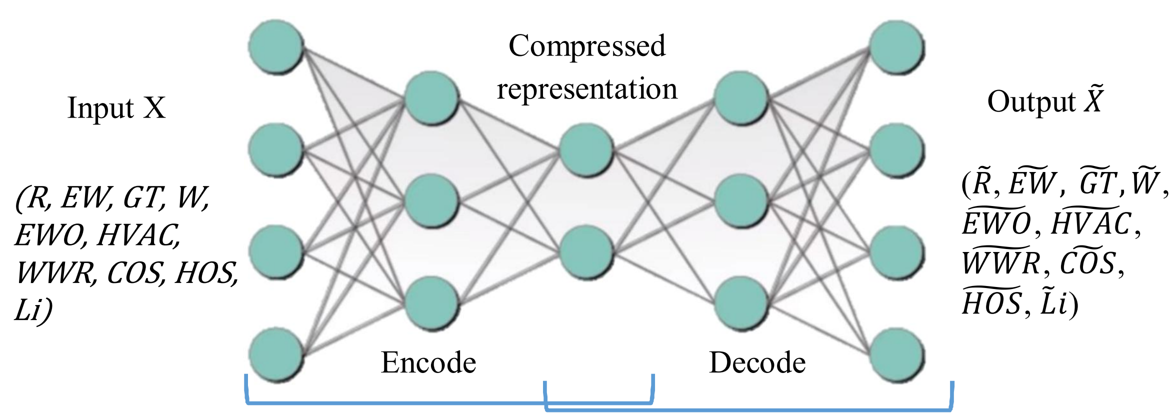
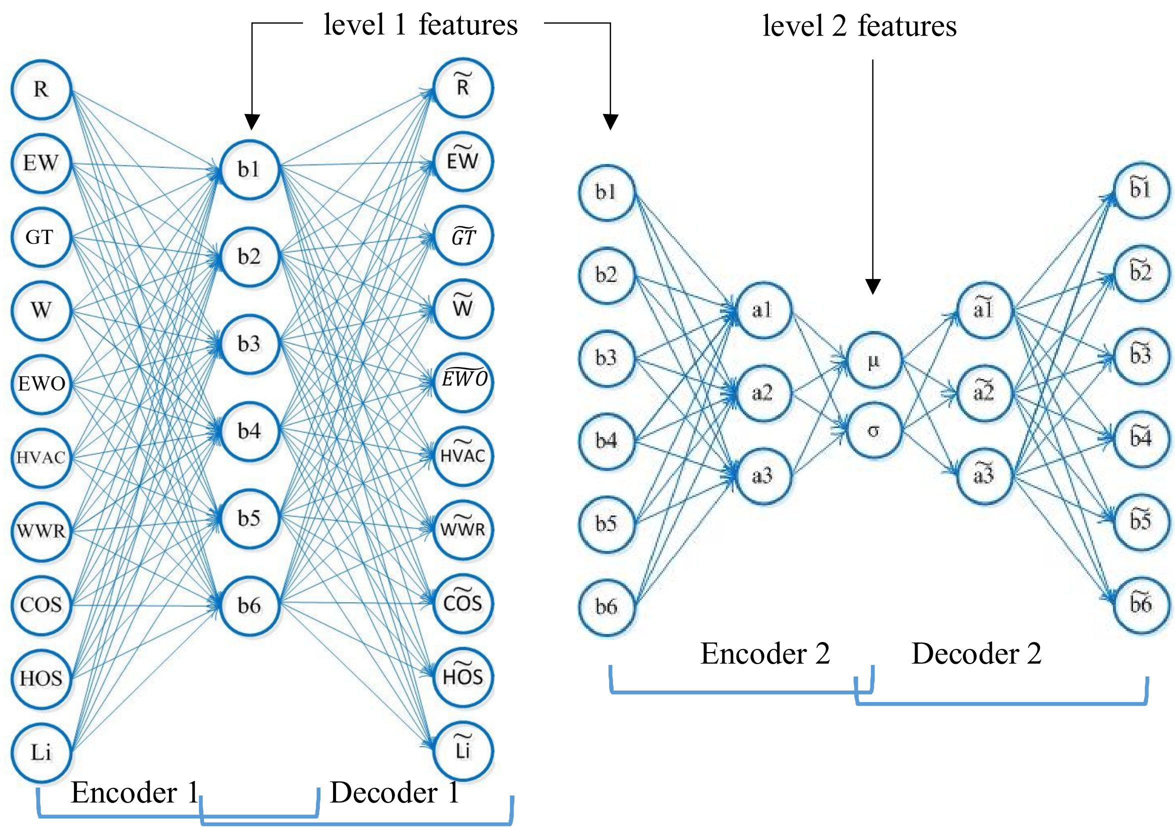


Figure 6-4. A schematic architecture of a dimensionality reduction VAE deep NN.

VAEs 0 and 1: Unsupervised learning method is selected for VAE-0, which is the capability of the VAE to regenerate both training and test data with low MSE evaluation metric. As shown in Figure 6-5(a) and (b), the training process of VAE-0 is a two-step process. In the first step, which is called the "pre-training" process, all of the hidden layers are trained separately. Consequently, the weights derived from pre-training and training are used to complete the network through a process called "fine-tuning".

In pre-training step, VAE-0 maps the original input to itself via the hidden layer "b_i", which is called *level 1 features* as shown in Figure 6-5(a). The second VAE takes the output of the hidden layer "b_i" from the first VAE and then maps the data to itself via three hidden layers (i.e., a_i, *level 2 features*, and $\tilde{a}_i$) as shown in Figure 6-5(b). Once all the hidden layers are pre-trained for the two VAEs, they are stacked together to form VAE-0 which is then fine-tuned using Averaged Stochastic Gradient Descent (ASGD) procedure. As mentioned in Section 2.10.2, fine-tuning is an important forward and backward propagation that improves the accuracy of a large and deep network (Ranzato, 2009). The first unsupervised VAE in this architecture is shown in Figure 6-5(a). The input of the first VAE is a comprehensive dataset of renovation scenarios. The input of the second VAE are the features extracted (features *b1* to *b6*) from the first step as illustrated in Figure 6-5(b). This architecture (VAE-0) has been used as a dimensionality reduction approach as shown in Figure 6-5(a) and (b). The unsupervised VAE-0 has no constraints in terms of labels, i.e., it is not possible to control the generated samples in terms of TEC or LCC. In other words, the generated samples from VAE-0 can have any TEC or LCC, so-called unconstrained generation as described in Table 6-1.



(a) First VAE (b) Second VAE

Figure 6-5. Unsupervised VAE-0 architecture (Unconstrained Generation).

For VAE-1, a semi-supervised learning method, which needs labeled data, is selected. This is implemented by adding neurons in a layer towards the end of the encoder, where VAE-0 learns from labeled data representing TEC and LCC, as shown in Figure 6-6. The labeled data is generated using the SBMO model from our previous study (Sharif and Hammad 2018), which improves the accuracy of the network as a semi-supervised network. In order to do so, a separate set of data is developed for each sample in the dataset and it is concatenated to the decoder layer's input, so that the decoder can use it internally. VAE-1 first computes the mean value (μ) and variance value (σ) for each feature in the dataset (as explained in Section 2.10.2). Subsequently, the proposed model merges these values with new input neurons including TEC and LCC data, and concatenates them to all features in the dataset, yielding one layer. Then the encoder layer distributed over all features and returns a single value for each of them. This layer could be inserted anywhere in the decoder, but we have found it best to insert it towards the input of the decoder network (Karras 2018). VAE-1 is retrained and fine-tuned using the labeled data. VAE-1 learns the inner data structure by discovering unlabeled data and utilizes labeled data for fine-tuning, better discrimination and accurate classification. Therefore, the use of unlabeled and labeled data for semi-supervised training can be considered as an advantage of this method over traditional VAE.

