Active BIM with Artificial Intelligence for Energy Optimisation in Buildings

by

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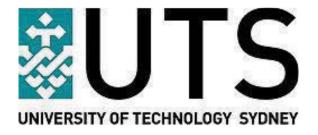
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Certificate of Original Authorship

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List of Abbreviations

2D CAD 2 Dimensional Computer Aided Drawing

3D 3 Dimensional
AC Air Conditioning
AI Artificial Intelligence

API Application Program Interface
ANN Artificial Neural Network

ASCE American Society of Civil Engineering

BIM Building Information Modelling
CDA Conditional Demand Analysis
CDE Common Data Environment
CFD Computational Fluid Dynamic

DBLink Database Link
DT Decision Tree

EED Energy Efficient Design

EU European Union
GA Genetic Algorithm
GB Green Building

GBS Green Building Studio

GHG Greenhouse Gas

HVAC Heating, Ventilation and Air Conditioning
ICT Information and Communication Technology

IES Integrated Environmental Solution

IFC Industry Foundation Class
IFP Implication for Practice
IT Information Technology
IS Information System

LEED Leadership in Energy and Environmental Design

LoD Level of Development
MLP Multilayer Perceptron
MSE Mean Square Error

ODBC Open Database Connectivity
POS Particle Swarm Optimisation

RC Reinforced Concrete

SVM Support Vector Machine

TMY Typical Metrological Year

PhD Publications

- S. Banihashemi, G. Ding and J. Wang. 2017. BIM and Energy Efficient Design: 10 Years of Review and Analysis. Journal of Renewable and Sustainable Energy Reviews, Elsevier (under review).
- S. Banihashemi, G. Ding and J. Wang. 2016. Developing a Hybrid Model of Prediction and Classification Algorithms for Building Energy Consumption Optimisation. Energy Procedia, Elsevier, Volume 110, pages 371-376.
- S. Banihashemi, G. Ding and J. Wang. 2016. Identification of BIM-Compatible Variables for Energy Optimization of Residential Buildings: A Delphi Study. 40th AUBEA, Cairns, Australia. July 6-8, 2016.
- G. Ding and S. Banihashemi. 2016. Carbon and Ecological Foot Printing of Cities. Sustainable Energy Technologies, Encyclopaedia of Sustainable Technologies, Elsevier, Volume 2, pages 43-51.
- S. Banihashemi, G. Ding and J. Wang. 2015. Developing a Framework of Artificial Intelligence Application for Delivering Energy Efficient Buildings through Active BIM. COBRA, Sydney, Australia. July 8-10, RICS 2015.

Abstract

Using Building Information Modelling (BIM) can expedite the Energy Efficient Design (EED) process and provide the opportunity of testing and assessing different design alternatives and materials selection that may impact on energy performance of buildings. However, the lacks of; intelligent decision making platforms, ideal interoperability and inbuilt practices of optimisation methods in BIM hinder the full diffusion of BIM into EED. This premise triggered a new research direction known as the integration of Artificial Intelligence (AI) into BIM-EED. AI can develop and optimise EED in an integrated platform of BIM to represent an alternative solution for building design. But, very little is known about achieving it. Hence, an exhaustive literature review was conducted on BIM, EED and AI and the relevant gaps, potentials and challenges were identified. Accordingly, the main goal for this study was set to optimise the energy efficiency at an early design stage through developing an AI-based active BIM in order to obtain an initial estimate of energy consumption of residential buildings and optimise the estimated value through recommending changes in design elements and variables.

Therefore, a sequential mixed method approach was designated in which it entailed conducting a preliminary qualitative method to serve the subsequent quantitative phase. This approach was started with a comprehensive literature review to identify variables applicable to EED and the application of a three-round Delphi to further identify and prioritise the significant variables in the energy consumption of residential buildings. A total of 13 significant variables was achieved and factualised with simulation method to first; generate the building energy datasets and second; simulate AI algorithms to investigate their functionality for energy optimisation. The research was followed with developing the integration framework of AI and BIM; namely AI-enabled BIM-inherited EED to optimise the interdisciplinary data of EED in the integration of BIM with AI algorithm packages. Finally, the functionality of the developed framework was verified using a real residential building and via running comparative energy simulation pre and post-framework application (baseline and optimized case). The outcomes indicated around 50% reduction in the electricity energy consumption and 66% saving in the annual fuel consumption of the case study.

Enhancing BIM applicability in terms of EED optimisation, shifting the current practice of post-design energy analysis, mitigating the less integrated platform and lower levels of interoperability are the main significant outcomes of this research. Ultimately, this research heads

toward the higher diffusion levels of BIM and AI into EED which contributes significantly to the current body of knowledge and its research and development effects on the industry.

CHAPTER 1

Research Background

1.1. Introduction

This chapter sets out a platform to outline the main elements of this PhD study and the driving forces behind the areas of investigation. It commences with providing an introductory background and problem statement in lined and articulating the aim and research objectives and questions broken down. It then briefly presents the methods applied to achieve the objectives. In the end, the content and structure of the thesis are mapped to depict the flow of this research.

1.2. Research Overview

Buildings have an enormous and continuously increasing impact on the environment, using about 50% of raw materials, consuming nearly 71% of electricity and 16% of water usage, and producing 40% waste disposed in landfills (Oduyemi et al. 2017). Moreover, they are responsible for a large amount of harmful emissions, accounting for 50% of carbon dioxide (CO₂) emissions, due to their operation, and an additional 18% caused indirectly by material exploitation and transportation (Kibert 2016). In order to mitigate the impact of buildings along their lifecycle, Green Building (GB) has emerged as a new building initiative. GB encourages the use of more environmentally friendly materials, implementation of techniques to conserve resources and reduce waste generation, and the improvement of energy consumption, among others (Reddy & Jagadish 2003). This would result in environmental, financial and social benefits.

According to Anastaselos et al. (2016), the potential to save operational energy by applying green building methods is known to be significant and estimates up to 40% of energy saving. Although there have been attempts to reduce energy use and carbon emissions by buildings, these efforts have yet to meet their fullest potential in the design and construction of high-performance buildings (UNEP 2014). This is mostly due to the lack of early decision making in an integrated Energy Efficient Design (EED) environment. It is widely believed that operational energy minimisation task should be made throughout a building project lifecycle (Bynum, Issa & Olbina 2013). However, the most effective decisions related to energy efficient and sustainable design of a building facility are made in the early design and preconstruction stages (Basbagill et al. 2013). Early assessment of the performance of the buildings can help the

Architecture, Engineering and Construction (AEC) groups to choose better alternatives for the design to minimise energy consumption for a building lifecycle (Ekici & Aksoy 2011).

Since the conventional 2 Dimensional Computer Aided Drawing (2D CAD) system requires investing large amounts of time for operational energy calculation, using Building Information Modelling (BIM) can expedite this process and provide the opportunity of testing and assessing different design alternatives and materials' impacts on the building (Oduyemi et al. 2017). "BIM is a digital representation of physical and functional characteristics of a facility" (Eastman et al. 2011, p. 2). According to BS1192, "it is the management of information through the whole life cycle of a built asset, from initial design all the way through to construction, maintaining and finally de-commissioning, through the use of digital modelling" (BS1192 2008, p. 1). Thus, decisions that are made in the early stages of design play a significant role on the level of sustainability throughout the lifecycle of the building (Attia et al. 2012). The ability to pinpoint the weaknesses of the design and implementing changes based on the available alternatives can help the construction industry to mitigate the adversarial impact of building on the surrounding environment and enhance the greenness of building.

Hence, using BIM can contribute positively to manage and control the design process more meticulously and systematically (Noack et al. 2017). A BIM model represents the building as an integrated database of coordinated information from AEC disciplines. Beyond graphically depicting the design, much of the data needed for supporting sustainable design is captured naturally as design of the project proceeds (Cerovsek 2011). In addition, the integration of BIM with performance analysis aspects greatly simplifies the often cumbersome and difficult analysis procedure. This approach can give architects an opportunity to obtain immediate feedback on design alternatives early in the design process (Azhar 2011).

1.3. Problem Statement

The current interface between BIM and EED process is mostly user driven (Wu & Issa 2014). In other words, once the building is modelled and analysed, BIM does not have the sufficient capacity to optimise operational energy based on the model. So the user should, based on his/her knowledge and experience, either change the elements' properties and positions or play with the variables to get the optimum result in EED (Wang, Li & Chen 2010). The optimisation of the design is especially important when the sustainability performance of the building is required. As mentioned earlier, BIM process is capable of offering advantages in energy consumption estimation and optimisation but these potentials are not effectively applied by

experts as to being user driven and disjointed. In the literature, several statistics and simulation based methodologies have been developed to estimate and optimise energy consumption (Machairas, Tsangrassoulis & Axarli 2014). On-line building energy predictions based on Artificial Intelligence (AI) applications and their web-based integrations can also be used in some areas (Foucquier et al. 2013).

Krygiel and Nies (2008) suggested several innovations within BIM such as improvements in software interoperability and integration of a carbon accounting tracker and weather data in order to provide for the next steps in enhancing its capabilities with sustainability. Azhar (2011) described the use of BIM to select building orientation, evaluate various skin options, and perform daylight studies for its positioning on the selected site during the design phase, thus enhancing its sustainability. Holness (2008) noted that because of the trend in sustainability toward net-zero energy buildings and carbon emissions reduction, designers need to analyse the building as a fully integrated dynamic design and construction process. Coasta et.al (2013) developed an integrated monitoring, analysis and optimisation toolkit based on lifecycle assessment for BIM using fault detection and diagnosis methodology.

Though, the current BIM can be called as the *passive BIM* (Welle, Haymaker & Rogers 2011a). *Passive BIM* is the BIM which does not effectively support decision making procedure, cannot provide thorough sustainability analysis data such as energy consumption level and the design variables that need to be optimised. Whereas, BIM, because of being parametric and object-oriented, could be transformed effectively into the *active BIM* (Moon et al. 2013). *Active BIM* is the BIM which endorses intelligent decision making platforms and can present the optimum values for the design variables to reduce the energy consumption of a building model. As a holistic view on the previous works, it can be inferred that the problem of lacking a simple, integrated and practical decision making procedures in BIM have been remained unsolved. While, if this affliction is managed, it can assist academics, operators and designers to have an early perception of building energy performance and propose solutions or alternatives in order for optimisation purposes.

Although lots of research such as calculative, predictive, simulative and optimisation methods on the energy simulation and modelling of buildings have been conducted so far, but as will be elaborated in the next chapters, these methods have not been practiced or presented inbuilt within the integrated environment of BIM. One of the reasons lies in the lack of ideal interoperability between BIM and energy analysis software packages (Sanguinetti et al. 2012). Interoperability is the key to the integration of BIM and external energy simulation and its

effective application enhances the inclusion and consistency of the information transition (Woo & Menassa 2014). The general unavailability of BIM vendor-neutral data formats and standards, as well as issues regarding accessibility and security of data is another reason which has hindered the dynamic integration of BIM and EED (Gray et al. 2013). The quality of data and its accessibility plays the central role with respect to the BIM integration studies but due to the proprietary nature of BIM applications, it is of complexity in the diffusion of energy optimisation into the BIM environment (Volk, Stengel & Schultmann 2014).

In addition, BIM-specific requirements are yet to be adequately embedded within the current state of the design phase, thus, it creates disruptive possibilities in reaching the optimum EED settings (Sawhney & Singhal 2013). The need for more inputs and technical specifications in preparing models for BIM package improves the semantic-rich content of BIM models. While, "the technology to collaborate on models has not yet delivered the industry requirements for BIM collaboration" (Oduyemi et al. 2017, p. 19). BIM can define an explicit and inbuilt configuration for digitised information of EED but the current procedures are inefficient in view of the abovementioned reasons. Thus, to proactively rectify building performance issues and improve energy efficiency, there is a need for robust methods and frameworks that can assist with detection, measurement and optimisation of energy performance (Ham & Golparvar-Fard 2013). These methods need to be rapid, non-destructive, smart and integrated so that they can be widely applied to building facilities.

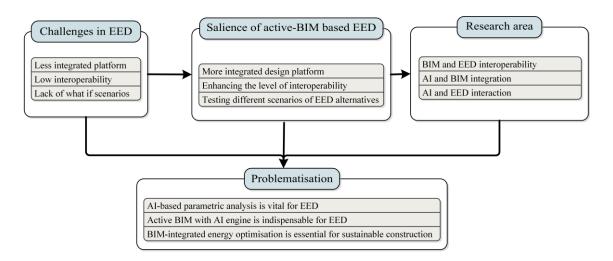


Figure 1.1. Research Problematisation

As inferred from Figure 1.1 and discussed earlier in this chapter, today's EED in the built environment context confronts with a wide range of challenges, such as less integrated platform, low interoperability between external energy simulation applications and lack of 'what if'

scenarios analysis (Azhar et al. 2011; Bynum, Issa & Olbina 2013; Oduyemi et al. 2017). In addition, the construction industry has faced the emergence of innovative methods of BIM and advanced data analytics like AI. AI is "the science and engineering of making intelligent machines" (McCarthy & Hayes 1968, p. 5). However, considering that these technological innovations heavily rely on integrated platforms to tackle the current challenges and issues of EED. These reasons point to the profound salience of AI enabled active BIM for contemporary EED (see Figure 1.1).

First and foremost, the introduction, inclusion and integration of AI into BIM and EED leads to the energy efficient generative design implementation. Such an approach comprises automatic practices to develop different design alternatives which meet a set of criteria like minimum energy consumption (Singh & Gu 2012). It consists algorithmic procedures which is driven by the immense working capacity of computer machines to generate a considerable amount of alternative solutions that would otherwise be impossible to create (Chakrabarti et al. 2011). In essence, the idea is that, for the same building facility, various possible energy performances can be corresponded to its design. Hence, if alternative designs are created, these can be analysed to obtain the optimum performance through applying estimation approaches such as building energy simulation (Soares et al. 2017). Furthermore, the potential of each design solution for a possible improvement can be assessed by AI-based optimisation algorithms.

AI can greatly alleviate the problem of interoperability through enabling BIM to analyse the energy consumption and optimise the design parameters within the BIM environment. The current post-design routine of energy analysis and optimisation in using the external software could be effectively shifted into the inbuilt EED in BIM (Banihashemi, Ding & Wang 2015). AI includes numerous categories of algorithms such as prediction, classification and optimisation which presents better flexibility in settings for EED (Yang et al. 2014). So, in line with the generative design remarks, it can pave the way of 'what if' scenario analysis for choosing various design parameters by applying different algorithms for prediction and optimisation of the operational energy of building model in the design stage.

Moreover, the issue of consistency and homogeneity of the data can be mitigated, founded on the integrated platform of AI and BIM. AI enhances the level of information from non-optimised to the optimised values based on the parametric capability (Tao, Zhang & Laili 2014). This capability is the key to keeping the homogeneity of data since AI could set the parametric attributes according to that of attributes in BIM (Noack et al. 2017). Hence, the non-proprietary semantics of information is fixed which, in turn, eliminates the inaccessibility and unavailability

of BIM vendor-neutral data formats problem. Such potential further leads to the superior diffusion of BIM into EED in the interim of AI function in prediction, classification and optimisation of building design parameters. Figure 1.2 illustrates the summary of the gaps among three main domains of BIM, EED and AI.

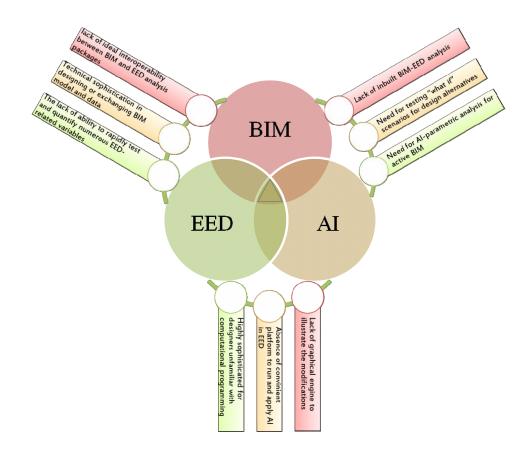


Figure 1.2. Research Gap Diagram

All in all, the rationale for the present study is derived from the lack of knowledge on AI-enabled active BIM development and the paucity of studies with this respect in the construction industry, as illustrated in Figures 1.1 and 1.2. In terms of problematisation, the review of the literature has established that the integration framework development for BIM, AI and EED is central to establishing AI-enabled active BIM, however this phenomenon continues to be regarded as an under-researched concept. In other words, a conspicuous paucity of AI-based active BIM inquiry on EED within the extant literature was found. As a result, clarifying the major aspects of AI-enabled active BIM within the boundaries of EED domain and within the built environment industry seems to be very relevant and necessary. It should be also noted that due to the very broad range of built environment facilities and their different characteristics such as design type and layout, materials, construction technologies and priorities in sustainable design, it is almost

impossible to develop a prototype which could cover all those criteria. Therefore, residential buildings, in view of their large share in worldwide energy usage and environmental impacts, stipulated by EIA (2016), set the scope for the context of this study.