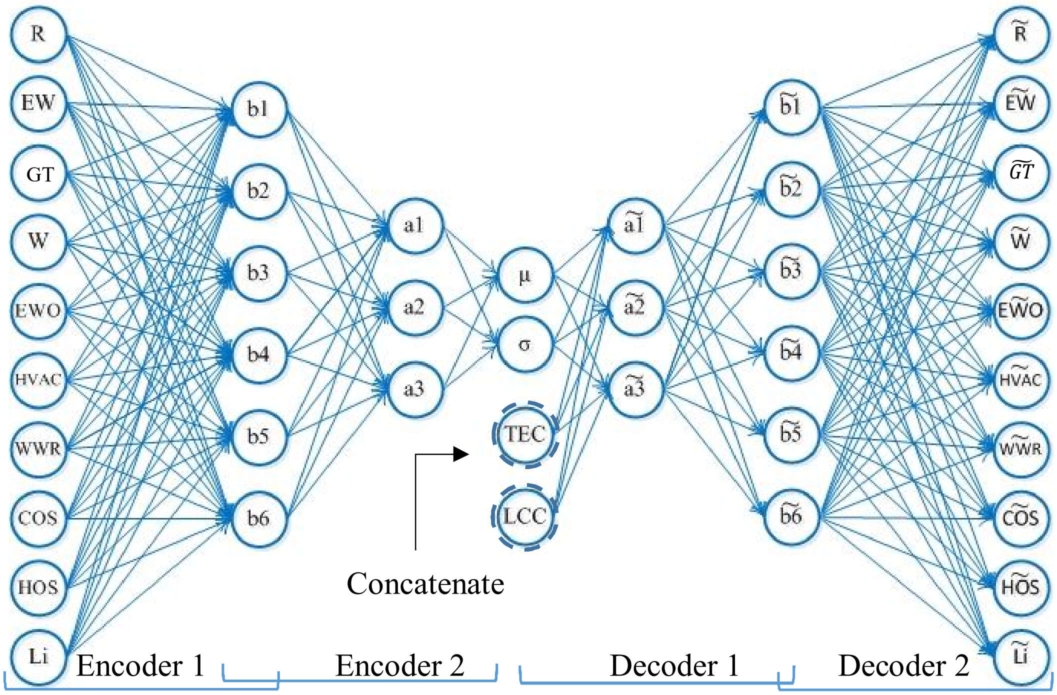


Figure 6-6. The overall semi-supervised VAE-1 deep NN architecture.

VAE-2: In this architecture (Figure 6-7), encoders are excluded since the regeneration of input data is necessary. The trained VAE-2 is capable of feature extraction considering TEC. Therefore, after validation of the VAE-2, the proposed MLM can be utilized as a generative model. This semi-supervised VAE-2 architecture has the ability of generating renovation scenarios considering the desired TEC.

VAE-3: Similar to VAE-2, after training and fine-tuning the overall VAE-1 model, the generative model can be developed by removing the encoder deep network. The LCC labeled dataset is concatenated to the model, so that the decoder can use it internally. The proposed VAE-3 is capable of generating renovation scenarios considering LCC, as shown in Figure 6-8.

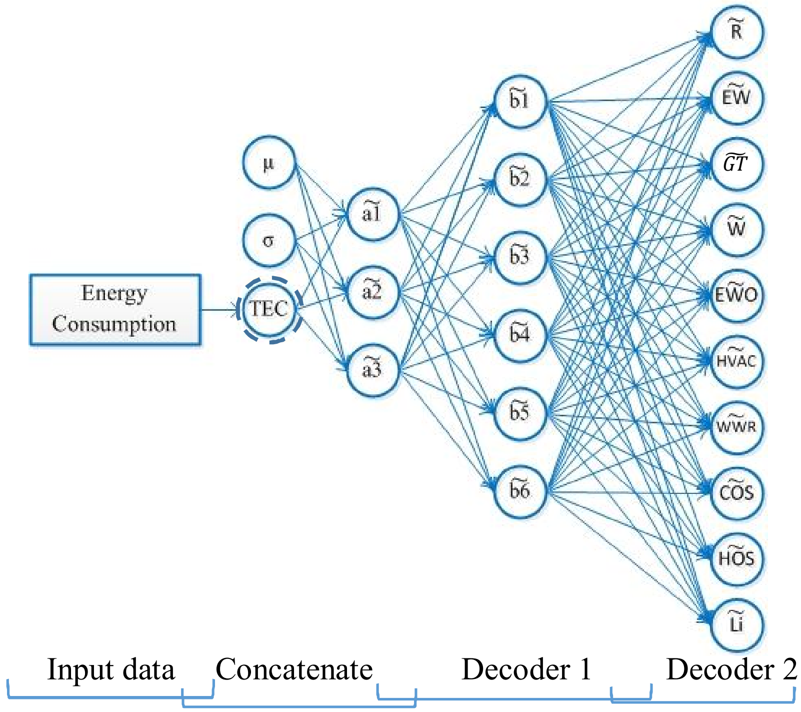


Figure 6-7. Generative VAE-2 considering energy consumption.

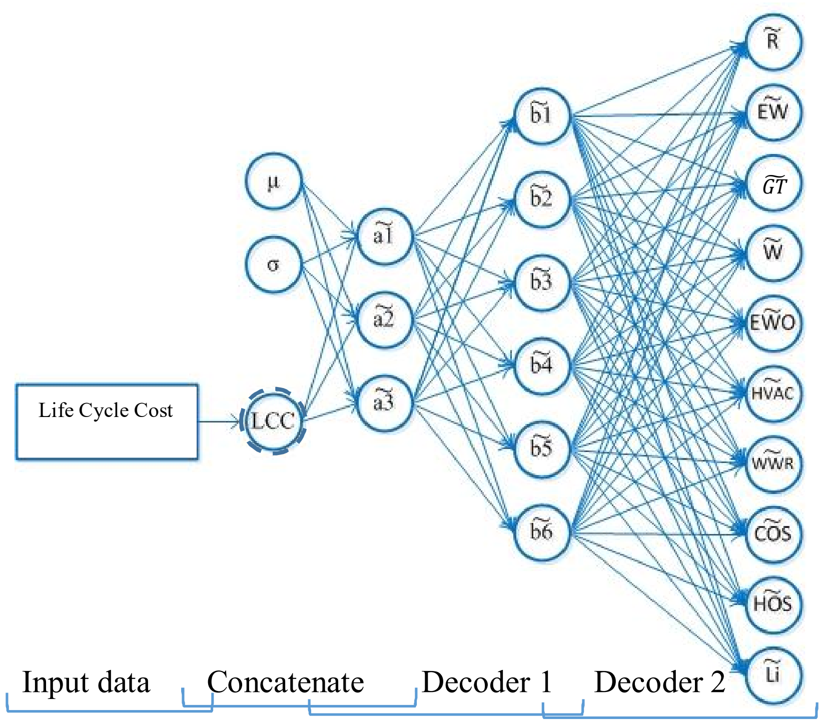


Figure 6-8. Generative VAE-3 considering renovation LCC.

6.2.2 Evaluation Metrics

There are different metrics to assess models' performance (Ahmad et al. 2017; Gallagher et al. 2018; Zhao 2011). In this study, the reconstruction error measured by MSE (Eq. 5.1) is selected for training validation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \qquad \text{Eq. 5.1}$$

where n is the number of data, y_i, and $\tilde{y}_i$ are the actual value and the predicted value for training and test dataset, for the ith experiment, respectively.

6.3 Implementation and Case Study

The goal is to generate new renovation scenarios, constrained by TEC and LCC. Therefore, VAE-1 is trained to constraint VAE-0, by adding our desired outcomes (labeled data) to the bottleneck of VAE-0. VAE-1 generates new renovation scenarios considering both TEC and LCC. In addition, VAE-2 and VAE-3 are proposed based on VAE-1, by adding TEC or LCC to the bottleneck of the VAE-1, respectively. A comprehensive dataset including 3097 samples has been used to train, validate, and test the VAE models. Each sample has 20 parameters. As explained in Section 3.4, the number of neurons in the layers can be different and it is only possible to find the correct number through trial-and-error in order to maximize a desired outcome. In this study initially a group of 34 parameters has been developed and different combination of parameters have been tested considering MSE metric.

Different algorithms have been tested regarding the convergence speed, overfitting problem, and generalization capability of the model. All models were trained and tested using PyTorch (Adam et al. 2017) on an Intel Core i7 with 16 GB of RAM. The optimization was carried by ASGD optimizer with a learning rate of 0.001. ASGD has good convergence speed for a large number of features while improving the generalization of VAEs and preventing over fitting. ReLU activations are used in encoder and decoder networks.

6.3.1 Description of Case Study Building Characteristics

The proposed methodology is applied to analyze the data retrieved from a multipurpose 5-story institutional building, which is explained in Section 4.3. A sample of the input data that summarizes the building characteristics is provided in Table 4-4.

The energy consumption data recorded in 2014-2015 are used for analysis. Different parameters of the building have been collected and can be generally categorized into five types as explained in Section 3.3: (1) Energy and cost variables; (2) weather conditions; (3) operating parameters; (4) Building envelope characteristics; (5) Building system parameters. These databases have been used to create a comprehensive BEM as a baseline model for calibration and comparison of results. Further information about the case study building is available in Section 4.3.

6.3.2 Identification of Intrinsic Parameters in VAE

Different variables related to the building characteristics have been collected to develop a database for SBMO. Among all various types of parameters (34 parameters), i.e., R [U_{roof}, R_{roof}, T_{roof}, C^{m}_{roof}, and C_{roof}], EW [U_{wall}, R^{s}_{wall}, h_{wall}, T_{wall}, and C_{wall}], GT [$U_{glazing}$, $L^{t}_{glazing}$, $SHGC_{glazing}$, $DST_{glazing}$, and $C_{glazing}$], W [U_{window}, R^{l}_{window}, C^{m}_{window}, and C_{window}], EWO [EWO], $HVAC$ systems [E^{aux}_{hvac}, H^{CoP}_{hvac}, C^{CoP}_{hvac}, Pr_{hvac}, C_{hvac}, C^{cool}_{hvac}, and C^{heat}_{hvac}], WWR [WWR], COS [COS], HOS [HOS], and Li [$NPD_{lighting}$, $Rf_{lighting}$, $PD_{lighting}$, and $C_{lighting}$] some have discrite values and the others have continuous values (as described in the Appendices B1-7). Other factors such as the occupancy features, DHW, and equipment have been modeled in the BEM, but they remain constant for SBMO and VAE models. Detailed list of variable and fixed values for each parameter is presented in Appendices B (1-7).