1.4. Research Questions

It is essential to develop research questions in order to help focus the research area and data collection for the study. Followings are some research questions to be answered for the research:

- i. What are the drawbacks of the current energy simulation and optimisation methods in buildings?
- ii. How is BIM capable of optimising the energy efficiency of buildings?
- iii. What are the important variables playing key roles in energy consumption of residential buildings?
- iv. What types of AI algorithms are suitable for being used in BIM in terms of predicting and optimising energy consumption?
- v. How can an algorithm be linked to the BIM packages?
- vi. What is the process of optimisation for identified variables?
- vii. How can the body of knowledge be benefitted from the developed framework?
- viii. To what extent does this framework deliver EED?

1.5. Aim and Objectives of the Study

The main goal of this study is to develop an AI-based active BIM to optimise energy efficiency at an early design stage in order to obtain an initial estimate of energy consumption of residential buildings and optimise the estimated value through recommending changes in design elements and variables. Thus, specific objectives include:

- i. Examining the potential and challenges of BIM to optimise energy efficiency in residential buildings
- ii. Identifying variables that play key roles in energy consumption of residential buildings
- iii. Investigating the AI-based algorithms in energy optimisation
- iv. Developing a framework of AI application in BIM in terms of energy optimisation purposes and processes

1.6. Research Method

Following the gap identification, research problematisation and developing research questions, aim and objectives of this PhD study, the research method should be established for recognising how the gap is filled and how the research questions, aim and objectives are addressed. Stipulated by Jackson (2009), the research objectives and the type of information required are two critical factors in adopting the research method and data collection and analysis techniques. With respect to the aim and objectives of this PhD, three methods of qualitative, quantitative or their combination as mixed methods can be applied. Asserted by Creswell (2013), qualitative study is mostly applied to unfold an area or a concept. It allows a greater explanation of a phenomenon through the voices and experiences of the actors involved while it is somewhat deficient in providing factual and objective evidence of a phenomenon. On the other hand, quantitative method is usually employed to establish or estimate numeric relationships and can reveal general trends but it often does not provide an in-depth understanding of a phenomenon (Yin 2013b).

Drawing on the capabilities and limitations of each methodology, linking these two types of research method greatly strengthens the validity of insights into the phenomenon at hand (Kothari 2011). Mixed method research is fitted very well to the interdisciplinary research areas such as management and engineering by combining qualitative and quantitative approaches (Bryman & Bell 2015). Therefore, a mixed method approach following a design of $QUAL \rightarrow QUAN$ is designated for this study. It entails conducting a preliminary qualitative data collection method to serve the subsequent quantitative phase. Such a sequence for conducting the mixed method strategy was termed by Creswell (2013) as sequential exploratory design. Contextualising the sequential exploratory design for this PhD implies that it commences with the application of qualitative instruments to the exploratory tasks of objectives one and two including examination of the potential and challenges of BIM and EED and identification of the significant variables in the energy consumption of residential buildings. It is then factualised with quantitative instruments to address the third to the fifth objectives by modelling and simulating AI algorithms to investigate their functionality for energy optimisation, developing the integration framework of AI and BIM and validating the framework through case study verification.

Therefore, from the research design angle of this study, it can be realised that more than one research instrument is required to fulfil the following steps:

- Identifying and prioritising the variables that play key roles in energy consumption of residential buildings
- Creating a comprehensive residential buildings dataset emphasising on covering the full range of identified variables
- iii. Developing AI-based algorithms using the collected dataset
- iv. Linking the developed algorithms to BIM application
- v. Testing the workability of the framework and evaluating its performance

Furthermore, the identified research steps should be scoped to be applicable during a normal PhD study period. Thus, the below remarks are taken into account:

- Among the project lifecycle, the design stage is on the focal point for this study. This
 decision is made in light of the significant importance of design stage in EED
 considerations. Henceforth, the construction and operation stages are excluded from the
 research.
- ii. The developed framework and algorithms are designed for residential buildings only. Other types of building facilities are out of the scope but the developed framework can be equally applicable to other types of building with the modifications in parameters and dataset range.
- iii. AI algorithms generally fall to two major functional categories of prediction and optimisation. So, two algorithms of Artificial Neural Network (ANN) and Decision Tree (DT) for prediction and Genetic Algorithm (GA) for optimisation are applied.
- iv. BIM includes a long list of tools from design to analysis, simulation and estimation. In this study, the focus would be on the Revit suite because of its popularity and parametric nature.

Considering the research scopes, as the first step and from the qualitative side, an extensive exploratory research must be constructed. This is to identify the potential and challenges of BIM and EED and variables that play key roles in energy consumption of residential buildings by analysing literature, creating a pool of variables and refining the list of variables. Qualitative method includes different instruments like interview, focus group and Delphi (Ritchie et al. 2013). Delphi method is selected here to compliment the literature as it consists of an organised procedure in reaching a consensus among the respondents (Hsu & Sandford 2007). As confirmed by Sourani and Sohail (2014), it has also the iterative nature and allows for running numerous rounds to achieve the outcome which in this study, a three-round inquiry is conducted with experts

for brainstorming about the variables and synthesisation with literature, their prioritisation and confirmation of the final list of significant variables.

As the second step and from the quantitative side, simulation method comes to the fore. This method enables researchers to analyse and investigate the eventual real influences or potential repercussions of various engineering situations and courses of actions (Prive & Errico 2016). Hence, by employing this method, a comprehensive residential building dataset which is simulated and analysed in BIM via considering identified variables should be provided and categorised. This dataset should cover all variables from the literature and Delphi and have a sufficient number of data for being used in developing AI algorithms. In the last few decades, many researchers focused on several AI methods of optimisation algorithms. For the third step, the present research is focused on machine learning algorithms (Engelbrecht 2007a) including ANN and DT for data prediction and classification and GA for optimisation in which suitable and adaptable algorithms are established through data size reduction studies.

As the next step and by continuing the simulation instrument, the written algorithm, based on the developed dataset in the previous step, should be linked to BIM application. The selected BIM application for this research is the Revit suite which is extensively used by BIM experts and has a great potential for improvement because of its high level of interoperability with parametric algorithms (Kensek & Noble 2014). The developed algorithm is simulated in Matlab software package and linked via Open Database Connectivity (ODBC) protocols of data exchange to the Revit suit. Finally, an engineering-based case study instrument is applied for observing the reliability and functionality of the developed framework for two conditions of pre- and post-optimisation. According to Algozzine and Hancock (2016), a case study is an in depth study of a particular situation and is useful for testing whether scientific theories, models or frameworks actually work in the real world and its physical context. Thus, a comparative deviation report between the energy optimisation results of the active BIM and the previous record is made in order to test and validate the feasibility and suitability of the developed framework. Figure 1.3 depicts a hierarchical diagram of the research aim, objectives, steps and instruments.

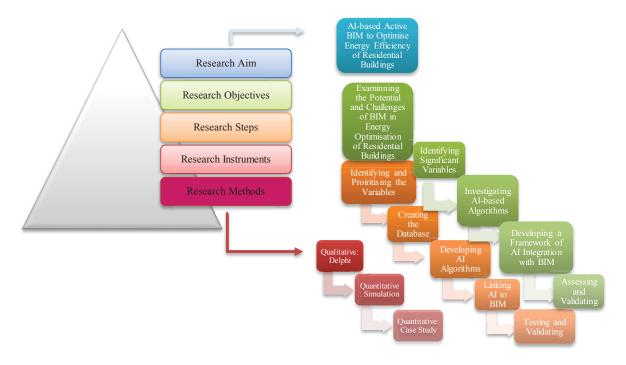


Figure 1.3. The Hierarchical Diagram of the Research Aim, Objectives, Methods, Steps and Instruments

1.7. Significance of the Study

Enhancing BIM applicability in terms of sustainability and energy optimisation through developing AI based active BIM is the main significant outcome of this research. There are many procedures, processes and platforms available now to model, simulate and optimise the energy consumption of buildings but there is not sufficient well-developed and integrated optimisation decision making framework which estimates automatically the energy consumption of buildings and then, recommends specific changes for optimising purposes. The outcome of this study provides early decision making platform in an integrated EED environment emphasising on the significant role of early stages of design on the sustainability of building lifecycle. It can effectively shift the current practice of post-design energy analysis and optimisation to the inbuilt and unified EED in BIM through AI inclusion and operation. Accordingly, the problem of the less integrated platform and lower level of interoperability between external energy application and BIM are mitigated.

In addition, the developed framework improves the semantic homogeneity and consistency of the information transfer in the EED. It aligns the parametric attributes of the AI and BIM model contents and as a result, the accessibility and availability of data are dramatically

enhanced and the issue of inconsistency of BIM vendor-neutral data formats problem is settled. Application of different batches of AI algorithms including prediction, classification and optimisation set the automatic capability of 'what if' scenarios for different design parameters of operational energy optimisation of the model. Therefore, through this study, a well-established framework of AI application in active BIM that gives an initial energy performance and introduces the optimised inputs for major design parameters automatically is developed. Ultimately, this research heads toward the higher diffusion levels of BIM and AI into the EED which can be very useful for expanding the academic body of knowledge and its research and development effects on the industry.

Besides, this study sheds a light on the prerequisites toward developing this framework. A comprehensive literature review fully reveals the current state of the art, challenges, solutions, themes and gaps in the extant literature of the EED, BIM and AI. Literature review and the three-round Delphi study lead to the identification, prioritisation and confirmation of the significant factors in EED of residential buildings. Developing different batches of AI algorithms along with using data size reduction techniques explore the most appropriate types of AI combination in order for being utilised in BIM platform.

1.8. Thesis Outline

This thesis structure is summarised in Figure 1.4 and consists of 8 chapters. These chapters are designed to cover details of the research, from the rationale for doing the research study to the research methodology and data collection and analysis and eventually presenting the discussion and conclusions.

Rationalising the background and justifications for the research, Chapter 1 puts forward the aim and objectives on the basis of discussed research manifest and questions. It is further presented with the methodological steps along with the research significance. The abridged account of the fundamental concepts and definitions associated with the topic is a focus of Chapter 2. Acting as the backbone of the study, the theoretical framework of sustainability, information theory and optimisation are jointly discussed with their resulted technological implications of EED, BIM and AI. Chapter 3 maps out the upstream concepts of Chapter 2 to a more detailed review focused on critical appraisal of literature and deploying gap spotting techniques of the body of the knowledge. In Chapter 4, first, a review of qualitative and quantitative methods, practical instruments and the mixed method strategy are elaborated. Second, data collection

methods and analysis steps are fully described for linking the research aim and objectives to their practical approaches.

Chapter 4 sets forth the results of data collection and analysis by running the Delphi method; qualitative research in dialogue with the extant literature. Chapter 5 lays the foundation for the quantitative research stage where the identified and prioritised variables of building energy parameters are employed to develop a complete dataset of building energy simulations, presented in Chapter 6. This chapter is also aimed at developing AI algorithms for energy optimisation purposes. The last chapter of analysis block is intended to indicate the procedural steps of developing the framework of BIM and AI integration with regard to EED. Chapter 7 further verifies the applicability and functionality of the framework in the context of the built environment through applying case study approach. Finally, chapter 8 concludes the study by summarising the research aim and objectives, discussing the contributions to the body of the knowledge, implications for practice, the current limitations and recommendations to the future of the topic (Figure 1.4).

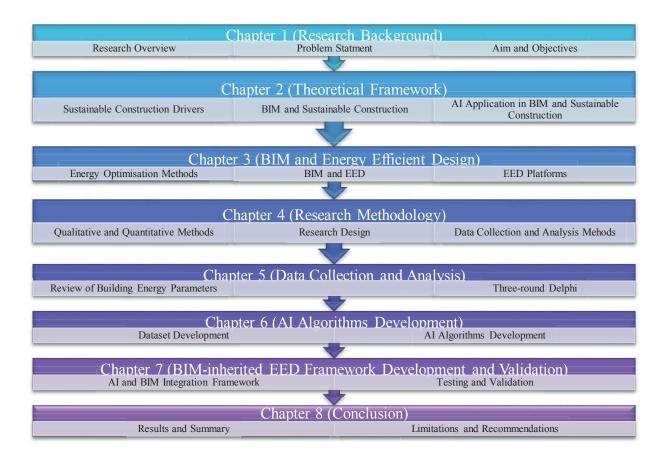


Figure 1.4. Thesis Outline

CHAPTER 2

Theoretical Framework

2.1. Introduction

This chapter introduces the theoretical framework for the research which includes three fundamental paradigms of sustainability, information and optimisation and their trilateral interactions toward their practical downstream including sustainable construction, BIM and AI. It is to develop a theoretical background for the aim and objectives of this study and narrow down into the attempts in gaining energy efficient buildings.

2.2. Theoretical Framework Development

2.2.1. Sustainability

Nowadays, there is an environmental problem outweighing critically other issues; the population growth has led to the excessive urbanisation and decreased the capacity of lands to support them (Ding & Banihashemi 2017). Developed and developing countries utilise hugely natural resources and even try to find other resources that may be intact (Maczulak 2010). Rapid depletion of these resources, global warming, climate change and economic and industrial expansions have sparked serious debates over the sustainability definition and implementation. Although it was found problematic to reach an international agreement regarding the theory of sustainability, it has been recognised that the ongoing expansion of humanistic activities will lead to endangering our ecosystem (Pawlowski et al. 2005).

Sustainable development principles have been stipulated through many local, regional and global policies and being applied in industrial and commercial sectors. Around forty-five years have elapsed from a campaign of environmental movement during the General Assembly of the United Nations in 1972 through nominating of World Environment Day. This seems to be an increasing responsibility to shift from unsustainable paradigms in development to the more sustainable one (Waseem & Kota 2017).

Sustainability is probably one of the most difficult concepts the science has confronted so far. Two popular statements for manifesting this concept have been defined by World Commission on Environment and Development and the National Research Council. The former

says "...development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland 1987, p. 42) and the latter states "the reconciliation of society's development goals with the planet's environmental limits over the long term" (Kates & Clark 1999, p. 1). Both definitions are process-oriented and attempt to address environmental, social and economic principles. However, the Brundtland's definition is the most established definition and can be applied on local, regional, national and international levels as to its generalisability (Glavič & Lukman 2007). This definition forms, therefore, the base for this research.

In the past four decades, because of an ongoing state of sustainability and sustainable development, new fields of science, information and philosophies have been added to the body of knowledge (Newman 2005). Furthermore, different creative and scientific endeavours have been practiced, including sustainability assessment indicators and models, in order for responding to the tremendous risks imposed by climate change and global warming imperatives (Faucheux & O'Connor 1998). Breaking this body of knowledge into interdisciplinary collaborations of research can be an important part to enhance the understanding of sustainability in the society (Bell & Morse 2008).

It needs to be embodied in the subtexts of different areas of knowledge ranging from engineering, physics and applied sciences to the social sciences and economy. But, unfortunately, this irresistible momentum cannot be maintained due to the absence of an underpinned theory for the sustainability which leads to many ambiguities (White 2013). For example, we do not exactly know how to measure accurately the sustainability level and what appropriate metrics are for covering a wide range of issues like global warming and climate change (Wise et al. 2014). Additionally, the criteria for identifying a sustainable procedure from an unsustainable one in cleaner production and activities such as resource use minimisation, improved eco-efficiency and source reduction and their underlying foundations are yet to be fully recognised (Waseem & Kota 2017).

Looking for methodologies and approaches that permit transdisciplinarity is a must for investigating what happens between, across and beyond the disciplines (Marinova & McGrath 2005). Nicolescu (1999, p. 3) states "transdisciplinarity concerns the dynamics engendered by the simultaneous action of several levels of reality". This capability is certainly required for the sustainability issue in order to develop knowledge at numerous levels in the meanwhile of keeping a holistic view of the world. Efforts of modelling and evaluating the sustainability are among the actions that can positively contribute toward this task (Todorov 2006).

Information theory along with its modern paradigms, prototypes and processes can establish a common ground for developing frameworks of sustainable development (Todorov & Marinova 2010). Also, the advanced state of this theory coupling with the opportunities that Information Technology (IT), cybernetics and informatics provide us with can be used to develop an integrated model for global issues.

2.2.2. Information Theory Paradigms

The concept of entropy of random variables and procedures set a stepping stone of information theory as "a conceptualisation and characterisation of processes that allows for storing and communicating of data" (Gray 2011, p. 1). Information theory includes three major paradigms of cybernetics, cognitive and informatics. In the information theory, data are carriers of meaningful content or message for the related recipient. This is a typical approach of cybernetics that was understood so far as the generic information theory. This approach is applied for creating a comprehensive model describing the characteristics and attributes of information in cybernetics as well (Cover & Thomas 2012).

The method of transmission of data between systems of the same nature, as introduced by Miller and Miller (1995) in their seminal study; technical, social and techno-social systems is called the information process. In fact, in cybernetics, it is identified by creation of a signal storing and transmitting data. As a consequent, information is considered as a particular signal preserving the contents of data as a message. In cybernetics, that is to say:

- Information process \equiv generating a signal
- Information ≡ data containing a message (Todorov & Marinova 2010)

Literally, developing of informatics and IT, conceptually and operationally, has been enormously influenced by cybernetics notion which is generated within information theory. However, some questions in terms of the nature and meaning of data cannot be answered through cybernetics and these are more explained with semantics paradigm (Todorov & Marinova 2010).