As explained in Section 6.2.1, a comprehensive dataset of renovation scenarios including different combinations of 20 parameters from all variable values (i.e., U_{roof}, C_{roof}, U_{wall}, T_{wall}, C_{wall}, U_{window}, R^{l}_{window}, C^{m}_{window}, C_{window}, $U_{glazing}$, $L^{t}_{glazing}$, $SHGC_{glazing}$, WWR, E^{aux}_{hvac}, C_{hvac}, COS, HOS, $NPD_{lighting}$, $C_{lighting}$, and EWO) are created. Subsequently, for each renovation scenario, TEC and LCC values obtained from the SBMO are added to the dataset.

In VAE-1, 22 parameters including 20 parameters and two concatenated features (i.e., TEC and LCC) have been used to regenerate the representation of 20 parameters. In the second and third architectures, TEC or LCC have been used to regenerate the representation of 20 parameters, respectively. Table 6-1 shows the input parameters in different architectures.

6.4 Results and Discussion

In this study, two VAEs were defined for each architecture. The VAE models, which generate the best training validation (i.e., MSE) are maintained. Initially a five-layer VAE was defined with 20 neurons in the encoder input layer, three hidden layers, and 20 neurons in the decoder output layer.

Then a three-layer VAE was defined with 20 neurons in the encoder input layer, only one hidden layer, and 20 neurons in the decoder output layer. It was found that the VAEs with three hidden layers have best performance. Generally, increasing the number of samples in a dataset improved the accuracy.

Each network was trained, tested, and validated using different samples and the best combination was selected for each architecture considering MSE. An increase in the amount of validation error is the indicator of overfitting. In this case, the backpropagation should be stopped. The training steps in VAEs are repeated many times for each architecture and the result with least validation error is reported in Table 6-2.

Different configurations of VAEs 1, 2 and 3 have been reported in Table 6-2 and the results of VAE-1 are investigated in this study. For training validation, MSE has been calculated (Eq. 5.1) and reported in Table 6-2. Convergence for the training is achieved if MSE is stabilized over certain iterations or if the maximum number of epochs is reached. The majority of these difference values are in the range of MSE=0.33 to 0.42, which is acceptable.

For validation of results, a comparison between the results of DesignBuilder as BEM and the output of the trained VAEs has been done, and an overall good agreement has been observed. Table 6-2 shows that the validation results have a confidence interval of 70-90%. For each VAEs about 10 different scenarios have been tested and the minimum and maximum accuracy have been reported in the last column of Table 6-2. In order to avoid repetition, the results of VAE-1 has been reported in Section 6.4.1.

These percentages are calculated for TEC and LCC results of each renovation scenario, by dividing the difference between VAE and BEM by the VAE results, respectively. The result shows that the networks have not committed underfitting. Validation of results for VAE-0 is not applicable because this architecture is unsupervised.

The results showed some interesting behaviors of the proposed models. Firstly, the approximation accuracy of different VAEs is high, as shown in Table 6-2. This is due to the generalization capability of the VAE. Secondly, overfitting should be considered if the loss function remains steady for a period of time or if the loss function has a value very close to zero. Finally, if the input parameters have higher levels of difference, the model has better capability for prediction. Using more parameters for training and testing was beneficial to avoid the loss of information problem. Furthermore, the computational time saving associated with the proposed VAEs is significant, and it is fair to say that the proposed model is feasible. The proposed VAEs can provide results in less than 1 second.

6.4.1 Results and Error Analysis for VAE-1

The proposed VAE-1 provides the best performance in the generation of the building renovation scenarios considering TEC and LCC simultaneously. Figure 6-9 shows a graphical representation of the performance of the model (VAE-1). In relative terms, the VAE-1 validation results have a confidence interval of 75-88% of the values calculated by the BEM, as shown in Table 6-2.

A sample generation using the VAE-1 and its validation results for one scenario is given in Tables 6-3 and 6-4, which is shown as "A" in Figure 6-10. In order to validate of the results for each generated parameter, the value of the selected parameter with the least difference from the original list of parameters (Appendices B1-7) has been selected and reported in the selected building element(s) column in Table 6-3. Then a list of selected building element(s) has been developed and uploaded into the BEM model. Finally, TEC and LCC associated with the list have been computed. Table 6-3 shows the difference between one generated scenario *A* and the BEM results. The MSE value for scenario *A* is 0.33. This level of confidence is in line with calculations based on BEM model, as shown in Table 6-3. The errors between generated scenario and BEM calculation for TEC and LCC, are relatively small when compared to the magnitude of the values (i.e., for TEC (5%) from 250 to 223 [MWh/yr.] and for LCC (8%) from $4 M to $3.7 M).

This agreement can be better quantified by investigating the difference between the BEM and VAEs results. Nine different results are shown in Figure 6-10. It is important to mention that the case study building has specific features and boundaries regarding its characteristics; therefore, the generated scenarios should be selected from specific ranges of TEC and LCC. The results show that VAE-1 is capable to generate renovation scenarios for the case study building. However, the generated results do not exhibit a clear pattern, which is due to the nature of the generative model. The majority of the values for TEC and LCC are in the ranges of 220 to 280 [MWh/yr.] and $3.6 M to $3.7 M, respectively.

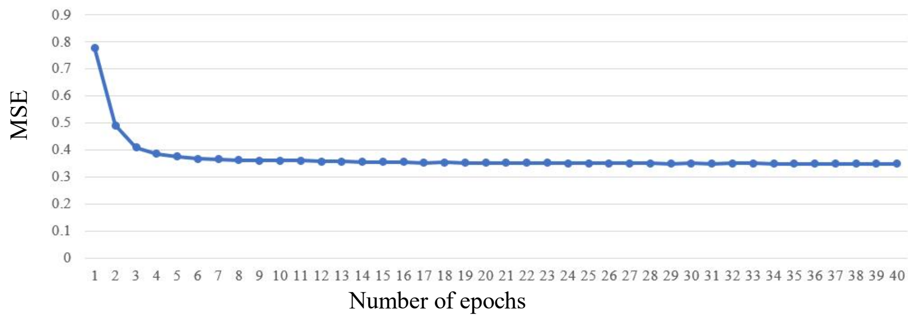


Figure 6-9. The performance of VAE-1 training (MSE).

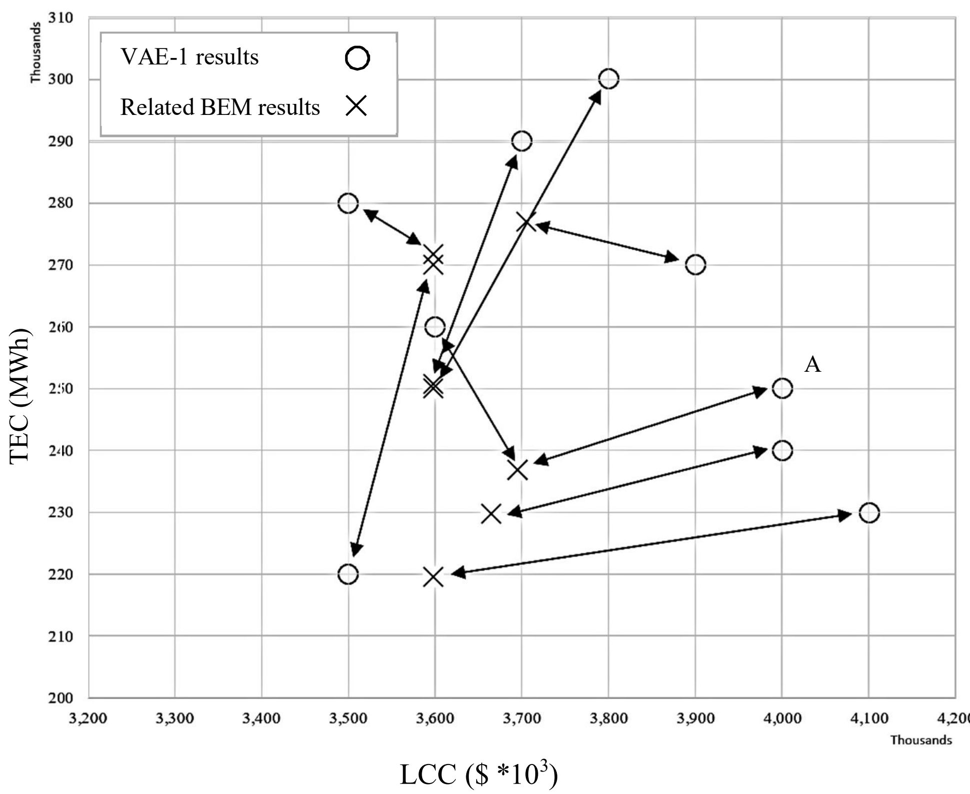


Figure 6-10. Validation of the results (VAE-1 and BEM).

Table 6-2. Performance evaluation between proposed VAEs and BEM.

ID	Description	Input	Output	Parameters	MSE	Difference with BEM results
VAE-0	Unsupervised Multi-variable	*R, EW, GT, W, EWO, HVAC, WWR, COS, HOS,* and *Li*	$\tilde{R}$, $\widetilde{EW}$, $\widetilde{GT}$, $\widetilde{W}$, $\widetilde{EWO}$ $\widetilde{HVAC}$, $\widetilde{WWR}$, $\widetilde{COS}$, $\widetilde{HOS}$, and $\widetilde{Li}$	*f*= ReLU; Opt.= ASGD; Encoder NoL=3; Decoder NoL=3; lr= 0.001; epoch= 40	0.2	--
				f= ReLU; Opt.= ASGD; Encoder NoL=1; Decoder NoL=1; lr= 0.001; epoch= 100	0.38	
VAE-1	Semi-supervised Multi-Variable	***In Training Phase***: *R, EW, GT, W, EWO, HVAC, WWR, COS, HOS,* and *Li* ***In Testing Phase***: *R*, *EW*, *GT*, *W*, *EWO*, *HVAC*, *WWR*, *COS*, *HOS*, *Li, TEC,* and *LCC*		*f*= ReLU; Opt.= ASGD; Encoder NoL=3; Decoder NoL=3; lr= 0.001; epoch= 40	0.33	0.75-0.88
				f= ReLU; Opt.= ASGD; Encoder NoL=1; Decoder NoL=1; lr= 0.001; epoch= 70	0.35	
VAE-2	Semi-supervised, Single-Variable	TEC		*f*= ReLU; Opt.= ASGD; Encoder NoL=3; Decoder NoL=3; lr= 0.001; epoch= 40	0.33	0.70-0.90
				f= ReLU; Opt.= ASGD; Encoder NoL=1; Decoder NoL=1; lr= 0.001; epoch= 70	0.40	
VAE-3	Semi-supervised, Single-Variable	LCC		*f*= ReLU; Opt.= ASGD; Encoder NoL=3; Decoder NoL=3; lr= 0.001; epoch= 40	0.35	0.75-0.85
				f= ReLU; Opt.= ASGD; Encoder NoL=1; Decoder NoL=1; lr= 0.001; epoch= 50	0.42	

Activation function (f), Optimizer (opt.), Number of Layers (NoL), Learning rate (lr), Total Energy Consumption (TEC), Life Cycle Cost (LCC),Roof Types (R), External Walls (EW), windows (W), Glazing Type (GT), Window to Wall Ratio (WWR), HVAC systems, Cooling Operation Schedule (COS), Heating Operation Schedule (HOS), Lighting systems (Li), and External Window Open (EWO), Regeneration of R, EW, GT, W, EWO, HVAC, WWR, COS, HOS, and Li are $\tilde{R}$, $\widetilde{EW}$, $\widetilde{GT}$, $\widetilde{W}$, $\widetilde{EWO}$, $\widetilde{HVAC}$, $\widetilde{WWR}$, $\widetilde{COS}$, $\widetilde{HOS}$, and $\widetilde{Li}$, respectively.

Table 6-3. A sample generation using VAE-1 (Scenario A).

Building Elements	Parameters	Unit	Generated Parameters	Selected Parameter Value	Selected Building Element(s)
Flat roof construction (R)	U_{roof}	W/ (m^2 K)	0.81	1.18	Roof, insulation entirely above deck
	C_{roof}	\$/m^2	151.2	140.23	
External wall construction (EW)	U_{wall}	W/ (m^2 K)	0.59	0.57	Brick air heavy weight concrete block and full mineral insulation and low weight plaster
	T_{wall}	m	0.27	0.27	
	C_{wall}	\$/m^2	211.7	218.13	
Window frame type (W)	U_{window}	W/ (m^2 K)	4.29	3.64	1. Wooden window frame 2. Painted Wooden window frame
	R^{l}_{window}	m^{2}K/W	0.32	0.27	
	C^{m}_{window}	KJ/m^{2}K	20.85	33.46	
	C_{window}	\$/m^2	34.8	62.32	
Glazing Type (GT)	$U_{glazing}$	W/ (m^2 K)	2.45	2.71	Dbl Blue 6 mm/13 mm Air
	$L^{t}_{glazing}$	-	0.52	0.51	
	$SHGC_{glazing}$	-	0.47	0.48	
Window to Wall ratio (WWR)	WWR	%	50	50	50
HVAC template (HVAC)	E^{aux}_{hvac}	kWh/m^2	25.05	30	Fan Coil Units (4-Pipe), Water-cooled Chiller, Water-side economizer
	C_{hvac}	\$/m2 GIFA	181.8	220	
Cooling operation schedule (COS)	COS	-	110.4	110	7:00 - 23:00 Mon - Fri
Heating operation schedule (HOS)	HOS	-	390.3	400	Max Outdoor temp for natural ventilation: Always 100
Lighting template (Li)	$NPD_{lighting}$	W/m^2·100lux	3.82	3.8	T8 (25 mm diam) Fluorescent, halophosphate, high-frequency control
	$C_{lighting}$	\$/m^2	101.54	93.50	
External window opens (EWO)	EWO	%	32.35	32	32

Table 6-4. The comparison of the results from VAE-1 and BEM (Scenario A).

Parameter		Input	BEM	Difference	MSE
Total Energy Consumption	$TEC\ (kWh)$	250,000	236,790	+5%	**0.33**
Life Cycle Cost	LCC (\$)	4,000,000	3,695,244	-8%	

6.5 Summary and Conclusions

Although research on MLMs for BEM is a rapidly growing area of study, the development of many innovative and powerful deep MLMs may bring new choices or even breakthroughs in building energy prediction. Therefore, it is important to have appropriate models and datasets available for the renovation stage to assist decision-makers in finding efficient scenarios. Furthermore, building energy renovation is affected by the uncertainty and complexity of the influencing parameters; therefore, generative renovation models for this application face issues such as accuracy, computational cost, robustness, and ease of use.

This Chapter proposes a generative deep learning building energy model using VAEs, which could potentially overcome the current limitations. A dimensionality reduction semi-supervised VAE is proposed to develop the network architecture. This type of VAEs performs very well and can extract features of the data and identify relationships within the data, which leads to an efficient network. The model generates different renovation scenarios for building envelope, HVAC, and lighting system considering TEC and LCC. First, unsupervised VAE-0 has been exploited as a basic model prior on the developments of the final models. Then, three different semi-supervised VAE architectures have been developed that can learn from a labeled dataset with very fast inference processes. The results show that generative VAEs 1, 2, and 3 can learn approximations of input features and deploy as generative models.

The performance of the proposed methods has been demonstrated using a simulated renovation dataset, and their applications for building energy renovation have been proven (i.e., dimensionality reduction, semi-supervised classification, and generative modeling). The majority of training validations are in the range of MSE=0.33 to 0.42. Furthermore, the VAEs validation results have a confidence interval of 70-90% of the values calculated by the BEM model as given in Table 6-2.

The proposed models can be used by the building industry for generating renovation scenarios and reducing TEC and LCC through renovation. Architects and engineers can check the effects of different materials, HVAC systems, etc., on the energy consumption, and make necessary changes in order to increase the energy efficiency of the building.

CHAPTER 7. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

7.1 Summary of Research

This research aims to optimize energy performance of whole building renovation considering LCC and LCA. The particular focus of this research was placed on:

Module 1: Developing SBMO model of institutional building renovation considering TEC, LCC and LCA. The proposed model initially develops a framework for data collection and preparation to define the renovation strategies and proposes a comprehensive database including different renovation methods. Using this database, different renovation scenarios can be compared to find the near-optimal scenario based on the renovation strategy. Each scenario is created from the combination of several methods within the applicable strategy. The methods include the factors related to the building envelope, HVAC, and lighting system. The SBMO model simulates the process of renovating buildings by using the renovation data in energy analysis software to analyze TEC, LCC, and LCA and identifies the near-optimal renovation scenarios based on the selected renovation methods. Furthermore, an LCA tool is used to evaluate the environmental sustainability of the final decision.

A case study of one floor of an existing building was studied to assess the implementation of the developed model. LCA and TEC have strong linear correlation in comparison with the LCC and TEC. It is worthy to mention that the optimization in the first case has a larger number of Pareto solutions because energy consumption and LCC are conflicting objectives. Comparing the ratio of LCC per TEC for the Pareto solutions clarifies their efficiency. This comparison demonstrates that there is a better potential in reducing TEC in Scenario B than in Scenario A since with a slight increase in LCC, significant decrease in TEC is attained. Furthermore, the energy saving improvement from scenario A to B is 24,325 kWh/year, which is significant.