Semantics is a critical factor of interpreting the meaning and nature of information in cognitive theory in which information processes are defined as a reflection of objects on human beings consciousness (Chase 1995). Semantics is also coupled with the developments in the cognitive process resulting from advances in psychology and neurophysiology together with attempts to cultivate AI and knowledge-based Information System (IS) (Morris, Tarassenko &

Kenward 2005). Equating information with new knowledge, achieved from the cognition mechanism, is an accurate description of the cognitive paradigm. In other words:

- Information process \equiv cognitive process
- Information \equiv new knowledge

The cognitive paradigm deals with information quite different in comparison with the cybernetics in which it mostly focuses on the subjective and cognitive rather than the objective and physical aspects of information. On the other hand, both of them define information processes as the theoretical foundation for formalising and characterising information (Todorov & Marinova 2010).

The third paradigm; informatics has a more functional and technical nature which is utilised in conjunction with information theory. From this point of view, information processes are the tasks primarily providing information for managing the technologies and maximising their effectiveness. Informatics, as a scientific discipline, is founded upon the cybernetics and extended to cover the practical implications of information but it does not distinguish data from information. Moreover, in line with the cognitive paradigm, it incorporates human agents as a necessary parameter in the information process (Curtis & Cobham 2008). Such a pragmatic paradigm can be represented as:

- Information process ≡ storing, transmitting and processing of data
- Information \equiv data process for a specific aim

Table 2.1. Information Theory Paradigms

Paradigm	Information Process	Information Meaning	Interpretation
Cybernetics	Generating a signal	Data containing a message	Meaningful signal content (information) preserving data characteristics as a message
Cognitive	Cognitive process	New knowledge	Equating information with new knowledge achieved from a cognition mechanism
Informatics	Storing, transmitting and processing of data	Data process for a specific aim	Providing information for managing the technologies and maximising their effectiveness

Source: Adapted from Todorov & Marinova 2010

The above mentioned information paradigms pinpoint particular facets of information but all of them deal with the same stuff; data (Table 2.1). All kinds of data are capable of conversion to information disregarding their disciplinary records. As it makes really hard to acquire the understanding of the optimal level of information generation for modelling sustainability (Liu, Nakata & Harty 2010). However, these paradigms emphasise on transdisciplinarity to portray an accurate picture of reality (White 2013). Among three discussed paradigms of information theory, informatics is chosen in this research in view of its pragmatic and technical approach toward the role of information in managing and maximising the effectiveness of sustainability. In fact, informatics paves the way of information process; storing, transmitting and processing data for the specific aim of maximising the effectiveness of sustainability (Todorov & Marinova 2010). But, in order to more analyse the modelling competency of informatics and its relevancy to sustainability, there is a need to study optimisation as a cohesive unit for information theory serving a robust interdisciplinary bridge.

2.2.3. Optimisation Theory Paradigms

Optimisation is a branch of knowledge that is extensively employed in engineering, applied sciences, social sciences and other fields. It involves with choosing the optimal solutions within different problems, introducing computational techniques to find the best decisions and exploring the calculus performance of them (Sarker & Newton 2007). The terminology of optimise is generally used for substituting the words of maximise or minimise and its basic principle is to identify the best choice for given alternatives. To do so, the whole possible choices should be tested and the authenticity of the optimum should be validated (Sun & Yuan 2006).

The mathematical function which generally contains more than one variable and is used for optimisation purposes is called the objective function (Deb 2011). Of course, a single variable function can be created but from an optimisation perspective, there would not be room for improvement in the optimisation results. Because it reaches quickly to the end without fully analysing the whole choices. In addition, objective functions including several functions are termed multi-objective optimisations that have usually complex interrelationships and take time for being optimised. However, these are more precise in the optimisation results (Fister Jr et al. 2013).

With reference to the character of the optimisation purpose, three types of variables including real, integer and a combination of them can be existed. For real (continuous) variable problems, experts are usually trying to find a group of real numbers (Coello, Lamont & Van

Veldhuizen 2007). For discrete variables, an integer, set or graph from either finite or infinite sets of objects are investigated. The third type is the combination of continuous and discrete variables and termed as combinatorial optimisation purposes. These types of problems usually need for completely different ways of optimisation and problem solving techniques (Sarker & Newton 2007).

Constrained and unconstrained are another optimisation problem classification. Nevertheless, this classification is a bit questionable as some experts believe that there are not any unconstrained problems throughout of the world and all optimisation problems have constraints indeed (Neri & Cotta 2012). Notwithstanding this critic, the current categorisation seems important within the optimisation theory because of the opportunity in converting constrained to a chain of unconstrained problems (Coello, Lamont & Van Veldhuizen 2007). Linearity or nonlinearity is the other significant attribute of optimisation problems in which nonlinear models need more complicated and advanced approaches in optimisation (Fister Jr et al. 2013).

Functions can also be broken into convex or non-convex and differentiable or non-differentiable parts (Sarker & Newton 2007). Several optimisation methods are devised assuming that the function curves outward and that is why the convexity is one of the major elements of classical optimisation theories. Finally, differentiability is the third subgroup of function classifications which is mostly applicable in continuous functions. It depends on derivative-based algorithms and cannot be implemented for derivative-free functions (Rao & Rao 2009). The general optimisation paradigms can be classified as shown in Figure 2.1.

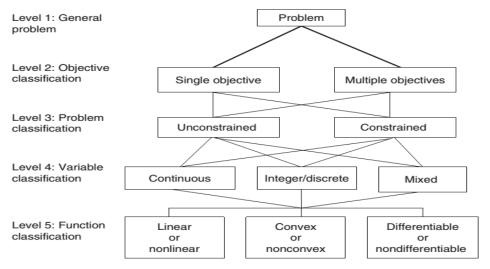


Figure 2.1. Classifications of Optimisation Paradigms Source: Sarker & Newton (2007)

Given the overview on the optimisation theory and its principles, it is of importance on linking this theory to the ultimate aim of this study. The reason for applying optimisation theory lies in assisting information theory and its pragmatic driver; informatics to reach an enhanced level of sustainability. That is; the unconstrained multiple objective function consisting of mixed variables of continuous and integer could convex the information contained in informatics toward the optimised level. Therefore, the optimised information is employed in informatics to run the information process and maximise the sustainability.

2.2.4. Interaction of the Three Theories

This section presents the interaction of three theories of sustainability, information and optimisation as the underlying theme for addressing this research and provides a schematic view on a conceptual model. In fact, this is the interaction and integration of these three theories which establishes a theoretical foundation for this study. In order for modelling this interaction, it is required for these systems to be depicted centrally. Following the literature of foundations of each theory in the previous sections, Figure 2.2 indicates the three domains of sustainability, information theory and optimisation theory as the main operating components of this model.

It is obvious that reaching an integration for these upstream will reveal uncharted territory and may even make it as an insoluble enigma. For instance, what the agreeable level of embracement these domains share with each other. New disputes may be sparked by conceptualising such a model to these upstream which in that situation, they are essential to be resolved in terms of their both atomistic and holistic perspectives. Moreover, the present interaction of sustainability, information and optimisation provokes some arguments that this study should address.

The first argument regards the characteristic of interactions and the type of the model among these theories. The current tools such as econometrics, environmental and sociometric models for sustainability, informatics for information theory and iterative, algorithmic and calculus techniques for optimisation theory can shape the nature of interactions within each theory (Komiyama et al. 2011). Nonetheless, a totally distinctive model involving with all major elements and coupled with new advanced technologies would be required for modelling this metasystem. It is axiomatic that these paradigms are continuously changing and shaping in virtue of different interplays.

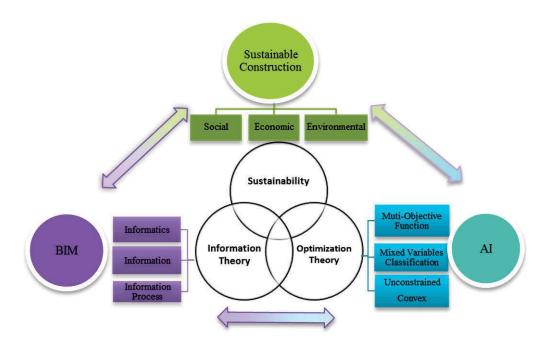


Figure 2.2. Interaction of Three Theories and Their Components

The second argument investigates the nature of information which is obtained from the interaction. The released information should be treated as a collection of system status relevant to generating, transmitting and receiving of information items and analysed as to the pragmatic informatics. The procedures are also to transform, transmit and optimise these status collections whereas the sustainability derivatives dictate the course, approach and content of these processes. Achieving sustainability makes it imperative for regularly generation, transformation, transmission, receiving and optimisation of information with respect to the target (Haymaker 2011).

Sustainable development has been becoming a globalising phenomenon strengthening the links and synchronising the movements among humanity, nature and the economy (Komiyama et al. 2011). Along with the growth of interest of policy makers and imposition of international environmental regulations, the need for environmentally and ecologically related information is perceived more than ever (Haymaker 2011). This procedure is a cycle of endless development and adjustment. It indicates the interaction of sustainability, information and optimisation theories which requires continues supervision and analysis for finding an intelligent decision. The cuttingedge scientific discoveries in information theory together with computer-aided algorithms in

optimisation theory can facilitate managing the scale and spectrum of sustainability issues and allow for working this framework properly (Todorov & Marinova 2010).

"Information is central to guidance, and guidance for a sustainability transition needs information on both where we want to go as well as how well we are doing at getting there" (Clark, Crutzen & Schellnhuber 2005, p. 20). What is claimed here is that information can offer such guidance and feed the transdisciplinarity pillars if optimised information exists through the power of intelligent agents during a sustainable phase. To bring the interaction idea of three theories of sustainability, information and optimisation in a practical context, a journey should be set from the upstream to the downstream. This journey conceptualises the relevant derivatives to reach a harmony in the system. According to the study conducted by White (2013), systematic integration is one of the high-frequent term reflecting the concerns of recognising the interconnections among different components for sustainability. This is especially a prominent finding which addresses a need for system thinking in elucidating this journey.

It should be noted that the evolution of data and its effective integration is the key problem in reaching a harmonised system. As to the informatics processes of information theory, well-structured data could be conceptualised as the Common Data Environment (CDE); a harmonic place for collecting, managing and sharing information amongst a team working on a system (BS1 2008). CDE is the single source of information used to collect, manage and disseminate documentation, the graphical model and non-graphical data for the whole system (i.e. all project information whether created in a BIM environment or in a conventional data format). Creating this single source of information facilitates collaboration between system members and helps avoid duplication and mistakes (Shafiq, Matthews & Lockley 2013).

Sciences and cutting edge technologies such as BIM and AI can play a crucial role with CDE. This knowledge helps constructing understandable foundations to reach a sustainable system through preserving a harmony among various domains (Todorov & Marinova 2010). It can compose or combine several separate branches of expertise or fields to draw appropriately from multiple disciplines in order to redefine problems outside of normal boundaries. It is to reach solutions based on a new understanding of complex situations (De Beaugrande 1980). So, interand-multidisciplinary approach is necessary to link the different levels of this study to determine the hierarchy of subsystems and direct, indirect and cross interactions among pertinent criteria.

Based on Figure 2.2, the described process of interaction among three fundamental theories of sustainability, information and optimisation is regarded as the core of this integration

system. It presents that the information theory and its functional driver; informatics works on the information process toward the sustainability. This batch of information is being optimised through optimisation theory paradigms via setting objective function, mixing continuous and integer variables and convex function for reaching the maximised effectiveness of sustainability. Therefore, such a theoretical integration sets the journey to the downstream and practical level which should be elaborated in the construction field as a science cloud of this study to translate the discourse into practical actions. Hence, sustainability is narrowed down into the sustainable construction drivers. BIM, then, comes to the fore as the representative of informatics applications and CDE driver in the construction industry (Guttman 2011).

BIM is to store, transmit and process the optimised information; the information which is optimised through AI as the practical machine of optimisation theory paradigms through CDE (Neustadt 2015). According to BS1192 (BSI 2008); "collaborative production of architectural, engineering and construction information, code of practice", CDE may contain a number of various information environments. It may comprise of a supply-side CDE used by the project delivery team, and the information environment which facilitates an employer-side document and data management system for the receipt, validation and approval of project information. Effective use of a CDE will build an accurate and well-structured data set as the stages progress. Through this setting, the integration of three fundamental theories of sustainability, information and optimisation is linked to their three functional drivers of sustainable construction, BIM and AI and establish a theoretical framework for the aim of this research. For this reason, in the next sections, sustainable construction, BIM and AI components are elaborated and their focus on the EED is justified.

2.3. Sustainable Construction Drivers

Extensive research has proven that among the myriad of industries, civil works consume 60% of the raw materials obtained from earth in which building sector contributes to 40% of this damage (Bribián, Capilla & Usón 2011). Likewise, Greenhouse Gas (GHG) emitted from buildings to the environment constitutes approximately 40% of total world GHG emissions (Wang et al. 2016). To give a full picture of this concern associated with construction, it is worth mentioning that among the top ten worst pollution problems in the world for the decade, *urban air quality* and *indoor air pollution* are directly and *contaminated surface water* and *industrial mining activity* are indirectly related to this industry (Ericson, Hanrahan & Kong 2008).

The need for environmentally friendly construction practices led to the advent of a movement known as GB. GB has been developed to encourage using less toxic materials, applying more resource conservation techniques and improving energy usage patterns, among others (Venkatarama Reddy & Jagadish 2003). "GB refers to both a structure and the application of processes that are environmentally responsible and resource efficient throughout a building's life-cycle: from planning to design, construction, operation, maintenance, renovation, and demolition" (EPA 2016, p. 1). The ultimate goal of GB is to eliminate the negative impacts of building on its surroundings and human health. This would result in environmental, financial, economic, and social benefits (Alwaer & Clements-Croome 2010).

A study published by Mc-Kinsey Company's Report on the Sustainability and Resource Productivity (2015) shows that by implementing GB, the emissions of GHGs can be reduced by 6 billion tons per year. Another study shows that well designed sustainable dwellings compared to conventional ones consume, on average, 25% less water and conserve energy up to 45% (Anastaselos et al. 2016). During the last decade, a plethora of researches, studies and tools have been carried out with respect to tackling sustainability issues in construction. Holistically, these works mainly focus on (Kibert 2012):

- GB assessment tools
- GB process implementation
- Energy and carbon footprint reduction
- Built environment hydrologic cycle
- Sustainable material loops
- Waste reduction
- Indoor air quality
- Sustainable site and landscape
- Sustainable technologies in green building

However, these efforts have yet to meet their fullest potential in managing sustainability of high-performance buildings. According to 2013-2014 annual report of Sustainable Building and Climate Initiative (SBCI) of United Nation Environment Program (UNEP), the performance of buildings are "far below current efficiency potentials" (UNEP 2014, p. 15). They still are the most contributors to GHG emission and consumer of the world's electricity. There are numerous barriers hindering the implementation of sustainable buildings (Häkkinen & Belloni 2011):

• Financial disincentives

- Lack of the whole system thinking
- Construction process complexity
- Lack of communication and coordination among parties involved
- Inadequate research studies
- Unavailability of novel methods and tools
- Lack of integrated design methods

As a glance at these barriers, it is obvious that they are falling to two major categories of organisational and technical ones. So, sustainable construction, to be effectively implemented, requires to overcome such barriers (Banihashemi et al. 2014). There are multiple strategies to follow (either through reducing consumption, increasing efficiency or finding the less adverse methods), but in all conditions, innovations are imperative (Larsson et al. 2016). This process requires agents promoting innovations by virtue of coordination, networking and communication (Yang 2016). Nevertheless, the broad content of sustainable construction and the plurality of the meanings of GB make it hard for experts to reach a consensus in concept. It may even cause a disagreement in problem formulations and lead to contradictory solutions (Stenberg 2006). This fact hampers cooperation, which in turn, hampers the developing innovative solutions.

Foxon and Perason (2008) criticise the dearth of connection between the innovation and sustainable construction. Construction experts typically have to innovate in order to improve performances to meet the increasingly complex and fast changing needs for a sustained quality of the built environment (Larsson et al. 2016). Of course, as Yang (2016) argued, sustainability is currently no more than a breakeven point and it is necessary to change to sustainable and then restorative and regenerative construction. He called this process a continual improvement in construction. So, conventional mono-disciplinary innovations are no longer capable of modifying the technology regime and perceptions of underlying concepts of current construction methods (van Egmond 2012).

Furthermore, construction is one of the most information-dependent industries, mainly due to its extended fragmentation (Chang et al. 2016). Construction projects are often complex and unique, involve a large number of activities, and require the employment of several human resources with various specialisations (Banihashemi et al. 2017). Thus, the amount of information generated and exchanged during the construction process is enormous even for small-sized projects (Chassiakos & Sakellaropoulos 2008). For this reason, Sodagar and Fieldson (2008) state that having efficient access to the information is a key for facilitating integrated design method, coordinated process of construction and analysing their sustainability and so, making construction

more sustainable. GB is prevented from deficiencies in the communication among parties involved whereas fluent cooperation and networking are very essential for it to acquire momentum in design, construction and operation of buildings (Hong et al. 2015). The efficient use of information and the active cooperation of parties involved via the management and sharing of information methods can contribute to the sustainable construction. It is through overcoming the obstacles of capturing and managing the data and information and the technical-organisational barriers mentioned (Passer et al. 2015).

The absence of a systematic information management has forced functional disciplines to follow their own decisions. These decision are mostly without considering the impacts on the other disciplines that obviously provoke clashes in coordination and communication in construction projects and impede the sustainability drivers (Gan et al. 2015). While an efficient information management can enable experts to consider the wide range of components of sustainable building including building performance, lifecycle costs, rapid adaption of design and environmental impacts (Kramers et al. 2014). In contrast, knowledge sharing is also considered problematic for sustainable construction especially when different sources of information are available. Stenberg (2006), by investigating the different sources of sustainability-related information for Swedish construction industry, indicated that providing biased or distorted information can be one of the possible risks with this regard.

All in all, in spite of serious attempts, construction experts still are deficient in tools helping them (1) to implement GB in all stages and (2) to contrast different alternatives and methods. It is vital to provide tools in terms of being objective, reliable and accessible (Kibert 2016). That is why in the recent years, different new and innovative methods have been introduced to converge technologies and knowledge from different disciplines and scientific theories to eliminate technical or organisational barriers of GB. Information and Communication Technology (ICT) is one of these new methods that has been being utilised in answering the aforementioned critiques through providing an integrated chain of software and hardware. "Using new information technologies gained and exchanged knowledge and experience shall become instrumental to the success of approaching sustainable buildings and sustainability generally" (Todorovic & Kim 2012, p. 6). The impressive use of such ICT methods and mechanisms require the integration of tools to design, construction and operation phases and the development of intelligent methods for information management (Kibert 2016). As a specially designed process and innovative approach, BIM that produces a parametric modelling and presents building

information dynamically, can significantly contribute to the sustainable construction (Zanni, Soetanto & Ruikar 2014).

2.4. BIM and Sustainable Construction

BIM represents the building as an integrated database of coordinated information. Beyond graphically depicting the design, much of the data needed for supporting sustainable building is captured naturally as design of the project proceeds (Howell & Batcheler 2005). It paves the way of superimposing multidisciplinary information in an integrated model which creates an opportunity for measuring the sustainability state of the project throughout its lifecycle (Azhar et al. 2011). According to the book of *Green BIM* by Krygiel and Nies (2008), BIM has the *potential* to aid sustainable design through:

- Selecting a suitable building orientation
- Analysing day-lighting
- Reducing water needs in a building
- Reducing energy consumption through an integration with energy analysis software
- Featuring renewable energy potentials
- Reducing material needs reduction
- Decreasing waste and carbon emission by logistic site management

Architects can import data into BIM model to locate the project geographically and present the conditions of climate, location and surrounding area. Then, the model can be reorientated and edited on site based on the real coordination for reducing required resources and exposing efficiently to solar radiation (Teicholz, Sacks & Liston 2011). BIM is capable of analysing the mass and form of models for envelops analysis and window to wall ratio. Likewise, engineers utilise BIM to decrease the energy consumption by exporting the 3D model to particular energy analysis software and calculating light reflectance and transmittance (Underwood, Isikdag & Global 2010). Effectively coordinating logistics through site analysis and modelling including wetlands and protected habitats can help contractors to eliminate the possible issues. It even easily quantifies the amount of materials extraction of buildings to simplify reusing or recycling measures (Wong & Fan 2013a). BIM can also be employed by subcontractors to reduce waste and integrate shipments to decrease carbon emission. Finally, the BIM file arranges an array of

required resources to advise the project team regarding sustainability issues from the incipient stages of a project (Hardin 2011).

In the recent years, scholars have attempted to research on BIM and GB design and construction potentials from different point of views (Table 2.2):

- BIM for modelling and analysing of building performance, including energy and thermal simulation (Hiyama et al. 2014; Park et al. 2012b; Seongchan & Jeong-Han 2011; Woo & Menassa 2014), lighting simulation (Huang, Lam & Dobbs 2008; Raminhos et al. 2013), daylighting simulation (Welle, Rogers & Fischer 2012; Yan et al. 2013a).
- BIM for optimising integrated design process (Oh et al. 2011a; Wang, Li & Chen 2010; Wong & Fan 2013b)
- BIM for evaluating sustainability of buildings with reference to Leadership in Energy and Environmental Design (LEED) and other environmental assessment tools (Azhar et al. 2011; Motawa & Carter 2013a; Nguyen, Shehab & Gao 2010; Wu & Issa 2012; Wu & Issa 2014)

Table 2.2. BIM and Sustainable Design Archetypes

No.	Reference	BIM & Building Performance		BIM & Integrated Design	BIM & Green Certification
		Thermal	Lighting	-	
1	(Dong et al. 2007)	✓			
2	(Seongchan & Jeong-Han 2011)	✓			
3	(Park et al. 2012b)	✓			
4	(Welle, Rogers & Fischer 2012)		✓		
5	(Raminhos et al. 2013)		✓		
6	(Yan et al. 2013a)	✓	✓		
7	(Hiyama et al. 2014)	✓			
8	(Woo & Menassa 2014)	✓			
9	(Wang, Li & Chen 2010)			✓	
10	(Oh et al. 2011a)	✓		✓	
11	(Wong & Fan 2013a)			✓	
12	(Nguyen, Shehab & Gao 2010)				✓
13	(Azhar et al. 2011)				✓
14	(Wu & Issa 2012)				✓
15	(Motawa & Carter 2013a)				✓
16	(Wu & Issa 2014)				✓

With the technological advancement and wider use of BIM, the joint BIM and sustainable design applications have become ubiquitous. As an instance, Inyim, Rivera and Zhu (2014) developed a BIM-based tool enabling decision making for sustainability of design phase. Clevenger and Khan (2013) analysed the contribution of BIM from design to fabrication processes for building materials. They contended that building delivery performance can be improved and

unnecessary environmental impacts can be mitigated as a result of reducing design errors and any miscommunications via BIM functions. Biswas and Wang (2008) established a BIM-extended tool to incorporating BIM technology in evaluating environmental consequences from design decisions. This study could be regarded as one of the earliest attempts in BIM employment to the rating and certification of GB. In the same vein, Gandhi and Jupp (2014) evaluated the potential utilisation of BIM for the Australian Green Star Building certification.

Apart from academic implications of BIM contribution to GB, Azhar (2010) investigated the applicability of this tool through a survey among 145 experts of AEC within US. First, with regard to the time saved in applying BIM-based sustainability analysis vis-à-vis traditional analysis, 54% of respondents stated that they are recognising *some time savings* and 23% declared that they are observing *significant time savings*. Then, with respect to monetary savings, similar to the first question, 51% of respondents asserted that they are experiencing *some cost savings* and 26% are realising *significant cost savings*. In a nutshell, it was observed that implementing BIM-based sustainability analysis resulted in "satisfaction" up to a certain degree as to the traditional approach.

Moreover, Malkin (2011) conducted multiple case studies during the design and construction stages of large scale projects in Australia and demonstrated the positive role of BIM in making these projects more sustainable. Results were recorded during designing a thirty-eight storey project of Regent Office Tower which was built through the partnership of Industry Superannuation Property Trust and Brookfield Multiplex. They used Revit Architecture and Structure together with Ecotect Analysis effectively to keep the overall concrete fly-ash volume up to 20% to meet the sustainability standards.

But there is a long way to reach the full implementation of BIM in the sustainable design. BIM is still in its infancy and attaining the desired quantum leap entails a radical reorientation in the current state. The main reasons for this fact are (Kibert 2012):

- The lack of ideal interoperability between BIM and analysis software packages
- The need for more inputs and technical specifications in the BIM model
- The need for integration of carbon accounting data
- The information lost in translation data between different parties
- The lack of ability to rapidly test and quantify numerous sustainability-related variables

These factors envision the core value of information as the bottom-line of a flawless BIM-based sustainability analysis. Bynum, Issa and Olbina (2013) conducted a survey among 123 pioneer companies of AEC in US, around 60% of respondents stated that 'BIM, as a multidisciplinary tool, currently does not operate in an optimal standardised format, making it difficult to translate data seamlessly'. More importantly, 84% of them pointed out that the need for interoperability and information dynamic improvement should be of paramount importance in the relevant research and development. In addition, the more sustainable designs are becoming complicated, the more technical properties designers would employ. They need to see thermal or visual properties of building components and how these affect the sustainability of design. Presently, BIM is to some extent insufficient in consisting of properties to analyse energy, lighting and water efficiencies inherently. So, embedding this capability directly into designing a model will become invaluable in the future (Kensek & Noble 2014).

However, this type of improvements can act as a double edged sword. On the one hand, the fundamental tenet in the success of this end is having an integrated, comprehensive and organised system of collection and dissemination of information among the tools and parties involved (Hardin 2011). On the other hand, pushing to keep all information either relevant or irrelevant may be a source of friction and errors (Sanguinetti et al. 2012). Idealism concept about BIM, promoted by commercial sectors, delves into this misconception that all information is required and the more is better. Consisting of detailed description of all components are often too "information-rich" to evolve into the design especially where continual changes happen (Holzer 2011). Likewise, observing the current trend of BIM platform development, designers notice a drive by software developers to promote all-round tools and assist users in their procedure throughout the project lifecycle (Zeng 2012).

This idealistic introduction of BIM possibly leads to a quick uptake in AEC instead of a critical discourse concerning the adoption, mobilisation and simplification methods (Holzer 2010). According to McGraw-Hill construction report of BIM contribution to green building, 54% of the companies that constitute the sample survey for this report claimed that the technical complexity of BIM is the reason behind not using it for green projects (Bernstein, Jones & Russo 2010). Consequently, by overloading of data or excessively technical sophistication in designing or exchanging BIM model, the receivers may have unreasonable expectations regarding the value of information they have received (Guttman 2011).

Given the above context, in line with the sustainable design leaning more and more toward intelligence, a significant breakthrough should be made in the current BIM to be smarter

but simpler (Heidari et al. 2014). Therefore, apropos of interdisciplinary application and the integration of sustainability, information and optimisation theories and their practical drivers of sustainable construction, BIM and AI, optimisation theory suggests a promising convergence. It helps with refining, optimising and classifying the batch of information content in BIM through its practical drivers such as AI and computational algorithms (Asl et al. 2014). BIM, because of its parametric nature, is a convenient platform for utilising AI in expert system developments. It can be based on the black box methods for predicting the current trend and optimising the future performance of design (Yuan, Yuan & Fan 2013).

2.5. Artificial Intelligence (AI)

Rich and Knight (1991, p. 2) defined AI as "the study of how to make computers do things at which people are doing better". The term of AI was coined by McCarthy (1968, p. 5) who gave a more primitive definition as "the science and engineering of making intelligent machines". In recent decades, several approaches including linear, non-linear, heuristic and metaheuristic methods have been developed on the basis of AI as alternatives for traditionally mathematical methods (Cohen & Feigenbaum 2014). In fact, a great trust in AI is the development of algorithmic models to assist with optimisation theory and its applications in refining data and finding most optimum choices automatically (Engelbrecht 2007b).

In principle, AI applications in engineering problems can be categorised into three main areas (Engelbrecht 2007a):

- Prediction
- Classification
- Optimisation

Prediction and classification are two relatively similar methods of data pre-processing analysis that are used to obtain a description of important classes of data or to predict future trends of data. While classification is usually used to classify categorical data, prediction is to model continues valued functions (Cohen & Feigenbaum 2014). These techniques first, need a training data to learn from them and second, to infer the results based on inputs. ANN, DT and Fuzzy system are among the popular AI methods used for these purposes (Kantardzic 2011).

Furthermore, for achieving the best option among different choices, optimisation methods can be applied that is normally considered as a post-processing data step. It is a procedure

executed iteratively by comparing various solutions still an optimum or a satisfactory solution is found (Fister Jr et al. 2013). The well-known used methods like GA and Particle Swarm Optimisation (PSO) are inherent in mimicking biological systems and appropriate for multivariables and non-linear problems (Tao, Zhang & Laili 2014).

2.5.1. AI Application in Sustainable Construction

Academics and professionals have employed AI in sustainable construction for the following aims:

- Forecasting. Different studies have been conducted to forecast electrical loads of utilities, short term and long term energy uses, weather variables and thermal load for buildings (Kreider et al. 1995; Virote & Neves-Silva 2012; Yang, Rivard & Zmeureanu 2005). Typically, Conditional Demand Analysis (CDA), ANN and Support Vector Machine (SVM) are used for forecasting because of their strong prediction capability (Foucquier et al. 2013; Zhao & Magoulès 2012).
- System modelling. For modelling various engineering systems in building such as Heating, Ventilation, Air Conditioning (HVAC), ANN and Fuzzy logic are often used which can find an accurate relation between inputs and outputs (Kalogirou 1999, 2000, 2001; Li, Su & Chu 2011). Of course, the former can be used for both continues and discrete variables but the latter is just used for continues ones (Foucquier et al. 2013).
- Optimising. Finding the most optimum values and states for different building design and operation problems is a real risk that can be mitigated by utilising AI (Griego, Krarti & Hernández-Guerrero 2012). Subsequently, evolutionary algorithms including GA and PSO have been used for optimising building envelopes, massing, thermal comfort, daylighting and lifecycle analysis (Caldas 2008; Evins, Pointer & Burgess 2012; Machairas, Tsangrassoulis & Axarli 2014; Palonen, Hasan & Siren 2009).

2.5.2. AI Application in BIM

Currently, the majority of BIM features focus on the visualisation function and information exchange with other simulative and analytic software. Designers can easily identify the visual status of projects by the current BIM environment but they cannot sufficiently obtain detailed scrutiny regarding the sustainability status of that project (Wong & Fan 2013a). Besides,

the current BIM is regarded as passive as it requires an additional analysis procedure in order to assess and optimise its sustainability after the visualisation (Moon et al. 2012). Passive BIM cannot sufficiently provide sustainability analysis data such as energy consumption level and the design variables that need to be optimised. It has been proven that half of the time it takes for simulating and analysing a sustainability analysis model is spent re-creating a BIM geometry in a new software (Krygiel & Nies 2008).

According to BuildingSmart (2007, p. 5): "During the design period, different options are evaluated and tested. In a project using BIM, the model can be used to test "what if" scenarios and determine what the team will accomplish." This is regarded as an "active BIM" (Moon et al. 2013) which can guarantee the design's sustainability through facilitating "what if" scenario tests that reflects on its design parameters. Hence, it can be expected that the active BIM would be successfully applied as a decision making tool for green building. Controllable parameters during the design phase including physical properties and building envelops have not been adequately managed under the present passive BIM. This fact leads to restrictions for actively application of BIM for critical processes such as daylighting and building energy simulation (Rahmani, Zarrinmehr & Yan 2013).

If these critics lead to classify the current BIM as a passive system, the "active BIM" system will provide the diverse decision making platforms to provide the optimal state of green design and construction (Moon et al. 2013). As a simple rule, the smarter the BIM, the more useful information it will contain specific to each of its contributors (Heidari et al. 2014). In order to achieve a high level of usefulness, that information needs to be managed, coordinated and associated with individual objects in the BIM (Kensek & Noble 2014). Leveraging the parametric definition inherited in the BIM-based sustainability analysis, AI through optimal use of IT in preventing data duplication and malfunction transforms data to an optimised level and contributes to the sustainable building (Succar, Sher & Williams 2012). However, little concern has been given to apply AI in BIM to transform the passive BIM to the active BIM; especially in terms of sustainability analysis. In the literature, AI has been recently used in BIM for strengthening its parametric analysis for the following purposes:

- Optimising BIM-based construction planning and scheduling (Moon et al. 2013)
- Optimising BIM model based on different variables (Asl et al. 2014; Yuan, Yuan & Fan 2013)
- Optimising HVAC control schedule for building energy management system (Jung et al. 2013b)

These studies are in embryonic steps but it is apparent that AI-based parametric analysis for active BIM function is a new trend which requires considerable progresses to aid sustainable design. This procedure is potential to empower BIM with creative exploration ability of different design alternatives by modifying the variables and their interrelationships automatically to make projects more sustainable.

2.6. Energy Estimation and Optimisation Methods in Buildings

As mentioned in Section 2.3, sustainable construction is a very broad spectrum from green policies to renewable energy initiatives. Whereas, the figures such as consuming 40% of total final energy and 54% of electricity (IEA 2012) and 9Gt of carbon dioxide (CO₂) emissions as a deleterious consequence (Jennings, Hirst & Gambhir 2011) put the energy efficiency concept in the limelight of research and development. Although energy consumption should not be treated as the single criterion for sustainability decision making (Ding 2008), spread of the majority of GB rating tools such as LEED, the most possible points are dedicated to energy-oriented criteria (Pohl 2011). Electricity energy costs account for around \$1.50 to \$2.00 (USD) per meter square of gross floor area of a building which, as an example for a 50,000 meter square of a building, it equals to \$75,000 to \$100,000 (USD) per year (Hodges & Elvey 2005). Thus, efforts in improving the energy efficiency of this case by only 10% amount to \$7,500 to \$10,000 (USD) of annual savings whereas the potential of saving energy through appropriate measures in design and construction is perceived to be substantial and can reach up to 40% (Costa et al. 2013).

With reference to International Energy Outlook of Energy Information Administration (EIA) in 2016, energy consumption of building sector will increase by 48% in the next two decades at a ratio of 1.4% per annum (EIA 2016). The building sector covers a wide variety of building types such as residential, commercial and industrial. More specifically, according to Lombard, Ortiz and Pout (2008), the energy consumption from residential sectors for both developed and developing countries will be overtaking that of non-residential parts by 67% more in 2030 (Figure 2.3). Figure 2.3 was chosen since it indicates the status of building energy consumption in the last decade and gives the projection toward the next decade.