Module 2: Developing surrogate ANN for selecting near-optimal building energy renovation methods considering energy consumption, LCC, and LCA. The proposed model can be used to predict TEC, LCC and LCA of the potential renovation scenarios of existing institutional buildings. The proposed model couples the optimization power of SBMO with modeling capability of ANNs. In the first phase, the optimization process, coupled with the SBMO, forecasts the building TEC, LCC, and LCA pairwise. Then, two different ANNs were developed to predict and model TEC, LCC, and LCA of renovating combinations of elements of an existing institutional building (i.e., *R, EW, W, FT, WWR, HVAC, COS, HOS, Li*, and *EWO*). To do so, initially five-layer ANNs were defined with ten neurons in the input layer, three neurons in the hidden layers, and two neurons in the output layer. Then a cross-validation method was used to reach the optimal values. It was found that in this model, the higher number of layers and neurons significantly improves the accuracy of the ANN. Finally, a five-layer ANN was defined with 10-5-6-4-2 neurons in input, hidden (three layers), and output layers.

The case study was implemented based on the results of the SBMO. Different ANNs are generated in MATLAB® by using the outcomes of DesignBuilder energy simulations for network training and testing. The regressions between the ANN predictions and target SBMO outputs plots show an acceptable agreement between the predictions and the SBMO, with regression coefficients close to 1.

Module 3: Developing a generative deep MLM for whole building renovation scenarios using semi-supervised VAE. The model can generate different renovation scenarios for building envelope, HVAC, and lighting system considering TEC and LCC. First, unsupervised VAE-0 has been exploited as a basic model prior on the developments of the final models. Then, three different semi-supervised VAE architectures have been developed that can learn from a labeled dataset with very fast inference processes.

Two VAEs were defined for each architecture. The VAE models, which generate the best training validation (i.e., MSE) are maintained. Initially a five-layer VAE was defined with 20 neurons in the encoder input layer, three hidden layers, and 20 neurons in the decoder output layer. Then a three-layer VAE was defined with 20 neurons in the encoder input layer, only one hidden layer, and 20 neurons in the decoder output layer. It was found that the VAEs with three hidden layers have best performance. Generally, increasing the number of samples in a dataset improved the accuracy.

Different configurations of VAEs 1, 2 and 3 have been studied. Convergence for the training is achieved if MSE is stabilized over certain iterations or if the maximum number of epochs is reached. Each network was trained, tested, and validated using different samples and the best combination was selected for each architecture considering MSE. An increase in the amount of validation error is the indicator of overfitting. In this case, the backpropagation should be stopped. The training steps in VAEs are repeated many times for each architecture and the result with least validation error is reported in Table 6-2.

For validation of results, a comparison between the results of DesignBuilder as BEM and the output of the trained VAEs has been done, and an overall good agreement has been observed. The result shows that the networks have not committed underfitting.

The results show that generative VAEs 1, 2, and 3 can learn approximations of input features and deploy as generative models. The results showed some interesting behaviors of the proposed models. Firstly, the approximation accuracy of different VAEs is high. This is due to the generalization capability of the VAE. Secondly, overfitting should be considered if the loss function remains steady for a period of time or if the loss function has a value very close to zero. Finally, if the input parameters have higher levels of difference, the model has better capability for prediction. Using more parameters for training and testing was beneficial to avoid the loss of information problem. Furthermore, the computational time saving associated with the proposed VAEs is significant, and it is fair to say that the proposed model is feasible. The proposed VAEs can provide results in less than 1 second.

Compared with traditional ANNs (Module 2), VAEs can be used for different proposes (i.e., dimensionality reduction, feature extraction, and feature generation) and adjust numbers of neurons and layers to fit for different labeled datasets. Furthermore, learning from large-scale labeled datasets based on DNN is efficient and suitable for generalization.

7.2 Contributions and Conclusions

This research made the following contributions to the body of knowledge:

(1) The proposed SBMO model encourages the selection of sustainable materials and components to decrease TEC, LCC, and negative environmental impacts considering LCA. Significant savings in buildings' energy consumption and having more environmentally friendly buildings within the predefined renovation budget are the ultimate results of the practical implementation of this part of the research. Considering this contribution, the following conclusions can be drawn:

- The proposed integrated renovation approach was practical for defining the renovation strategies based on the different scenarios of building renovation methods and appropriate coupling of methods while avoiding undesirable side effects.

- The developed SBMO can be used to identify the near-optimal renovation scenarios based on the available methods.

(2) An accurate surrogate MLM was developed to predict the TEC, LCC, and LCA using data from Module 1. The developed ANNs significantly decreased the computational time and effort while achieving acceptable accuracy. The developed ANNs were able to capture the inner data structure considering input renovation parameters and outputs, i.e., TEC vs. LCC and TEC vs. LCA. Based on the case study that verified the accuracy of the proposed ANNs, the following conclusions are drawn:

- The ANNs provide satisfactory approximation to the SBMO, with the MSE for TEC vs. LCC and TEC vs. LCA of 0.016 and 0.056, respectively.
- Simulations were performed for the SBMO model with the total time of 170 hours to generate about 5000 renovation scenarios. The total computation time for training and testing the ANNs was about 150 seconds using a dataset of 463 renovation scenarios. It is worthy to mention that each simulation takes about 180 seconds using the SBMO model. The applicability of the ANNs were tested by different sets of renovation scenarios. It was found that the ANNs can provide accurate results in less than 1 second.

(3) A novel generative deep MLM was developed that uses the generative power of VAEs. A dimensionality reduction semi-supervised VAE is proposed to develop the network architecture. This type of VAEs performs very well and can extract features of the data and identify relationships within the data, which leads to an efficient network. With regard to this contribution, the following conclusions are made:

- The performance of the proposed methods has been demonstrated using a simulated renovation dataset, and their applications for building energy renovation have been proven (i.e., dimensionality reduction, semi-supervised classification, and generative modeling).
- The majority of training validations are in the range of MSE=0.33 to 0.42. Furthermore, the VAEs validation results have a confidence interval of 70-90% of the values calculated by the BEM.

Overall, the proposed MLMs can work as part of BEM to select renovation methods for different renovation scenarios; thereby making a significant decrease in computational time and efforts while achieving acceptable accuracy.

The proposed VAEs can be used as a pre-trained model on new building datasets. In more detail, instead of training VAEs from the scratch to generate renovation scenario for another types of building, trained VAEs can be used to perform fine-tuning or transfer-learning. Therefore, VAEs can be fine-tuned using their properly trained weights for another building application that leads to enhance the accuracy and generalization capability of the generative models.

Furthermore, architects and engineers can check the effects of different materials, HVAC systems, etc., on the energy consumption, and make necessary changes in order to increase the energy efficiency of their buildings. Finally, these models can also be used by owners to receive more governmental incentives for energy renovation projects. They will have the tools to predict the near-optimal renovation scenarios that will help in better planning and minimizing the negative impacts on the surrounding environment.

7.3 Limitations and Future Work

Although this research has successfully addressed its objectives, the following limitations and challenges have been faced during various phases of the research:

Module 1:

From the point of view of the tools used in this research, DesignBuilder and ATHENA do not capture all aspects of renovation projects. There is a difference between these tools, due to differences in methods, databases, and reporting formats. For instance, the impact of the components that have been removed in the renovation process is not included in the calculation. Therefore, the future efforts can be dedicated to avoiding inconsistency problem by developing another software.

Lack of data is also an important problem that makes the model development process more challenging. The availability of BIM with higher levels of detail would improve the accuracy of the SBMO model. Despite these limitations, the SBMO model developed in this study remains accurate (as explained in Section 4.3.5). One feasible way to gather more accurate data is using sensors data.

Module 2:

The developed ANNs, as presented in Chapter 5, do not have the generalization capability due to the number of hidden layers and number of samples in the datasets as explained below.

The complexity of an ANN model is determined by the number of hidden layers. To minimize the training dataset error, the number of hidden layer neurons should be increased, which, as a result, will compromise the generalization ability of the ANN. However, an increase in the number of neurons in hidden layers may result in overfitting/overtraining problem. In this case, the generalization accuracy of ANNs may be impaired because of fitting some *noise* in the dataset. Concurrently, another problem that also effects the ANNs performance is the underfitting, which occurs in shallow ANNs with too few neurons in hidden layers. Underfitting can result in large errors in the ANN (Ahmad et al. 2017).

Additionally, one dataset of an institutional building was used for training, testing and validation of the ANNs. Therefore, the trained ANNs are only suitable for similar buildings. The ANNs energy consumption results have 6.1% difference with the existing situation based on the energy bills. Future development involves training and fine-tuning of the ANNs for feature extraction and prediction, improving algorithms, and generalization. Including more buildings in the training is expected to significantly improve the ANNs prediction capability.

Module 3:

While the developed generative VAEs are fairly accurate and successful, further study is required in terms of the generalization of the models; therefore, the proposed VAEs will be trained, tested, and validated in more complex cases to improve their performance and generalization capability. Further development also involves considering more input parameters and using different deep learning algorithms (e.g., GAN).