Million Tonnes of Oil Equivalent

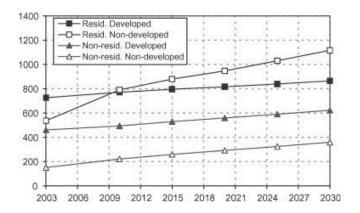


Figure 2.3. Building Energy Consumption Outlook Source: Pérez-Lombard, Ortiz & Pout (2008)

Concerning these certain facts, familiarity with EED and construction for residential buildings has been steadily increasing in recent years. Several methods and techniques in the scientific community have been developed, tested and verified for calculation, simulation, prediction and optimisation of buildings energy performance.

2.6.1. Calculative Methods

Calculative methods are based on the building thermal behaviour measuring through three main approaches of Computational Fluid Dynamic (CFD), zone and multizone modes (Pedersen 2007). CFD is a microscopic and 3D method to model the thermal transfers and allow for detailing flow field. As an advantage, it is well-performed for studying precisely thermal performance of complex geometries but it is very time-consuming and requires deep knowledge on fluid dynamics and software (Zhai & Chen 2005). Zonal approach is a simplified version of CFD that divides each zone of a building into assorted cells corresponding to small parts of rooms in two dimensions. The determination of local parameters in 2D map and the possibility of visualising airflows are the usefulness. Nonetheless, the relatively inaccurate results are the disadvantages of this method (Inard, Meslem & Depecker 1998). The last and probably the simplest approach, as to its one dimensional nature, is the multizone or nodal mode which approximates a zone to a node specifying heating or cooling loads. Linearizing the equations, the calculation time can be immensely decreased whereas the interrelationships of loads and their impacts on each other are not quantifiable (Megri & Haghighat 2007).

Looking briefly at the calculative methods, CFD is the most complete approach to formulate building energy performance but at the same time, is the most complex one. It hinders the simulation of all phenomena due to the extreme computation time (Zhai & Chen 2005). Zonal

mode is an intermediate method that delivers less accurate results compared to CFD but more decent information in comparison with nodal mode (Zhai et al. 2002). Furthermore, for all calculative approaches, a wide range of parameters such as geographical, physical, climatic and occupancy data are required as inputs yet, these variables are usually presented by a degree of uncertainty (Swan & Ugursal 2009). Ultimately, detailed analysis of the physical characteristics of a target is the main shortcoming of these methods that necessitates the extensive knowledge on the physical mechanisms of heat, air and moisture transfers (Woloszyn & Rode 2008).

2.6.2. Simulative Methods

A growing number of simulative methods have been developed and tested in the context of different simulation software in the last decade for the evaluation of building energy performance. EnergyPlus, DOE-2.1E, Ecotect, Eco-designer, Green Building Studio (GBS), Integrated Environmental Solution (IES), Modelica and DesignBuilder are the most popular software among the myriad of tools which are being majorly used by experts¹ (EERE 2014). The inconsistency in the outcomes and functions of these tools is one of the problems damaging the confidence on them. Raslan and Davies (2010) revealed the predictive deviation for such software with respect to compliance checking with energy efficient standards and guidelines.

As another issue stated in the literature, the significant time is required for learning and achieving proficiency in using these applications. In addition, by reviewing the procedural instruction of these applications in the literature, it can be inferred that designers usually create models in architectural and construction tools and then follow the energy assessment by importing them into these applications (Kavgic et al. 2010). Schlueter and Thesseling (2009) pointed out that there is a need to integrate seamlessly this simulation practice into the design process. BIM may consist of almost the whole data required for energy assessment. If it is employed properly, a great volume of time and tasks can be saved in preparation of model for building energy simulation in the meanwhile of minimising inaccuracies (Kumar, 2008). This is seen as a necessity to enable the replacement of traditional sequential processes with interactive concurrent design.

¹ Fully detailed analysis of the simulative methods has been presented in Chapter 3.

2.6.3. Predictive Methods

The peculiarity of predictive methods as compared to calculative and simulative ones is this fact that they do not necessitate to gather detailed physical information, work out heat transfer equations or simulate a complex energy model (Li, Su & Chu 2011). In fact, they are based on machine learning algorithms; a subgroup of AI, deducing patterns only from training datasets to predict the energy consumption of buildings. Hence, they are well-performed when the comprehensive physical, geometrical or geographical characteristics of the target building are not fully recognised (Zhao & Magoulès 2012). On the contrary, the predictive methods completely depend on the measures and reliability of data and if the data are neither accessible nor properly collected, it will be a serious concern (Neto & Fiorelli 2008). A wide range of algorithms have been used in the literature for building performance prediction. However, according to a thorough review of articles conducted by a group of prominent experts about the state of the art of this field in 2013, three methods of CDA, ANN and SVM have been identified as the most popular and suitable methods with this regard (Foucquier et al. 2013).

CDA is a linear multivariable regression method and its principle is to forecast y as a linear aggregation of input parameters in addition to an error constant ϵ_i .

$$y_i = x_0 + x_1 \times x_{i1} + x_2 \times x_{i2} + \dots + x_p \times x_{ip} + \epsilon_i \quad i \in [1, n]$$
 (2.1)

Where n is the number of datasets, p the number of parameters and x_{θ} is a bias (Aigner, Sorooshian & Kerwin 1984).

Although CDA is a very simple method for prediction of building energy performance by non-expert practitioners, it is very limited where the problem is non-linear (Ghiaus 2006). This drawback is resulted in the inflexibility in prediction plus a trouble in handling the multicollinearity issue which is a correlation among variables. So, the lack of flexibility in its structure as a consequence of linearity nature makes it impractical to utilise for the whole building energy performance (Aydinalp-Koksal & Ugursal 2008).

The second method; ANN is an AI based computational model that tries to simulate the structure or functional aspects of biological neural networks (Wang 2003). The thermal equations used to analyse and calculate heat loads are often complex, making ANN a good platform to be used for mitigating this complexity (Ahmad et al. 2014). In this form, the network is established with collected datasets and the weights of inputs that are fed into each neuron or nod. The weights

are then adjusted through feed forward-back propagation iteratively until a suitable output is produced. A suitable output is the one which is as close as to the actual one and has a least error between the values of network outputs and target values for them (Hagan, Demuth & Beale 1996). Back propagation is a method which feeds back the size of the error into the calculation for the weight changes.

Each neuron in the input layer represents one variable; $Input_i$ multiplied by a weight, W_{ij} , and the results are added to give the output in the $Output_i$ layer:

$$Output_{j} = f\left(\sum_{i}^{j} Input_{i} \times w_{ij} + B_{j}\right)$$
(2.2)

Where f is the activation function that is converting weighted input to an output function and B_j is the bias for the $Output_j$ (Figure 2.4).

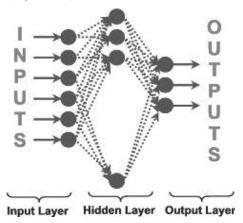


Figure 2.4. The Conceptual Structure of ANN Source: Flores (2011)

ANN is greatly powerful in deducing the relationships between inputs and finding the relevant pattern toward the output through training procedure, without requiring a prior assumption or hypothesis and without being threatened by the multicollinearity phenomenon (Dreiseitl & Ohno-Machado 2002). Moreover, it minimises the discretisation error; an error that is caused by representing continues variables in the computer with an integer value (Kantardzic 2011). Given this effective faculty, ANN can function a diversified range of variables from continues to binary and yes/no types in an efficient computational time. In contrast, requiring a huge and consistent database is a deficiency that limits ANN application. It is essential to train the model with a comprehensive learning dataset with the equal number of data for all variables without any missing of information (homogenous database) (Dounis 2010). The other barrier which may hinder its functionality lies in the lacking of accredited rules in arranging the structure.

Although for the selection of architecture for a neural network some heuristic rules have been suggested in the literature (Shahidehpour, Yamin & li 2002), but some criteria such as the number of hidden layers and the associated neurons still come down to a rule of thumb and trial and error.

SVM is another predictive and AI based method used for prediction and forecasting purposes. With this regard, the assumption of SVM is to find the best fitting equation model for a training data of $[(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)]$ in which x_i is in the input and y_i is in the output space (Smola & Schölkopf 2004). The function f for this dataset is as the following:

$$f(x) = <\omega, \varphi(x) > +b \tag{2.3}$$

Where φ indicates a variable in the three dimensional space, <...> a scalar function and ω and b are the constants for linear combination of relative percentage error of the training data (James et al. 2013).

Estimating these constants is the main complexity in SVM developing as they correspond to the dots produced by scalar function in a three dimensional space and so, the regularisation process is somewhat difficult for beginners (Meyer, Leisch & Hornik 2003). On the other hand, its flexibility in dealing with heterogeneous database can alleviate its difficulty in the establishment (Smola & Schölkopf 2004). This method can be run and trained through various types of data with different natures. There is usually no restriction on the database except the fact that vector data are required. As a huge advantage, it supports a database where all variables do not have the same amount of information or where we can find missing data (Li et al. 2009).

As a holistic view on the predictive methods, the linear multiple regression is probably the easier predictive method. It is capable of giving good prediction and does not need a real expertise to be implemented. But it is hugely limited by the fact that it assumes a linear description of phenomenon (Clarke 2007). ANN overcomes the linearity problem. Nevertheless, it runs as a black-box system which makes the interpretability very difficult (Tso & Yau 2007). Moreover, an important drawback of the ANN is the fact that it requires a large amount and a completeness of learning data (Wang 2003). In contrast, SVM has the huge advantage in not necessitating for completeness of data. However, contrary to ANN, it requires to assume the constants (Foucquier et al. 2013).

2.6.4. Optimisation Methods

Numerous optimisation methods have been applied for optimising the energy consumption of buildings focusing on the different important parameters but reviewing and discussing all of these methods may not seem reasonable. So, this section is based on a comprehensive review article by Evins (2013) in analysing 74 publications which used AI based optimisation methods including direct search, evolutionary methods and bio-inspired algorithms in sustainable building design. It is inferred from this review that the most common approaches with respect to building energy performance optimisation are the GA and PSO used in more than half of these publications (Evins 2013).

GA originally developed by Holland (1975), use adaptive heuristics to solve optimisation problems by mimicking the principles of natural selection. First, GA starts with a randomly generated initial population of potential solutions for the optimisation problem. These potential solutions, often called chromosomes, are coded as binary or real strings. Then, a new population of children chromosomes is generated from the parent chromosomes through crossover and mutation procedures (Davis 1991). While the crossover process combines parent chromosomes to produce children chromosomes, the mutation procedure consists of local modifications of chromosomes. The selection of the chromosomes is achieved based on their fitness values (Figure 2.5). The search of GA is terminated using a convergence threshold within a tolerable number of generations (Gendreau & Potvin 2010). Compared to conventional optimisation methods, GA has several distinctive features including (Sumathi & Paneerselvam 2010):

- Probabilistic rather than deterministic transition rules are considered to develop future generation of potential solutions from the current one.
- No derivatives are required, thus, any non-smooth objective function can be optimised.
- Global search can be used to avoid local minimum points.

An important advantage of GA is the fact it deals with a powerful optimisation method to resolve energy problems and provide the convexity of the describing function (Houck, Joines & Kay 1995). Another essential advantage of GA is its ability to give several final solutions to an optimisation problem with a large number of input parameters. It allows the user to choose with his/her judgement about the most probable one (Caldas & Norford 2003). Obviously, this is also a drawback by the fact that the user can never be sure to have chosen the best solution, especially as GA will not necessarily generate the optimal solution (Davis 1991). Another disadvantage of

GA is the large computation time especially when practitioners address several variables ranging from building envelop to climatic data (Engelbrecht 2007a). Another difficulty of GA is the manual adjustment of the algorithm. Indeed, no rules are able to determine the number of individuals in the population, the number of generation or crossover and mutation probability. So, the only way to adjust the model is to test different combinations (Rao & Rao 2009).

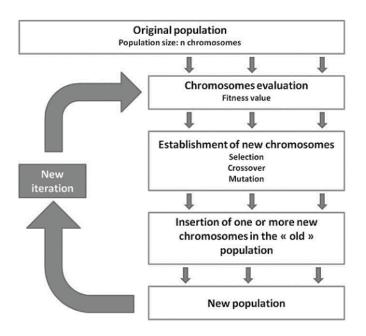


Figure 2.5. The Conceptual Procedure of GA Source: Adapted from Foucquier et al. (2013)

PSO introduced by Kennedy and Eberhart (1995) is a population-based stochastic optimisation technique. It is based on the movement of swarms and inspired by the social behaviour of insects, animals herding, birds flocking, and fish schooling, where a collaborative search for food had the potential for a computational model. In comparison with other metaheuristic algorithms including GA, PSO has less complicated operations and less defining parameters. Moreover, it can be coded in just few lines and is highly dependent on stochastic processes (Marler & Arora 2004). Because of the simplicity and performance of PSO, this algorithm has received increasing attention in recent years in building energy optimisation (Banos et al. 2011).

In PSO, the potential solutions of the optimisation problem are called particles, which is a point in the search space (initialisation). Compared to GA, PSO updates the particles iteratively by considering their internal velocity and the position obtained by the experience of all the particles (Shi & Eberhart 1999). Each particle's movement is influenced by its local best known

position but, it is also guided toward the best known positions in the search-space. Then, particles are updated as better positions and are found by other particles (evaluation and updating). This process is iteratively conducted till to move the swarm toward the best solutions (Kennedy, Kennedy & Eberhart 2001) (Figure 2.6). PSO performs very well in global searches for a near optimal solution for building design especially when it is combined with other metaheuristic algorithms for prediction and optimisation simultaneously (Bukhari, Frazer & Drogemuller 2010). However, increasing the number of particles prevents the particles to cluster early in the search leading to much time for simulation and computation (Wetter & Wright 2004).

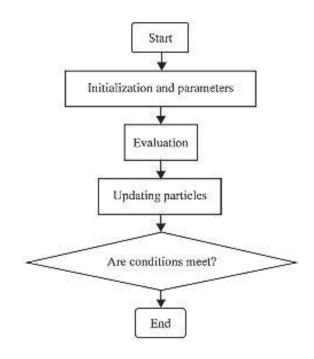


Figure 2.6. The General Flowchart of PSO Source: Adapted from Kennedy, Kennedy & Eberhart (2001)

2.7. Summary

This chapter was set to introduce the three underlying theoretical domains of this research namely; sustainability, information and optimisation theories. These theories are mostly implemented sporadically in the built environment field via their practical drivers of sustainable construction, BIM and AI. However, the missed element here is the effectively trilateral interaction of them in an integrated manner to contribute to the minimised energy consumption of residential buildings. Henceforth, in line with the aim and objectives of this study, a thorough understanding of the core concepts and sub-concepts of the EED is necessary to identify the current processes utilised with. More detailed and comprehensive analysis of the critics and

comments should be done in supporting the current need for developing an active BIM function by virtue of AI to deliver more energy efficient and optimised residential buildings. In addition to identifying the research gap, utilising the information obtained through existing literature and current market trends will aid in the further development of the research aim and objectives.

CHAPTER THREE

BIM and Energy Efficient Design

3.1. Introduction

This chapter primarily focuses on the conceptual, theoretical and technical aspects of BIM and EED and the contribution of AI as the emerging research agenda through a sophisticated review. This review is a significant step in establishing a foundation for the aim and objectives of this study because it pinpoints the current trends and state of the art, the EED methods via BIM, the required improvements and the remarks which should be considered in conducting this research and the framework development. It presents the findings of a systematic review, thematic and gap analysis on the studies conducted on BIM and EED in the built environment over the past 10 years (2006-2016). To this end, a total of 161 studies collected from three major bibliographic databases of Web of Science, Scopus and Google Scholar were thoroughly reviewed. The findings bring to light that studies on BIM and EED are sporadic, isolated and focused on narrowed, limited and disjointed areas associated with the domain. The study contributes to the field through presenting state of the art of BIM and EED, descriptive, content and thematic analyses and highlighting the focused gaps in the extant literature on the topic. This provides a sound basis to direct future research agenda and inquiries that target on EED, BIM and AI and the ultimate aim of this research; developing a framework of active BIM with AI for energy optimisation of residential buildings.

3.2. Background

The building energy efficiency concept refers to the energy required to provide the suitable environmental conditions (comfort band) which can minimise the energy consumption of a building facility (Pacheco, Ordóñez & Martínez 2012). Hence, the EED scrutinises the design aspects of such a concept and includes the identification of design parameters, their optimisation and their application in the design process (Ekici & Aksoy 2011). To effectively put the EED into action, it is always recommended to target the design stage, among the building lifecycle. As it is very effective period of integrating energy saving criteria into the design in order to minimise the energy consumption and financial costs throughout the project lifecycle (Soares et al. 2017).

In essence, the EED of a building facility is a multi-objective and multi-variable design effort. The traditional trial and error design techniques rely on the knowledge and skills of designers which can be inefficient in complex design tasks (Shi et al. 2016). In terms of the architectural design methodology, two major elements of function and form consolidate the conventional design principles. In fact, the driving force behind this methodology is the architect's rationality and sensibility (Shi & Yang 2013). However, EED of a building is performance driven. It means that the driving force behind this design method is a quantitative performance figure such as the amount of energy consumption reduction (Larsson et al. 2016). Therefore, this methodology of design requires much systematic and organised way of design generation to overcome the drawbacks of conventional design. It should pave the way of a rapid and accurate calculation of energy performance and a systematic technique for searching the optimal solution among a large design space (Machairas, Tsangrassoulis & Axarli 2014).