Most of the limitations in deep MLM come from data gathering and dataset preparation, which significantly affects the final models. Therefore, more data for different buildings would enhance the accuracy and generalization of the generative models. Furthermore, more data about the building's characteristics could be used to improve the MLMs and would also help the MLMs to provide more detailed recommendations for renovation.

Also, this study has used annual data related to TEC, energy bills, and weather conditions for the simulation of the ES, which does not capture the seasonal fluctuation in energy consumption. One solution would be to consider sensors data for indoor energy consumption and seasonal weather data for buildings throughout the year.

Other potential future work respecting proposed modules:

The developed MLMs improves the computational capabilities and the accuracy of BEMs to work at the urban level, which is critical for developing interactive and real-time Urban Building Energy Model (UBEM) especially in a dense urban area. Furthermore, current UBEMs are limited in their ability to fully consider detailed buildings energy performance and inter-building energy influences at urban level, which have a considerable impact on urban energy prediction.

The results of this research could be used to develop an automated UBEM to accurately generate renovation scenarios at urban scales, which is very beneficial, especially where data analysis is very time consuming or data is missing or difficult to evaluate. Another key benefit of this study is using deep learning techniques as a valuable tool for Big Data mining that is utilized to automatically extract, learn, and analysis large volumes of raw data.

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APPENDICES

Appendix A: VAEs Input and Output Parameters

Layer	Parameter	ID	Node	Unit
Input	Flat roof construction (R)	1. U_{roof}	U-Value	W/ (m^2 K)
		2. R_{roof}	R-Value	(m^2 K)/W
		3. T_{roof}	Thickness	m
		4. C^{m}_{roof}	Km - Internal heat capacity	KJ/m^{2}K
		5. C_{roof}	Cost per aria	\$/m^2
	External wall construction (EW)	6. U_{wall}	External wall U-Value	W/ (m^2 K)
		7. R^{s}_{wall}	Surface resistance	(m^2 K)/W
		8. h_{wall}	Convective heat transfer coefficient	W/ (m^2 K)
		9. T_{wall}	Thickness	m
		10. C_{wall}	Cost per area	\$/m^2
	Window frame type (W)	11. U_{window}	U-Value	W/ (m^2 K)
		12. R^{l}_{window}	Upper/Lower Resistance Limit	m^{2}K/W
		13. C^{m}_{window}	Km - Internal heat capacity	KJ/m^{2}K
		14. C_{window}	Cost per surface area	\$/m^2
	Glazing Type (GT)	15. $U_{glazing}$	U-Value	W/ (m^2 K)
		16. $L^{t}_{glazing}$	Light transmission	
		17. $SHGC_{glazing}$	Total solar transmission (SHGC)	-
		18. $DST_{glazing}$	Direct solar transmission	
		19. $C_{glazing}$	Cost	\$/m^2
	Window to Wall ratio (WWR)	20. WWR	Window to Wall %	%
	HVAC template (HVAC)	21. E^{aux}_{hvac}	Auxiliary energy	kWh/m^2
		22. H^{CoP}_{hvac}	Heating system seasonal CoP	
		23. C^{CoP}_{hvac}	Cooling system seasonal CoP	
		24. Pr_{hvac}	Pressure rise	Pa
		25. C_{hvac}	Cost per area	\$/m2 GIFA
		26. C^{cool}_{hvac}	HVAC cost per cooling load	\$/kW
		27. C^{heat}_{hvac}	HVAC cost per heating load	\$/kW
	Cooling operation schedule (COS)	28. COS	Cooling operation schedule	-
	Heating operation schedule (HOS)	29. HOS	Heating operation schedule	-
	Lighting template (Li)	30. $NPD_{lighting}$	Normalized Power Density	W/m^2·100lux
		31. $Rf_{lighting}$	Radiant fraction	
		32. $PD_{lighting}$	Power Density	W/m^2
		33. $C_{lighting}$	Cost per area	\$/m^2
	External window opens (EWO)	34. EWO	% External window opens	%
Output	Life Cycle Cost	35. LCC	LCC (Present Value)	\$
	Total Energy Consumption	36. TEC	Total Energy Consumption	kWh

Appendix B-1: Flat Roof Construction Methods

Roof construction methods	U-Value	R-Value	Thickness	Km - Internal heat capacity	Cost
	U_{roof}	R_{roof}	T_{roof}	C^{m}_{roof}	C_{roof}
	[W/ (m² K)]	[(m² K)/W]	[m]	[KJ/m²K]	[$/m²]
19mm felt/bitumen on 25 mm EPS slab on 3mm steel	1.25	0.80	0.05	32.30	205.66
Combined flat roof - U - HW	2.1	0.47	0.32	129.00	280.45
Combined flat roof - U - MW weight	1.54	0.65	0.52	129.00	288.24
Flat roof - Energy code standard - HW	0.49	2.06	0.38	39.90	257.08
Flat roof - Energy code standard - LW	0.25	3.97	0.35	39.90	70.11
Flat roof - Energy code standard - MW	0.49	2.06	0.38	39.90	257.08
Flat roof - State-of-the-art - HW	0.49	2.06	0.38	39.90	257.08
Flat roof - State-of-the-art - LW	0.59	1.68	0.28	39.90	70.11
Flat roof - State-of-the-art - MW	0.49	2.06	0.38	39.90	257.08
Flat roof - Typical reference - HW	0.49	2.06	0.38	39.90	257.80
Flat roof - Typical reference - LW	0.25	3.97	0.35	39.90	70.11
Flat roof - Typical reference - MW	0.49	2.06	0.38	39.90	257.08
Flat roof - U - HW	1.55	0.65	0.33	39.90	249.29
Flat roof - U - MW	1.55	0.65	0.33	39.90	249.29
Roof - Part L 2013 Notional Building - Metal Cladding	0.18	5.58	0.24	3.35	54.53
Roof - Part L 2013 Notional Building - No Metal Cladding	0.18	5.66	0.40	8.75	121.53
Roof - Section 6 2015 Notional Building (Cooled / Mech Vented) - No Metal Cladding	0.15	6.54	0.44	8.75	121.53
Roof - Section 6 2015 Notional Building (Cooling / Mech Vent) - Metal Cladding	0.16	6.27	0.27	3.35	54.53
Roof - Section 6 2015 Notional Building (Heated / Nat Vent) No Metal Cladding	0.18	5.66	0.40	8.75	121.53
Roof - Section 6 2015 Notional Building (Heating / Nat Vent) - Metal Cladding	0.18	5.58	0.24	3.35	54.53
Roof sub-surface construction	4.73	0.21	0.10	176.40	327.19
Roof, Ins Entirely above Deck, R-1 (0.2), U-0.562 (3.191)	3.19	0.31	0.0163	31.8828	140.23
Roof, Ins Entirely above Deck, R-4 (0.7), U-0.209 (1.187)	1.19	0.84	0.0354	40.1549	140.23
Roof, Ins Entirely above Deck, R-9 (1.6), U-0.102 (0.579)	0.58	1.73	0.0672	42.2918	140.23
Flat roof U-value = 0.25 W/m2K	0.25	3.97	0.15	4.90	70.11

HW: Heavyweight; MW: Medium weight; LW: Lightweight; Nat Vent: Natural Ventilation; Ins: Insulation; U: Uninsulated

Appendix B-2: External Walls Construction Methods

External walls construction methods	U-Value U_{wall} [W/ (m² K)]	Surface resistance R^{s}_{wall} [(m² K)/W]	Convective heat transfer coefficient h_{wall} [W/ (m² K)]	Thickness T_{wall} [m]	Cost C_{wall} [\$/m²]
Brick air HW concrete block & full mineral Ins. & LW plaster	0.57	0.13	2.15	0.27	218.13
Brick cavity full mineral Ins. & LW plaster	0.54	0.13	2.15	0.27	272.66
Brick cavity with dense plaster	1.56	0.13	2.15	0.37	271.10
Brick cavity with mineral Ins. & LW plaster	0.74	0.13	2.15	0.40	278.89
Brick cavity with UF foam Ins. & LW plaster	0.85	0.13	2.15	0.25	264.87
Brick mineral Ins. thermolite block & LW plaster	0.40	0.13	2.15	0.32	202.55
Cavity wall (E&W) 1995 Part L	0.51	0.13	2.15	0.31	465.86
Cavity wall (E&W) 2002 Part L	0.35	0.13	2.15	0.34	476.77
Fully filled-50mm min. wool	0.53	0.13	2.15	0.29	465.86
Fully filled-75mm min. wool	0.41	0.13	2.15	0.31	465.86
LW concrete block air gap & plasterboard	0.71	0.13	2.15	0.24	216.57
LW concrete block grp Ins. & plasterboard	0.57	0.13	2.15	0.23	109.06
LW concrete block poly Ins. & plasterboard	0.46	0.13	2.15	0.24	148.02
LW concrete clad wall (Ins. to 1985 regs)	0.57	0.13	2.15	0.13	224.36
LW curtain wall (Ins. to 1995 regs)	0.35	0.13	2.15	0.10	241.50
LW curtain wall (Ins. to 2000 regs)	0.35	0.13	2.15	0.11	171.39
Semi-exposed wall State-of-the-art - MW	0.25	0.13	2.15	0.34	202.55
Standard wall construction (Ins. to 1995 regs)	0.50	0.13	2.15	0.27	202.55
Super Ins. brick/block external wall	0.16	0.13	2.15	0.43	202.55
Wall - Energy code standard - HW	0.35	0.13	2.15	0.29	202.55
Wall - Energy code standard - LW	0.35	0.13	2.15	0.11	171.39
Wall - Energy code standard - MW	0.35	0.13	2.15	0.29	202.55
Wall - Part L 2013 Notional Building - No Metal Cladding	0.26	0.13	2.152	0.25	163.60
Wall - Part L 2013 Reference Building	0.35	0.13	2.152	0.12	57.65
Wall - State-of-the-art - MW	0.25	0.13	2.15	0.34	202.55
Wall - Typical reference - HW	0.35	0.13	2.15	0.29	202.55
Wall - Typical reference - LW	0.35	0.13	2.15	0.11	171.39
Wall - Typical reference - MW	0.35	0.13	2.15	0.29	202.55
Wall, Mass, R-1.0 (0.18), U-0.367 (2.08)	2.08	0.12	2.79	0.22	132.44
Wall, Mass, R-10.0 (1.76), U-0.088 (0.50)	0.50	0.12	2.79	0.28	805.06
Wall, Mass, R-10.0 (1.76)	0.62	0.12	2.79	0.26	797.27
Wall, Mass, R-11.0 (1.94)	0.90	0.12	2.79	0.24	155.81
Wall, Mass, R-11.4 (2.01)	0.47	0.12	2.79	0.28	124.65
Wall, Mass, R-13.0 (2.29)	0.86	0.12	2.79	0.24	155.81

Wall, Mass, R-14.0 (2.46)	0.45	0.12	2.79	0.28	124.65
Wall, Mass, R-15.0 (2.64)	0.83	0.12	2.79	0.24	155.81
Wall, Mass, R-2.0 (0.35)	1.39	0.12	2.79	0.23	132.44
Wall, Mass, R-30.8 (5.42)	0.55	0.12	2.79	0.27	124.65
Wall, Mass, R-5.6 (0.99)	0.87	0.12	2.79	0.24	119.97
Wall, Mass, R-50.0 (8.80)	0.11	0.12	2.79	0.53	132.44
Wall, Mass, R-6.0 (1.06)	0.77	0.12	2.79	0.25	805.06
Wall, Steel-Framed, R-0 (0.0)	1.99	0.12	2.79	0.14	140.23
Wall, Steel-Framed, R-13+R-19c.i. (2.3+3.3c.i.)	0.21	0.12	2.79	0.21	179.18
Wall, Steel-Framed, R-15 (2.6),	0.67	0.12	2.79	0.09	155.81
Wall, Mass, R-17.0 (2.99)	0.30	0.12	2.79	0.32	132.44
Wall, Mass, R-30.8 (5.42)	0.57	0.12	2.79	0.26	155.81
Wall, Mass, R-11.0 (1.94)	0.46	0.12	2.79	0.278	805.06
Brick/block wall (Ins. to 1995 regs)	0.35	0.13	2.15	0.29	202.55

HW: Heavyweight; MW: Medium weight; LW: Lightweight; Ins: Insulation;

Appendix B-3: Window Frame Types

Window frame types	U-Value	Upper/Lower resistance limit	Km - Internal heat capacity	Cost
	U_{window}	R^{l}_{window}	C^{m}_{window}	C_{window}
	[W/ (m^2 K)]	[(m^2 K)/W]	[KJ/m^{2}K]	[\$/m^2]
Wooden window frame	3.63	0.28	33.46	70.00
Painted Wooden window frame	3.63	0.28	33.46	62.32
Aluminium window frame (no break)	5.88	0.17	12.32	124.65
Aluminium window frame (with thermal break)	4.72	0.21	11.18	130.88
UPVC window frame	3.47	0.29	25.02	6.2320

UPVC: Unplasticized polyvinyl chloride

Appendix B-4: Glazing Types

Glazing Types	U-Value	Light transmission	SHGC	Direct solar transmission	Cost
	$U_{glazing}$	$L^t_{glazing}$	$SHGC_{glazing}$	$DST_{glazing}$	$C_{glazing}$
	[W/ (m² K)]	[-]	[-]	[-]	[$/m²]
Dbl Blue 6 mm/13 mm Air	2.71	0.51	0.48	0.37	160
Dbl Bronze 3mm/13 mm Air	2.76	0.62	0.62	0.54	150
Dbl Clr Low Iron 3mm/6 mm Air	3.23	0.84	0.83	0.81	150
Dbl Ref-A-L Clr 6 mm/6 mm Air	2.76	0.07	0.14	0.05	160
Dbl Ref-A-L Tint 6 mm/13 mm Air	2.26	0.05	0.12	0.03	160
Dbl Ref-B-L Clr 6 mm/13 mm Air	2.46	0.18	0.21	0.12	160
Dbl Ref-C-H Clr 6 mm/6 mm Air	2.90	0.20	0.27	0.16	160
Dbl Ref-C-H Tint 6 mm/13 mm Air	2.43	0.12	0.20	0.10	160
Dbl Ref-C-M Clr 6 mm/6 mm Air	2.86	0.17	0.24	0.14	160
Dbl Ref-C-M Tint 6 mm/13 mm Air	2.38	0.10	0.18	0.08	160
Project BIPV Window	1.98	0.74	0.69	0.62	249
Project external glazing	3.16	0.78	0.69	0.60	150
Thermochromic Glazing Example	1.72	0.54	0.35	0.26	180
Trp Clr 3mm/13 mm Air	1.78	0.74	0.68	0.60	170
Trp Clr 3mm/30mm Air for mid-pane blinds	1.96	0.74	0.67	0.59	210
Trp LoE (e2=e5=.1) Clr 3mm/13 mm Air	0.99	0.66	0.47	0.36	180
Trp LoE (e5=.1) Clr 3mm/13 mm Air	1.27	0.70	0.57	0.46	180
Trp LoE Film (77) Clr 3mm/13 mm Air	1.25	0.64	0.46	0.38	180
Trp LoE Film (77) Clr 3mm/6 mm Air	1.76	0.64	0.46	0.38	180

BIPV: Building-integrated photovoltaics; e: emissivity; Dbl: Double; Clr: Clear; Ref: Reflect

SHGC: Total solar transmission; Trp: Triple

Appendix B-5: HVAC Systems

HVAC systems	Auxiliary energy	Heating system seasonal CoP	Cooling system seasonal CoP	Pressure rise	Cost per area	Cost per cooling load	Cost per heating load
	E_{hvac}^{aux}	H_{hvac}^{CoP}	C_{hvac}^{CoP}	Pr_{hvac}	C_{hvac}	C_{hvac}^{cool}	C_{hvac}^{heat}
	[kWh/m^2]	[-]	[-]	[Pa]	[$/m2 GIFA]	[$/kW]	[$/kW]
ASHP Hybrid with Gas Boiler, Nat Vent	10.00	1.80	1.80	150	150	1459	1459
ASHP, Convectors, Nat Vent	10.00	2.00	1.67	150	90	875	875
CAV, Air-cooled Chiller	120.00	0.85	1.19	700	200	1945	1945
Chilled ceiling, Air-Cooled Chiller	15.00	0.85	2.50	600	220	2140	2140
Electric Convectors, Nat Vent	3.00	1.00	2.50	50	40	0	944
Electric storage heaters, Nat Vent	0.00	1.00	4.50	0	40	0	944
Fan Coil Units (4-Pipe) with District Heating + Cooling	25.00	1.00	1.00	150	150	1459	1459
Fan Coil Units (4-Pipe), Air-cooled Chiller	25.00	0.85	1.80	150	150	1459	1459
Fan Coil Units (4-Pipe), Air-cooled Chiller, DOAS	40.00	0.85	1.80	150	180	1751	1751
Fan Coil Units (4-Pipe), Water-cooled Chiller, Water-side economizer	30.00	0.85	1.80	150	220	2140	2140
Natural ventilation - No Heating/Cooling	0.00	0.85	4.50	0	0	0	0
PTAC Electric Heating	9.00	1.00	2.50	50	100	973	973
PTAC HW Heating	9.00	0.85	2.50	50	120	1167	1167
PTHP	9.00	2.00	2.50	50	120	1167	1167
Radiator heating, Boiler HW, Mech vent Supply + Extract	3.00	0.85	2.50	600	125	0	2950
Radiator heating, Boiler HW, Mixed mode Nat Vent, Local comfort cooling	3.26	0.85	1.80	100	150	1459	1459
Radiator heating, Boiler HW, Nat Vent	3.26	0.85	4.50	0	60	0	1416
Radiators Electric, Nat Vent	3.00	1.00	2.50	50	40	0	944
Split + Separate Mechanical Ventilation	25.00	2.25	1.80	400	150	1459	1459
Split no fresh air	0.00	2.35	1.80	400	100	973	973
VAV, Air-cooled Chiller, Fan-assisted Reheat (Parallel PIU)	35.00	0.85	1.80	700	250	2431	2431
VAV, Air-cooled Chiller, HR, Outdoor air reset	35.00	0.85	1.80	700	265	2577	2577
VAV, Air-cooled Chiller, HR, Outdoor air reset + mixed mode	35.00	0.85	1.80	700	270	2626	2626
VAV, Air-cooled Chiller, Outdoor air reset	35.00	0.85	1.80	700	255	2480	2480
VAV, Air-cooled Chiller, Reheat	35.00	0.85	1.80	700	230	2237	2237
VAV, Air-cooled Chiller, Steam humidifier, Air-side HR, Outdoor air reset	35.00	0.85	2.00	700	230	2237	2237
VAV, Dual duct, Air-cooled Chiller	80.00	0.85	1.80	700	300	2918	2918
VAV, Dual duct, Water-cooled Chiller	35.91	0.85	3.00	700	330	3209	3209
VAV, Water-cooled Chiller, Air-side HR, Outdoor air reset	35.00	0.85	1.80	700	300	2918	2918
VAV, Water-cooled Chiller, Full Humidity Control	35.00	0.75	1.75	700	330	3209	3209