Hence, EED is mostly dealt with two main elements of AI application in the design parameters optimisation and a design integration platform; CDE (Shi et al. 2016). AI based optimisation alleviates the trial and error design routine through generating various designs and finding the optimal or near-optimal design solutions (Asadi et al. 2014). Design integration platform built in CDE establishes an automated workflow to apply different energy simulation and analysis packages to realise the optimisation outcomes in the design procedure (Ahn et al. 2014). Therefore, more integrated energy related design optimisation is imperative to be fitted effectively into the architectural design workflow and deliver the EED (Aquino 2013).

Thus, considering the above remarks, a BIM-enabled EED refers to a procedure involving relevant BIM processes and tools to generate, exchange and manage energy efficient built environment. Success in delivering this concept largely relies on how effective BIM adopts into EED. As a result, BIM and EED has become a growing field of research while a review of studies on the topic is still missing. In the recent years, scholars have attempted to research on BIM and EED (hereafter referred to BIM-EED) potentials from different point of views. As a result, this topic has been given considerable amount of attention in the body of knowledge which has resulted in a rapid rise in the number of related publications (Yalcinkaya & Singh 2015). Such a substantial increase in research on the topic presents a potential risk of being failure to assessing the status of the body of knowledge precisely. This becomes a major barrier to identifying required directions for research on the topic, thus increasing the potential for overlooking pivotal aspects as asserted by Yalcinkaya and Singh (2015). In essence, the emerging body of existing

research on BIM-EED warrants conducting a rigorous critical review to uncover certain research requirements, which have not been adequately met in the current research trends (Lu et al. 2014b).

Furthermore, the body of the knowledge on BIM-EED is fragmented with limited systematic attempts to evaluate it from a widely held view (Eleftheriadis, Mumovic & Greening 2017). Some reviews such as broad studies of Foucquier et al. (2013) and Negendahl (2015) have been for the most part qualitative, based on manual reviews, thus the findings are fairly prone to subjectivity (Hammersley 2001). On top of that, some review papers have also focused one-sidedly on studies targeting narrowed aspects associated with the topic. For example, Shi et al. (2016) and Wang and Srinivasan (2017) were narrowed towards studies that focused on building energy modelling and prediction. Therefore, there is a conspicuous lack of quantified, methodical and comprehensive assessment of the body of the knowledge on BIM-EED. The present study aims to go beyond such attempts based on the state of the art, systematic review, content, thematic and structured gap analyses to present the concise and precise picture of academic research on BIM-EED. The findings facilitate the development and improvement of research on BIM for the EED through discussing the current state of the art, existing gaps and themes and links between the concepts involved and future research agenda.

3.3. Previous Reviews

The core concepts associated with BIM-EED have been around for a decade. Yet, there have been few content analysis and review studies on the available scientific literature to present an integrated picture of academic research on the topic (Soares et al. 2017). With this respect, Table 3.1 illustrates an initial summary of review studies available in the energy efficient built environment literature. For this purpose, three keywords of *review*, *BIM* and *energy* were screened through Web of Science®, Scopus® and Google Scholar® and 15 review works were found. It can be inferred from this table that few review studies hitherto investigate the EED of buildings from an integrated view of BIM. The primary methods used in these studies were also classified based on the taxonomy of literature reviews by Cooper (1988). This is a seminal study which comprehensively categorises reviews according to focus, goal, perspective, coverage, organization; and audience. The methods used in Table 3.1 indicate that there is a need of an analytical approach in which more meticulous content, thematic and gap analysis should be conducted in coupling with systematic and state of the art reviews in order to portray a realistic image of the current body of the knowledge.

Table 3.1. Pervious Review and Content Analysis Studies on Energy Efficiency in Built Environment

No.	Reference	Objective	No. of Reviewed Publications	Primary Method
1	Swan & Ugursal (2009)	A review of modelling techniques of end-use energy consumption in the residential sector	91	State of the Art
2	Attia et al. (2013)	Assessing gaps and needs for integrating building performance optimisation tools in net zero energy buildings design	165	Systematic Review
3	Evins (2013)	A review of computational optimisation methods applied to sustainable building design	74	Systematic Review
4	Foucquier et al. (2013)	State of the art in building modelling and energy performances prediction	145	State of the Art
5	Nguyen, Reiter & Rigo (2014)	A review on simulation-based optimisation methods applied to building performance analysis	200	Systematic Review
6	Wong & Zhou (2015)	A review of enhancing environmental sustainability over building lifecycles through green BIM	84	Systematic Review
7	Cao, Dai & Liu (2016)	Building energy-consumption status worldwide and the state- of-the-art technologies for zero- energy buildings during the past decade	84	State of the Art
8	Chalal et al. (2016)	Energy planning and forecasting approaches for supporting physical improvement strategies in the building sector	77	State of the Art
9	Chenari, Dias Carrilho & Gameiro da Silva (2016)	A review of sustainable, energy- efficient and healthy ventilation strategies in buildings	186	Systematic Review + State of the Art
10	Chong, Lee & Wang (2016)	A mixed review of the adoption of Building Information Modelling (BIM) for sustainability	91	Systematic Review
11	Jáñez Morán et al. (2016)	A review of Information and Communications Technologies (ICTs) for energy efficiency in buildings	105	State of the Art
12	Shi et al. (2016)	A review on building EED optimisation from the perspective of architects	116	Systematic Review + State of the Art
13	Wang & Zhai (2016)	A review of advances in building simulation and computational techniques	397	State of the Art

14	Eleftheriadis, Mumovic & Greening (2017)	A review of lifecycle energy efficiency in building structures and BIM capabilities	144	Systematic Review + State of the Art
15	Wang & Srinivasan (2017)	A review of artificial intelligence based building energy use prediction	42	Systematic Review + State of the Art

Therefore, to achieve the aim of this study, this review was focused to fulfil the following objectives:

- 1) Exploring the state of the art knowledge regarding BIM-EED
- 2) Presenting a systematic review of the current literature of BIM-EED
- Content and thematic analysis, classifications and gap spotting of the extant literature domain
- 4) Drawing up an agenda for setting out grounds of necessary research in the future
- 5) Providing scholars with seminal research references to existing studies on BIM-EED

3.4. The Current State of the Art of BIM-EED

According to the major stages of knowledge evolution around emerging technologies and their adoption cycles introduced by Day, Schoemaker and Gunther (2004), the current state of the art of BIM-EED can be categorised into three levels of BIM-compatible, BIM-integrated and BIM-inherited EED in terms of BIM adoption processes, as illustrated in Figure 3.1 and elaborated in the following subsections. This classification is made by the author of this research and it aligns three phases of discovering, probing and learning and, committing and competing (knowledge evolution steps) with the BIM-EED cycles. It is worth mentioning that this classification is in line with the data evolution stages toward CDE as the single source of BIM data. Therefore, BIM-inherited EED signifies CDE elaboration and the ultimate aim of this study to develop the integration framework of active BIM with AI. The next sections of 3.4 and 3.5 and 3.7 to 3.11 fully discuss this evolution, the differences, contributions and the recommended approaches.

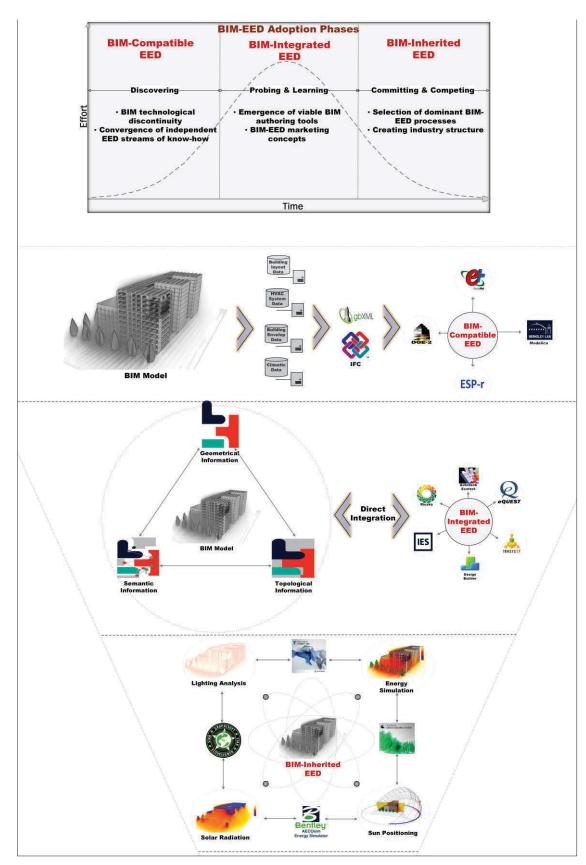


Figure 3.1. The Current State of the Art of BIM-EED

Source: Adapted from Crawley et al. (2008), Day, Schoemaker & Gunther (2004), Wang & Zhai (2016)

3.4.1. BIM-Compatible EED

BIM-compatible EED is the first level (2006-2016) of BIM adoption into EED which commenced with the efforts of Chaisuparasmikul (2006) and Zeng and Zhao (2006) by introducing the data exchanges possibility between building 3D models and EnergyPlus® application. This process can be generally summarised in BIM modelling of the case, extracting the available and relevant data of the model such as building layout, HVAC system, building envelop and climatic data and populating these data through data exchange platforms into building energy simulation tools (see Figure 3.1).

BIM-compatible EED involves with the first generation of building energy simulation software including EnergyPlus®, DOE2®, ESP-r® and Modelica® which are considered as "not BIM aware applications" due to the lack of an intimate relationship with a BIM authoring tool (Crawley et al. 2008). This observation is corroborated with BIM-EED adoption phases which establishes the foundation of this review and is adapted from a seminal study on managing emerging technologies (Day, Schoemaker & Gunther 2004). Figure 3.1 indicates that BIM-compatible EED is corresponded to the discovering phase. It is featured with the BIM technological discontinuity and convergence of independent EED streams of know-how (Watson 2011). Discontinuity brings the necessity of a common file format as a hub of data exchange to the light in which one software writes and the other reads (Watson 2011). Such a data transfer process may be occurred inadvertently or deliberately and may be involved with a non-proprietary data exchange platform such as Industry Foundation Class (IFC) or the registered energy data transfer platform of gbXML. It is evident that this type of information exchange is not rigorous as much as that of BIM aware tools because it is not especially designated and has unlikely been extensively tested (Kim et al. 2016).

3.4.2. BIM-Integrated EED

The second level (2008-2016) of adopting BIM into EED can be labelled as the BIM-integrated EED which is mainly characterised by the direct integration between BIM authoring applications and energy simulation software (Banihashemi, Ding & Wang 2015). In this stage, the maturity of intelligence grows from data to the information level. It allows for understanding relations, dashboard visualisation and interpretation between the initial inputs in the BIM model and results obtained from the energy analysis applications (Mencarini 2014). Specifically, three groups of geometrical, topological and semantic which contain the information required for an energy analysis assessment are integrated with the second generation of building performance

simulation tools; IES®, DesignBuilder®, Trnsys 17®, eQuest®, Autodesk Ecotect® and Riuska® (Wang & Srinivasan 2017) (see Figure 3.1). These applications are "BIM aware" as to the capability in making API (Application Program Interface) calls to BIM authoring tools and extracting the information directly from the BIM model (Watson 2011). IES® and DesignBuilder® are even among the EED BIM aware packages which update the information held in the BIM database and create a round-trip of information cycle (Attia 2011). Hence, it can be seen in Figure 3.1 that the emergence of viable BIM authoring tools leads to the probing and learning of BIM-EED concepts and shifts the efforts to the second phase of BIM-integrated EED.

3.4.3. BIM-Inherited EED

The trend in the selection of dominant BIM-EED processes and creating an industry-based structure for energy efficient built environment result in committing and competing stage of BIM-EED adoption phases which in turn embarks on BIM-inherited EED (Figure 3.1). The focus of this level (2008-2016) of implementation is on delivering a strategic value of coherent and structured digital information of a project together with a package of building performance simulation (Watson 2011). What distinguishes this process from the previous ones is situated in the ability to perform such package in the homogenous environment of BIM. Therefore, BIM market leaders develop a new generation of EED applications which are hinged on the utility of the underlying database of BIM design repository. This category of BIM which is adopted into EED is internally interoperable utilising the inbuilt information and includes Autodesk GBS[®], Autodesk Formit 360[®], Graphisoft EcoDesigner[®] and Bentley AECOsim Energy Simulator[®] (Wang & Zhai 2016). It is depicted in Figure 3.1 that four groups of energy simulation, solar radiation, sun positioning and lighting analyses are presented by BIM-inherited EED.

3.5. Review Methodology

Manual review of available studies is prone to be biased and limiting in terms of the quality of the reviews, the depth of the analysis and the number of studies to be reviewed by researchers on a topic with a large corpus of literature (Mulrow 1994). This has resulted in the emergence of quantified systematic techniques through use of seminal taxonomies to analyse available body of knowledge in an area (Yalcinkaya & Singh 2015). In the macro scale and from a coverage perspective, the approach followed for the purpose of this review could be titled as an exhaustive review with selective criterion (Randolph 2009). It should be also mentioned that the study was conducted based on the *focus approach*, according to the taxonomy of literature reviews by Cooper (1988). It means that the focus is on the outcomes, methods and practices/applications

of the previous research. Hence, paying attention to goals, perspectives, organisations and audiences of the previous studies is out of the scope of this review. In line with the focus approach in the macro scale, the review design was built on three stages of systematic review, research themes and outcomes and gap analysis in the micro scale. This is to address both quantitative and qualitative methods of review on the outcomes, methods, practices and applications.

3.5.1. Systematic Review

The primary method deployed in this study entailed a systematic review of literature on BIM-EED. It adds an important contribution to the body of knowledge of a novel topic through conceptualising, linking and synthesising the existing information (Mulrow 1994). Systematic reviews are required on the wide range of studies as they enable researchers of assessing the consistency and adequacy of scientific attempts and uncovering the gaps within the extant literature (Torraco 2005). Figure 3.2 indicates that this method encompassed collecting the relevant material, reviewing and evaluating the publications, defining typologies and integrating the findings as recommended by Major and Savin (2011). The protocol adopted for searching literature relevant to the domain of this topic largely drew from Hosseini et al. (2015). The primary keywords used were *BIM*, *energy* and *EED* but the terms such as *Building Information Modelling*, *energy simulation* and *energy consumption* were also considered as the equivalent keywords. In order to balance the quality of the review vis-à-vis the number of literature on BIM-EED, as illustrated in Figure 3.2, applicable publications were identified through screening the title/abstract/keyword within three major bibliographic databases of Web of Science[®], Scopus[®] and Google Scholar[®].

Initially 915 relevant records, breaking down into 326, 535 and 54 obtained from Web of Science®, Scopus® and Google Scholar®, were picked up on the 1st of December, 2016. The abstract and introduction sections of these records were subsequently analysed and repetitive items were removed. In addition, as this research is scoped on the design stage of building facilities, the studies of the BIM and energy relevant to the construction and operation stages, lifecycle assessment, embodied energy, facility management, block and urban scales, retrofit, renovation and as-built applications were filtered out. Thus, applicable works fitting clearly with two keywords of *BIM/Building Information Modelling* AND *energy/EED/energy simulation/energy consumption* were retained and 161 peer-reviewed publications were eventually identified to form the foundation of this review.

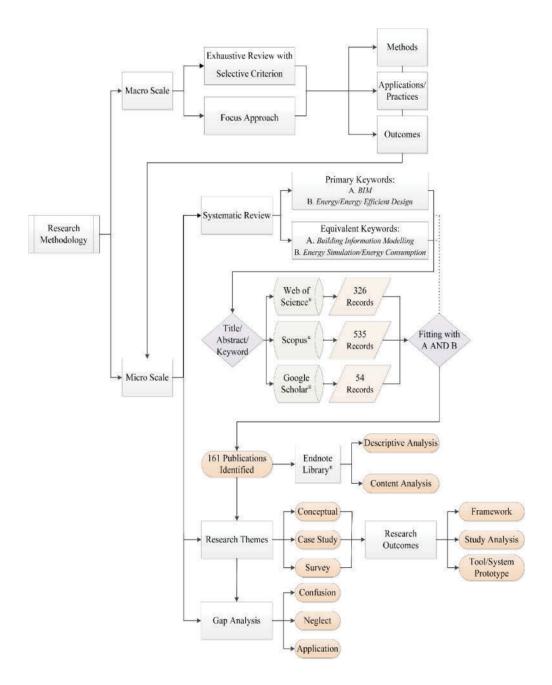


Figure 3.2. Review Methodology Diagram

Source: Adapted from Cooper (1988), Major & Savin-Baden (2011), Hosseini et al. (2015)

The EndNote library for these records was created and then converted to a spreadsheet with categories comprising year of publication, type of publication, author, country, region and the title of the outlet for descriptive analysis as described next. Moreover, the simulation software, BIM adoption appreciation, interoperability methods used by each study and Level of Development (LoD) of BIM models were identified and added as another category for content, thematic and gap analyses. Since the systematic review protocol of the present research fulfilled

the requirements introduced in the previous seminal studies of Cooper (1988), Mulrow (1994), Torraco (2005) and Major and Savin (2011), thus, the methodological robustness of the literature review process was deemed acceptable.