ASHP:	Air to Water Heat Pump	HR:	Heat Recovery	PTAC:	Packaged Terminal Air Conditioner
COP:	coefficient of performance	HW:	Hot Water	PTHP:	Packaged Thermal Heat Pump
DOAS:	Dedicated Outdoor Air System	Max:	Maximum	VAV:	Variable air volume
FPID:	Fan-Powered Induction Unit	Nat. Vent.:	Natural Ventilation		

Appendix B-6: Lighting Systems

Lighting systems	Normalized power density $NPD_{lighting}$ [W/m²·100lux]	Radiant fraction. $Rf_{lighting}$ [-]	Power density $PD_{lighting}$ [W/m²]	Cost $C_{lighting}$ [$/m²]
Canadian energy code	3.40	0.42	10.20	109.06
Fluorescent, compact (CFL)	5.00	0.42	15.00	85.69
High-pressure Mercury	7.60	0.42	22.80	93.48
High-pressure sodium	4.50	0.42	13.50	77.90
LED	2.50	0.42	7.50	132.44
LED with linear control	2.50	0.42	7.50	155.81
T5 (16 mm diam) Fluorescent, triphosphor high-frequency control, LINEAR dimming daylighting control	3.30	0.37	9.90	116.86
T5 (16 mm diam) Fluorescent, triphosphor, high-frequency control	3.30	0.37	9.90	93.48
T8 (25 mm diam) Fluorescent - triphosphor - with LINEAR dimming daylighting control	3.40	0.37	10.20	116.86
T8 (25 mm diam) Fluorescent - triphosphor - with ON/OFF dimming daylighting control	3.40	0.37	10.20	112.18
T8 (25 mm diam) Fluorescent - triphosphor - with STEPPED dimming daylighting control	3.40	0.37	10.20	116.86
T8 (25 mm diam) Fluorescent, halophosphate, high-frequency control	3.80	0.37	11.40	93.48

CFL: Compact Fluorescent Lamp; LED: Light-Emitting Diode

Appendix B-7: Heating/ Cooling Operation Schedule

Heating Operation Schedule	**ID**	**Cooling Operation Schedule**	**ID**
7:00 - 23:00 Mon - Fri	100	7:00 - 23:00 Mon - Fri	110
6:00 - 18:00 Mon - Fri	200	6:00 - 18:00 Mon - Fri	120
Max Indoor temp for Nat Vent: Always 100	300	Max Indoor temp for Nat Vent: Always 100	130
Max Outdoor temp for Nat Vent: Always 100	400	Max Outdoor temp for Nat Vent: Always 100	140
Mixed mode temperature control	500	Mixed mode temperature control	150
On 24/7	600	On 24/7	160
Two season schedules (Northern Hemisphere)	700	Two season schedules (Northern Hemisphere)	170

Max: Maximum; Nat Vent: Natural Ventilation

Appendix C: Pareto Front Results of SBMO Considering LCC Vs. TEC

R	EW	FT	W	HVAC	HOS	COS	Li	EWO	WWR	LCC (CAD)	TEC (kWh)
Project flat roof	Semi-exposed wall - LW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Indoor temp for NV:100	Max Indoor temp for NV:100	LED	44	42	3,636,157	246,710
Project flat roof	Semi-exposed wall- LW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Indoor temp for NV:100	Max Indoor temp for NV:100	T5 , Fluorescent	50	42	3,579,913	261,115
semi-exposed	Wall - Energy code - MW	Fixed- H:1.0m, W:0.5	BIPV	VAV, Air-cooled Chiller	Max Indoor temp for NV:100	Max Indoor temp for NV:100	LED-linear	54	68	4,968,300	228,999
Project flat roof	Wall - State-of-the-art - MW	Preferred H: 1.5m, 10º	Wood	Radiators Electric, NV	On 24/7	6:00 - 18:00 Mon - Fri	Energy code	54	32	3,621,290	250,936
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	6:00 - 18:00 Mon - Fri	6:00 - 18:00 Mon - Fri	LED	48	36	3,653,460	238,813
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	LED	54	36	3,653,386	238,852
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	6:00 - 18:00 Mon - Fri	6:00 - 18:00 Mon - Fri	T5, Fluorescent	54	36	3,596,585	252,807
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Indoor temp for NV:100	6:00 - 18:00 Mon - Fri	LED	62	36	3,653,347	238,935
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	7:00 - 23:00 Mon - Fri	6:00 - 18:00 Mon - Fri	T5, Fluorescent	70	36	3,596,421	252,914
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	T5, Fluorescent	46	38	3,596,710	252,767
semi-exposed	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	LED	50	38	4,115,746	231,602
semi-exposed	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:1.0	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	Mixed mode temperature	LED-linear	54	38	4,161,893	230,342
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	T5,Fluorescent	62	38	3,596,509	252,865
Project flat roof	Wall - State-of-the-art - MW	Preferred H: 1.5m, 10º	BIPV	Radiators Electric, NV	On 24/7	6:00 - 18:00 Mon - Fri	LED-linear	66	42	3,695,244	236,790
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	T5,Fluorescent	50	58	3,596,611	252,770
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Two season schedule (NH)	6:00 - 18:00 Mon - Fri	LED	56	62	3,653,375	238,873
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Two season schedule (NH)	6:00 - 18:00 Mon - Fri	LED	64	62	3,653,308	238,937
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Two season schedule (NH)	6:00 - 18:00 Mon - Fri	LED	68	62	3,653,304	238,988
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Two season schedule (NH)	6:00 - 18:00 Mon - Fri	LED	44	64	3,653,560	238,812
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Indoor temp for NV:100	6:00 - 18:00 Mon - Fri	LED	50	64	3,653,456	238,839
Project flat roof	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Outdoor temp for NV:100	6:00 - 18:00 Mon - Fri	LED	52	64	3,653,415	238,844
semi-exposed	Wall - State-of-the-art - MW	Fixed- H:1.0m, W:0.5	BIPV	Radiators Electric, NV	Max Indoor temp forNV:100	Mixed mode temperature	LED	60	64	4,115,673	231,691

BIPV: Building Integrated Photo Voltaic

LW: Light weight

MW: Medium weight

NA: Not applicable

VAV: Variable air volume

LED: Light-Emitting Diode

Max: Maximum

Appendix D: List of Related Publications

Journal Papers:

- Sharif, S. A., and Hammad, A. (2018). Simulation-Based Multi-Objective Optimization of Institutional Building Renovation Considering Energy Consumption, Life-Cycle Cost and Life-Cycle Assessment. Journal of Building Engineering, Elsevier Ltd, 21, 429–445. (Related to **Chapter 4**)
- Sharif, S. A., and Hammad, A. (2019). Developing surrogate ANN for selecting near-optimal building energy renovation methods considering energy consumption, LCC and LCA. Journal of Building Engineering, Elsevier Ltd, 25, 100790. (Related to **Chapter 5**)
- Sharif, S. A., Eshraghi, P, and Hammad, A. (2020). Generation of whole building renovation scenarios using variational Autoencoders. Journal of Energy and Buildings, Accepted. (Related to **Chapter 6**)

Conference Papers:

- Sharif, S. and Hammad, A. (2017). Simulation-Based Optimization of Building Renovation Considering Energy Consumption and Life Cycle Assessment. International Workshop on Computing in Civil Engineering (IWCCE). Seattle: University of Washington.

Conference Posters:

- Sharif, S. A., and Hammad, A. (2019). AI-Based Generative Energy Optimization Tool. The 6th Canadian Society for Civil Engineering 2019 (CSCE 2019), the second rank in the "Poster Presentation Award" competition.
- Sharif, S.A., Hammad, A., (2016). Optimizing the Energy Performance of Multiple Buildings Renovation Considering Life-Cycle Cost, CYCLE 2016- the 5th edition of the International Forum on the Life Cycle Management of Products and Services.