3.5.2. Thematic and Gap Analysis

The research themes of the publications were differentiated via the classification made by Seuring and Müller (2008) as: (1) theoretical and conceptual articles; (2) case studies and (3) surveys. Likewise, their research outcomes were framed into three realms of study analysis, framework and tool/system prototype according to the end result and product delivered by the afore-mentioned themes (Randolph 2009). In order for the gap analysis, it can be stated that although it is deemed as the most prevalent way of developing research questions in the empirical studies, it is often applied intuitively in the built environment research. It can be due to the lack of awareness about the structured way of gap problematisation (Fellows & Liu 2015). There are three particular modes of gap analysis which are titled as confusion, neglect and application spotting and are elaborated based on the seminal study of Sandberg and Alvesson (2010) to present the methodological framework of the gap analysis for this review (Figure 3.2):

- Confusion. The identification of some sort of confusion in the existing body of knowledge is the main focus of this strategy. In fact, previous studies exist on the subject however; available explanation, interpretation or evidence is antagonistic. The research question is pointed on figuring out the specified confusion in the literature and explaining it. The practical way of such analysis is to look for competing explanations in the body of knowledge.
- Neglect. The most dominant method of research questions development is to spot
 something which is neglected in the body of knowledge. The aim is to find a
 realm of research where is a virgin territory and imperative for scholars to expand
 the knowledge and call for more investigations. This mode of gap analysis is
 further categorised into three versions of spotting an overlooked area, an underresearched area and a lack of empirical support.
- Application. The third mode of gap analysis spots an area in the existing body of knowledge in which a shortage of an exact theory or a distinct perspective in a particular domain of research is targeted. The task here is to identify the researches which are solely focused on some case studies and their applications. These are attributed by the limited contribution to the body of knowledge or the lack of presenting an alternative viewpoint to expedite the understanding of the

scientific community in that specific research question. Typically, advocates of the application spotting claim that specific frameworks and/or research pathways should be developed so that the body of literature is extended or complemented in some way or another (Sandberg & Alvesson 2010).

3.6. Descriptive Analysis

As illustrated in Figure 3.3, the identified 161 peer-reviewed publications which are focused on BIM-EED, started appearing in 2006 with a gradual increase over the next ten years. Their breakdown into a total of 89 conference papers and 72 journal articles indicate a numerical difference between the preliminary and consolidated researches in BIM-EED. However, this gap has been closed, as the time goes by, particularly in 2016 when the number of journal articles has significantly overtaken the conference proceedings (until the 1st of December 2016). This trend attests to the wider acceptance of the concept of BIM-EED among built environment researchers in the recent years. Nevertheless, according to Table 3.2, this concept has, for the most part, been disseminated through the construction tier 1 journals (Lu et al. 2014a) such as Automation in Construction (11 records) and American Society of Civil Engineering (ASCE) Grade A conferences (8 items). Therefore, the share of the built environment-energy relevant tier one journals such Energy & Buildings and Energy are minor and just include 4 and 2 items, respectively.

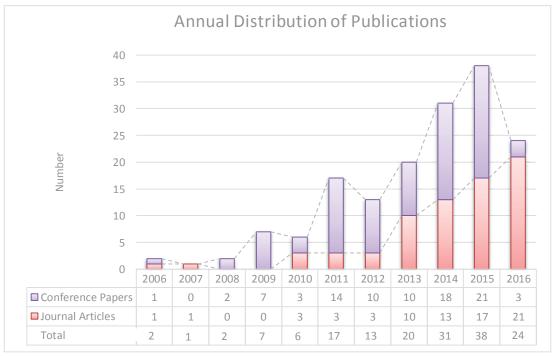


Figure 3.3. Annual Distribution of the Publications

Table 3.2. Frequency of Publications in the Primary Outlets with More Than One Record

Primary Outlet	Number of Records	Publisher	Journal	Conference Proceeding
Automation in Construction	11	Elsevier	✓	
Applied Mechanics and Materials	8	Trans Tech		✓
Building Simulation 2015	7	International Building Performance Simulation Association (IBPSA)		√
The 10 th European Conference on E-work and E-business in Architecture Engineering and Construction 2014	7	European Conference on Product and Process Modelling (ECPPM)		√
The 2014 International Conference on Computing in Civil and Building Engineering	6	International Society of Computing in Civil and Building Engineering (ISCCBE)		√
Building Simulation 2011	5	IBPSA		√
Congress on Computing in Civil Engineering	4	ASCE		✓
Energy and Buildings	4	Elsevier	✓	
Building Simulation 2013	4	IBPSA		✓
Procedia Engineering	4	Elsevier		√
ASHRAE Transactions	3	American Society of Heating, Refrigerating and Air- Conditioning Engineers (ASHRAE)	√	
Journal of Green Building	3	College Publishing	✓	
Journal of Information Technology in Construction	3	N/A	✓	
Buildings	3	MDPI	✓	
The 28 th International Symposium on Automation and Robotics in Construction 2011 ASHRAE Journal	2	International Association for Automation and Robotics in Construction (IAARC) ASHRAE	√	√
Advanced Materials Research	2	Trans Tech		
Energy	2	Elsevier	√	•
Journal of Civil Engineering and Management	2	Taylor & Francis	✓	
Journal of Computing in Civil Engineering	2	ASCE	✓	
Winter Simulation Conference 2011	2	Simulation Society		✓
2010 International Symposium on Advancement of Construction Management and Real Estate: Towards Sustainable Development of International Metropolis	2	Malaysia-Chinese Research Institute of Construction Management		√
Sustainability	2	MDPI	✓	
Building a Sustainable Future Proceedings of the 2009	2	ASCE		✓
Construction Research Congress Building Simulation 2009	2	IBPSA		√
Dunding Dimulation 2007		IDI 3A		·

This observation reveals a common trend that dominates within the literature. That is, technology-related journals are the desired destination for the studies on BIM-EED while the respected outlets focusing on the energy aspects of BIM are overlooked. This could be translated to the corresponding aims and objectives of the published studies on these journals. In a big picture, it can be stated that energy implications of BIM, its interoperability studies and contributions to the sustainable built environment should be more integrated with the technology angle of BIM within the published studies.

With regard to the regional and national distribution of the publications, Figure 3.4 depicts that the total of 37 countries have contributed to the body of the knowledge of BIM-EED so far. This indicates an acceptable coverage of international scope of the topic. In the national level, US, South Korea, China, UK and Germany are placed in the first to the fifth ranks with having 48, 27, 17, 13 and 10 number of track records, respectively. Interestingly, it is seen that the first and second rankings of this list have published around 50% of the peer-reviewed studies of BIM-EED. This fact shows the concentration of the research and development on the topic within these two countries whereas the rest of the word lags significantly behind. In the regional term, Asia-Pacific and Europe carried equally 36% of the publications followed by 28% of American contributions. However, there is not any found record from Africa. The possible reason may be due to the lack of a demand on the EED in this area and/or a lowest level of technological advancement and required infrastructures for such studies (Bernstein et al. 2014).

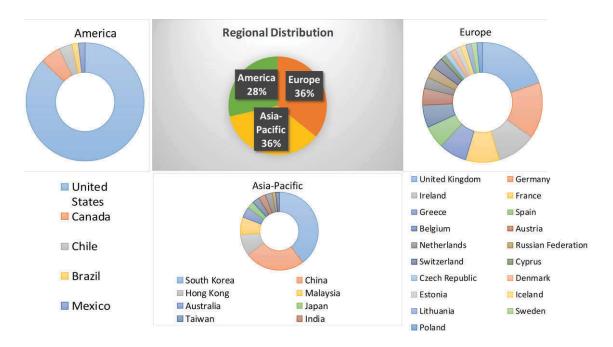


Figure 3.4. Regional and National Distribution of the Publications

3.7. Content Analysis

3.7.1. BIM-EED Adoption

As mentioned earlier, there are three levels of BIM-compatible, BIM-integrated and BIM-inherited EED which elaborate the BIM adoption processes into the energy efficient built environment. Given the importance of grasping clear perception toward the current status of each group of BIM-EED in the literature, the percentage and the annual distribution of each category were depicted in Figure 3.5. It shows that 41% of the identified literature fall to the BIMcompatible group while BIM-integrated and BIM-inherited EEDs are ranked as the second and third priorities with 36% and 23% of the studies, respectively. This fact aligns with the knowledge evolution of BIM as an emerging technology and its adoption cycles (Day, Schoemaker & Gunther 2004). As illustrated in Figure 3.5, the rate of BIM-compatible adoption experiences some fluctuations by 2015 but then decreases to 8 studies in 2016. On the other hand, BIMintegrated and BIM-inherited studies are in a gradual rise over this period, taking into account that in 2016, the BIM-inherited studies are of the highest interest among the researchers. Holistically, the key of the shift from BIM-compatible to the BIM-integrated and BIM-inherited EEDs is in the light of the growing BIM implementation levels in AEC; from level 1 to the level 3 and it is expected that the current state will follow the same trend in the future (Yalcinkaya & Singh 2015).

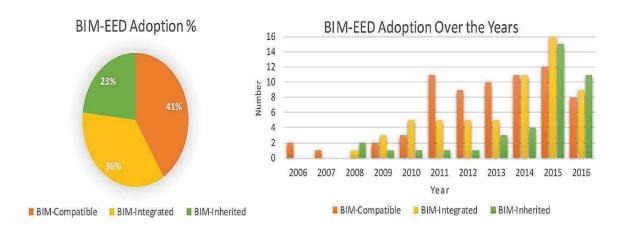


Figure 3.5. The Percentage and Number of BIM-EED Adoption Categories in the Decade

Technically, the BIM adoption into EED procedure is tied to the advent of the different energy simulation software and their performance rate and effectiveness in the application phase. As illustrated in Figure 3.1, each level of BIM-EED is run through the specific software or procedure and hence, the role of simulation is at the heart of our understanding from BIM-EED

adoption. Building performance simulation can be defined as "the science of estimating future states of single or multiple physical phenomena within an existing or proposed built environment" (Williamson 2010, p. 2). Considering this definition, the 'tool function wish list' characterises a comprehensive, efficient and precise building performance simulation as the below (Augenbroe 2001):

- Supporting design simulation decision making under risk and uncertainty,
- Recognising regular analysis with minimum variations by supporting incremental design strategies,
- Embedding application validity rules to detect whether the application results beyond its validity range,
- Performing robust solvers for non-linear, mixed and hybrid simulations.

The technical criteria for assessing these characteristics can then be framed into the accuracy and validity of the simulation, transferability (interoperability) of the model and data and confirmability of the construction and information level behind the simulation model (Williamson 2010).

3.7.2. Simulation Software

Figure 3.6 indicates the share of simulation software employed in BIM-EED adoption levels for building performance simulation purposes. As it can be seen, EnergyPlus®, DOE 2® and Modelica® are the most popular software among the tools which, as mentioned, are categorised as the first group; BIM-compatible EED. EnergyPlus® is a simulation engine imputing and outputting text files to calculate heating and cooling loads in a variable point of time. It provides accurate results allowing users for evaluating realistically the radiant heating, cooling and inter-zonal loads. However, it hugely suffers from the lack of Graphical User Interface (Crawley et al. 2001). EnergyPlus® has maintained its first place in BIM-compatible EED and the second place among the myriad of tools in the literature over the decade as to its great accuracy by including 32 studies (details refer to Appendix A at the end of thesis).

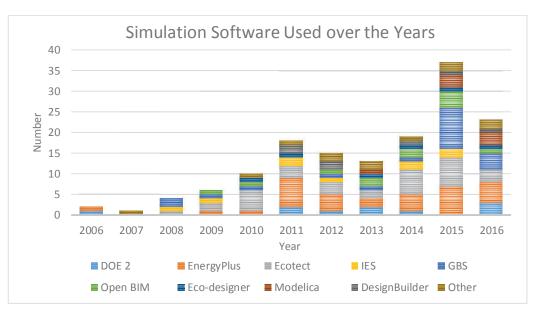


Figure 3.6. Simulation Software Used Over the Studied Years

As depicted in Figure 3.6, DOE 2[®] is the second rank of this category software which forecasts hourly energy consumption and its associated costs based on climatic data, HVAC information and building geometry. It was used in 10 pieces of research investigating BIM and building energy simulation because of its scientific precision. But having said that employing four different simulation sub-programs (Loads[®], Systems[®], Plant[®] and Econ[®]) make it very complicated tool for application (Crawley et al. 2008). Being applied in 8 publications, Modelica[®] is the third priority; it is an object-library based free open-source dynamic simulation models for building energy and control systems. It is fast and flexible but doesn't present an interface to the user. Accordingly, the least applied tool of this category is IDA ICE[®] software that is classified in the 'other' group by 2 relevant publications (Jansson, Schade & Olofsson 2013; Kurnitski et al. 2012).

The second group; BIM-integrated EED is mostly addressed in the literature via using Ecotect[®], IES[®] and DesignBuilder[®] (Figure 3.6). As a highly visualised tool, Ecotect[®] is benefitted from a powerful 3D modelling engine. It covers thermal, daylighting, acoustic and cost analysis and allows for real-time animation features. Though, it is argued that Ecotect[®] cannot rigorously estimate the heating and cooling loads in buildings and in the incremental design steps due to the weaknesses in its thermal engine (Ryan & Sanquist 2012). This fact warns the professional and scientific community of the reliability of the results of the literature when it is revealed that Ecotect[®], with 33 studies (Appendix A), not only holds the first place of the BIM-integrated EED group, but also possess the first grade within the whole BIM-EED.

The second position is belonged to IES® comprising 10 items of research ranging from 2008 to 2015 (Figure 3.6). IES® is reputable to be one of the most "architect friendly" building performance simulation tools based on Attia, Beltrán, Hensen, et al. (2009) and is further recognised as the strongest tool based on its range of analysis options (Azhar, Brown & Farooqui 2009). Nevertheless, it suffers from the lack of interoperability with IFC exchange protocol (Reeves, Olbina & Issa 2015). Seven pieces of publication, from 2011 to 2016, puts DesignBuilder® in the subsequent position of the energy simulation package within BIM-integrated EED. It is a powerful parametric building energy modelling tool which exploits a good direct integration with BIM authoring tools and the rapid interoperability with none BIM-aware applications through gbXML capability. However, its different simulation and thermal calculation methodologies makes the comparison of its intermodal validity difficult (Somboonwit & Sahachaisaeree 2012). In this category, Trnsys®, eQuest® and Riuska® are the least popular tools which have been only dedicated by 4 (Balaras et al. 2013; Cormier et al. 2011; Giannakis et al. 2015; Robert et al. 2015), 2 (Abdalla & Law 2014; Guo & Wei 2016) and 1 (Kim, Jin & Choi 2010b) studies, respectively.

The third classification; BIM-inherited EED includes Autodesk GBS® and Graphisoft EcoDesigner® as its most popular applications, including 22 and 6 publications, respectively (Appendix A). With respect to the inbuilt simulation engine of Autodesk GBS® in Autodesk Revit® and the less efforts required for the model preparation and simulation in BIM-inherited EED, the utilisation of this package has increased to its highest rate in 2015-16 (Figure 3.6). Nonetheless, Graphisoft EcoDesigner® has been significantly disregarded in the literature. As revealed by Batueva and Mahdavi (2015), in the EcoDesigner environment, the different levels of model resolution are not supported for different design phases. In addition, more intelligence is required to provide a comparison capability for multiple design variants. Finally, another BIM authoring tool of this category is the Bentley AECOsim Energy Simulator® which was only used in one study (Kota et al. 2016).

Scrutinising the identified publications disclosed that a new group of simulation procedure; namely 'Open BIM' can be established within BIM-compatible and BIM-inherited EEDs to describe unique type of simulations. Open BIM simulations can be defined as the building performance software-free prototypes. These work either with the data exchange protocols such as IFC and gbXML or BIM authoring tools databases to capture the required information and estimate the energy consumption of buildings based on the mathematical or predictive methods (Choi, Kim & Kim 2015). Therefore, the first approach; using data exchange

protocols falls to the BIM-compatible and the second way of working with BIM databases is grouped within BIM-inherited EED. Altogether, there are 13 number of studies of open BIM, breaking down into 6 items within BIM-compatible and 7 items of BIM-inherited EED.

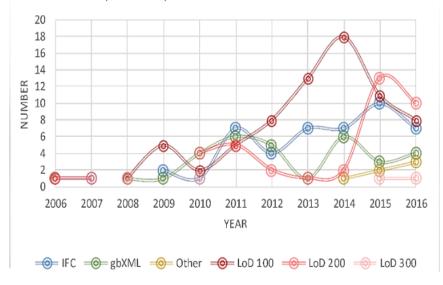
As illustrated in Figure 3.6, 2009 is the emerging year of this type of simulation while 2015 is the top year with 4 pieces of research. The Open BIM simulation is benefitted from the higher level of flexibility in the prototype development but, in turn, suffers from the lack of graphical interface. More importantly, its validity and accuracy cannot be rigorously evaluated. The open prototype development and applying personal judgments during the data acquisition and calculation lead to the weak analogy fallacy and generates meaningless discourse in the analytical verification and intermodal comparisons.

3.7.3. Interoperability

According to the building energy performance simulation ethics by Williamson (2010), interoperability is a clue in checking whether the states or outcomes of a simulation can be transferred to a context beyond its initial instinct or stage. Considering the BIM-EED levels, it can be expressed that the interoperability concept is more in the spotlight for BIM-compatible EED rather than the other two groups. As mentioned in the previous sections, in BIM-compatible EED, the studies considering BIM as the pivotal information repository for building energy analysis are concentrated on the automatic development of the design model applicable for energy simulators. The typical practice here is to transform the BIM model into input files for resolving the interoperability phenomenon utilising IFC, gbXML and other sub-exchanges to forge an automated link between BIM authoring tools and energy performance software (Bahar et al. 2013).

However, the inconsistency in the outcomes and functions of these tools is one of the problems damaging the confidence on them. Raslan and Davies (2010) revealed the predictive deviation among IFC and gbXML through different pass/fail results with respect to the compliance checking with energy efficient standards and guidelines for a same case study. This procedure indicates the present routine of post-design performance evaluation. It does not develop the simulation combined with the design decision making, as opposed to the BIM-inherited EED (El Hjouji & Khaldoun 2013). The technical problem in the course of this procedure is the back and forth import and export of model between the design and energy simulation software.

The Annual Distribution of Applied Interoperability and LoD in BIM-EED Literature



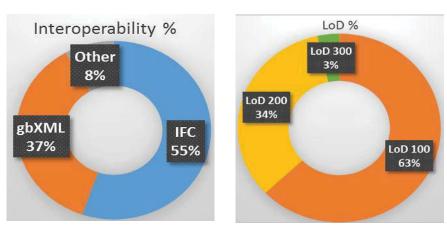


Figure 3.7. The Annual and Percentage Distribution of Interoperability and LoD in BIM-EED Literature

As depicted in Figure 3.7, the pie chart of the interoperability methods used in BIM-EED body of knowledge indicates 55% usage of IFC in comparison with 37% of gbXML and 8% of the other formats such as XML, IFC XML and DXF. Moreover, annual distribution plot illustrates extended efforts in using gbXML and IFC formats starting from 2008 and 2009 and continuing till 2016 and beyond for both. In terms of the coverage, Moon et al. (2011) stated that wide range of BIM and energy simulation applications support gbXML format but as pronounced by Eastman et al. (2008), IFC is regarded as the only public, non-proprietary and well-developed data protocol for built environment thus far. IFC is employed broader than gbXML in advanced engineering informatics, as stressed by Cemesova, Hopfe and Rezgui (2013). However, it is claimed that

gbXML, because of being grounded on the widely used XML standard, is more understandable and applicable for building performance simulation software (Nasyrov et al. 2014). From the database features perspective, IFC includes more detailed and exhaustive semantics and syntax throughout the building disciplines and lifecycle. Hence, it provides more reliable data export and import functionality. In a holistic view, gbXML is disadvantageous with this respect as it consists of a portion of building information. On the other hand, gbXML schema facilitates better exchanging of building geometry, material properties, HVAC information and location of the building; the generic information required for building energy simulation (Nasyrov et al. 2014).

All in all, additional information including the thermodynamic properties of building materials, systems for building services and occupants programs are not or only partially exchanged via these formats. For the most part, the geometry data of models are stored or imported and the data modelling capabilities of gbXML and IFC formats are not fully implemented. Lately, among the BIM authoring tools, Revit is found to better aid the conversion of 3D meshes modelled in the design software into data applicable for energy analysis in simulative tools (Hitchcock & Wong 2011a). However, manual adjustments should be implemented in the model and mesh during the back and forth procedure especially where the mesh is complex and the model is full-scale.

Existing energy simulation software (first and second generations) cannot provide with conclusive parametric capabilities within model and related objects in the discussed tools so far (Ahn et al. 2014). For example, if an object such as wall is edited or changed in an energy modelling tool, the other objects like roofs, doors or windows are not revised automatically (Hensen & Lamberts 2012). In other words, parametric powers exerted in BIM are not implanted in the energy simulator (Cho, Alaskar & Bode 2010). The same scenario is turned out to be true in the flipside. Any alteration or correction in BIM design cannot be implemented simultaneously in the energy modelling software. Therefore, any modification either from energy simulator to BIM or vice versa has to be conducted manually. Evidently, it is tedious, error-prone and time consuming especially for the models with higher level of information (Asl et al. 2014).

3.7.4. Level of Development

The level of information richness of BIM models in all BIM-EED levels is defined via the concept of Level of Development (LoD), termed by the American Institute of Architects (AIA) in AIA G202-2012 Building Information Modelling Protocol Form (AIA 2012). "The level of development describes the minimum dimensional, spatial, quantitative, qualitative and other data

included in a Model Element to support the authorised uses associated with such LoD" (AIA 2012, p. 3). LoD was categorised in five levels as the below (NATSPEC 2013):

- LoD 100 (conceptual). The Model Element may be graphically represented in the Model with a symbol or other generic representation, but does not satisfy the requirements for LOD 200. Information related to the Model Element (i.e. cost per square foot, tonnage of HVAC, etc.) can be derived from other Model Elements.
- LoD 200 (approximate geometry). The Model Element is graphically represented within the Model as a generic system, object, or assembly with approximate quantities, size, shape, location, and orientation. Non-graphic information may also be attached to the Model Element.
- LoD 300 (precise geometry). The Model Element is graphically represented within the Model as a specific system, object or assembly in terms of quantity, size, shape, location, and orientation. Non-graphic information is also attached to the Model Element.
- LoD 400 (fabrication). The Model Element is graphically represented within the Model as a specific system, object or assembly in terms of size, shape, location, quantity, and orientation with detailing, fabrication, assembly, and installation information. Non-graphic information is also attached to the Model Element.
- LoD 500 (as-built). The Model Element is a field verified representation in terms of size, shape, location, quantity, and orientation and other semantic information.

Translating the above concepts into EED discourse, it can be stated that *LoD 100* by including overall building massing, area, height and volume can only be used to analyse the conceptual energy and building orientation. In the next level; *LoD 200* can be conducted if the BIM model can be equipped with some preliminary topological information, basic energy and thermal studies as well as performance analysis of daylighting (Nasyrov et al. 2014). *LoD 300* contains the volume of information input in the models equivalent to the construction documentation. It can then be used for the detailed energy consumption, lighting and solar radiation analyses and optimisation of systems. This LoD generates the most profound effect on the building performance when it is particularly performed early in the design stage (conceptual, schematic and design development phases) (Aksamija 2012). As it is clear, the higher levels of *LoD 400* and *LoD 500* correspond to the construction and operation phases of building projects lifecycle which are not within the scope of this study and should not then be investigated in this context.

The proportional fraction of LoDs in the BIM-EED literature presents around double number of the studies applying *LoD 100* (63%) vis-à-vis that of *LoD 200* (34%) (as in Figure 3.7). It is also indicated that *LoD 300* by 3% of the publications is completely neglected in the domain. Of course, the yearly statistics implies a recent trend in BIM-EED in which from 2014 onward, research studies have been more inclined to enhance the LoD of BIM models and shift from *LoD 100* into *LoD 200* and *300*. One of the reasons for low LoD (100 and 200) in BIM-EED literature is that the significant time is required for learning and achieving proficiency in using BIM authoring tools to enhance their LoD. Practitioners regularly ask for assistance and consultation from the experts in their network and rely on "pass down knowledge from person to person" (Tupper et al. 2011, p. 740).

In addition, reviewing the procedural instruction of these applications indicates that there is a lack of comprehensive guideline in advising the academic body to create and implement BIM models in the appropriate LoD applicable for an accurate energy assessment (Kavgic et al. 2010). For instance, in the EcoDesigner environment, the level of model detail cannot be exactly matched to the level and resolution of the query. Thus, model input requirements remain the same, independent of what analysis is made. Therefore, the tool does not support varying levels of model resolution for different design phases (Batueva & Mahdavi 2015). In the end, Figure 3.8 is to represent the LoD and its embedded information in BIM-EED categories.

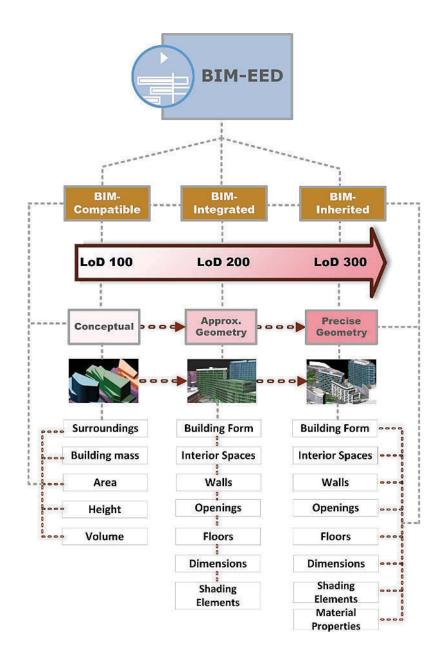


Figure 3.8. LoD and the Contained Information in BIM-EED Source: Adapted from AIA (2012) and Aksamija (2012)

3.8. Thematic and Gap Analysis

3.8.1. Research Theme

For performing thematic and gap analysis, each identified paper was critically reviewed and the contents were analysed in comparison with the research themes, research outcomes and the gap spot as the yardstick of the study. Figure 3.9 depicts the percentage distribution of the literature based on the research theme and Appendix A delivers thorough outcomes of the analyses made for the whole collection of the publications. As illustrated, 112 studies on BIM-

EED, for the most part (69%), have targeted case study as their research themes. Such studies are mostly indicating the various technical aspects of BIM authoring tools and their interactions with energy analysis packages.

In the second rank, theoretical and conceptual articles account for 27% of the literature which are generally to introduce a foundation or groundwork falling to BIM-compatible e.g. (Kim & Woo 2011; Thomas & Schlueter 2012), BIM-integrated e.g. (Cao et al. 2015; Hu 2013) and BIM-inherited EED e.g. (Banihashemi, Ding & Wang 2015; Hu, Corry, et al. 2016). Survey-based research studies with 6 items are the least theme taken into account by the scientific community. This fact brings to light the lack of large scale surveys to understand the perception of the experts and practitioners toward the BIM-EED domain. Besides, there should be a shift from case studies to industry scale investigations in order to address the shortcomings of the body of knowledge to answer functional and industrially performance doubts pertaining to BIM-EED.

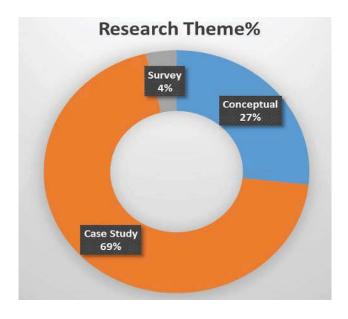


Figure 3.9. Research Theme Distribution of the Literature on BIM-EED

3.8.2. Research Outcome

In the research outcome level, half of the collection (79 items) are concentrated on the study analysis-based outcomes. This is the category of the outcomes which mainly arises from the case study research themes. It provides an analytical account of employing BIM-EED levels and the associated barriers and procedures e.g. (Batueva & Mahdavi 2015; Tahmasebi, Banihashemi & Hassanabadi 2011). The next type; tool/system prototype constitutes 45

publications (28%) of the research outcomes. These are resulted from both conceptual and case study themes and can be regarded as the cutting-edge of BIM-EED literature.

For example, Park et al. (2012) proposed a BIM-based energy performance assessment system for energy performance index in Korea applying open BIM, visual basic and Microsoft Access® as to the BIM-compatible class. Chen and Gao (2011) developed a multi-objective generic algorithm approach for optimisation of building energy performance grounded on BIM-integrated EED. In like manner, Hu et al. (2016) presented a system porotype of energy management of large airport projects using a multi-scale BIM model within BIM-inherited EED level. In the third position, framework development is found to be prominent with 37 publications (23%). As expected, the majority of such deliverables are generated from conceptual-based themes which present logics or rules of establishing BIM-EED concepts e.g. (Motawa & Carter 2013b; Yu et al. 2013) for BIM-compatible, (Remmen et al. 2015; Zhu & Tu 2015) for BIM-integrated and (Kota et al. 2016; Lee 2016) for BIM-inherited EED.

3.9. Gap Spotting

As discussed in the research method section, this review reveals the scant regards of the body of the knowledge on BIM-EED in view of the gap-spotting modes namely; confusion, neglect and application. Appendix A delivers the gaps identified for each study and the following key observations can be made.

3.9.1. Confusion

There is a confusion in the literature between BIM as a tool or BIM as a process by recording 13 pieces of research, amounted to 7% of the total. BIM can be interpreted from different angles such as a tool providing nD modelling, an activity developing a building information model or a system of building project lifecycle management and coordination (Alsaadi 2014). According to Succar (2009), BIM is the integration of processes, technologies and policies that interact with each other and generate a methodology to manage the information and design systems in digital schema over the building lifecycle. Whereas as identified by (Stumpf, Kim & Jenicek 2011), BIM model is a digital representation of functional and physical characteristics of a building. Since there are competing explanations on BIM interpretation, this vice indulges in BIM-EED adoption levels confusion.

As a consequence, studies of Jašek et al. (2014), Kim, Jin and Choi (2010a) and Reeves, Olbina and Issa (2015) were trapped in losing a focus on BIM-compatible, BIM-integrated or

BIM-inherited adoption levels. Likewise, Choi et al. (2016) and Ham and Golparvar (2015) were confused with targeting the design or operational phase of the project lifecycle and the BIM-based output applicable for BIM authoring tools. Therefore, BIM-EED confusions can be due to the lack of the appreciation on the dimensions associated with the maturity of BIM interpretation. Notably, the conceptual definition is the base of further research and discussions on the subject. Therefore, any ambiguity in this area could directly end up in the vagueness of all issues regarding BIM-EED.

3.9.2. Neglect

The neglected realms of BIM-EED amount to the half of the records, breaking down into 25% for both overlooked and under-researched areas and 50% of the publications for the lack of empirical research. Needless to say that the interoperability, in spite of being extensively investigated in the literature, is still a fundamental issue in BIM-EED domain specifically within BIM-compatible EED. It should be noted that when it is to analyse the interoperability matter, data exchange specifications such as temporal data management, transaction management and dynamic synchronisation capabilities should also be studied. However, the literature is to some extent neglected; overlooked toward the interoperability phenomenon (Bank et al. 2010; Delghust et al. 2015). This gap is more widened by using imprecise and unsuitable LoD in the body of the knowledge. Studies such as Charalambides (2009) and Jansson, Schade and Olofsson (2013) utilise BIM models containing *LoD 100* and even *LoD 200*. Thus, these studies do not seem reliable enough for pinpointing the interoperability and the technical information aspects of BIM-EED due to the poor level of complexity and data organisation. Eventually, the over-simplified energy calculation denotes another overlooked area of the topic which is exemplified with (Jones et al. 2015; Stojanovic et al. 2014).

As the second subgroup of the neglect gaps, the under-researched areas are primarily around two majors of data analytics function and the lack of user graphical interface. In line with the increasing use of linked data analytics, as expressed by Bradley et al. (2016), AI can assist EED through facilitating "what if" scenarios tests that reflects on the design parameters. So, it can be expected that such platforms could be successfully applied as a decision making tool. Nevertheless, by reviewing the studies such as Chen and Gao (2011) and Gokce (2014), it is inferred that the potentials of inbuilt data analytics, integrated machine learning and optimisation procedures have been ignored in the field. Exploiting an appropriate level of graphical user interface also leads to the enhanced utilisation of BIM adoption into the EED because it facilitates the usage of ontologies and structured data formats within BIM.

Neglecting the integrated graphical interface is disclosed in the publications which mostly belong to the open BIM studies e.g. (Banihashemi, Ding & Wang 2015; Park et al. 2012a; Verstraeten et al. 2009). The lack of empirical support presents the third subgroup of the neglect gaps and constitutes a considerable part in this review. Providing a proof of concept guarantees the feasibility of an idea or verifies a concept or theory that has the practical potential. However, the gap spotting showed that the majority of the theoretical or conceptual frameworks that were supposed to present the nature of the BIM-EED application and integration, have not had empirical supports. This fact raises the scepticism toward the extent to which conceptual-based research themes by Grinberg and Rendek (2013) and Gudnason et al. (2014) could be employed in the industry-scaled BIM-EED problems.

3.9.3. Application

Recording 42% of the publications puts highlight on the spots labelled with the application gap. This mode of gap in the BIM-EED literature is solely derived from the case study relevant research themes and, for the most part, rooted in the study analysis-based outcomes. Concentrating on the simulation of building energy performance e.g. (Alam & Ham 2014; Douglass & Leake 2011; Shakouri & Banihashemi 2012) and treating BIM as a tool e.g. (Ferrari, Silva & Lima 2010; Li et al. 2014) feature the technical characteristics of this gap. More remarkably, this group of studies delivers limited contributions to the theoretical and conceptual foundations of the body of the knowledge of BIM-EED. Accordingly, it affects the fundamental research and development efforts by the academic body. This gap may lie in the dominance of the technology-oriented view among the contributors and the engineering-based scholarships in BIM-EED. It may further be due to the bias toward the quantitative aspects of BIM-EED and the dearth of sufficient awareness about the depth of the knowledge and methodical approaches.

3.10. Future Research Agenda

As a result of the comprehensive literature review reflected thus far and taking into account the viewpoints mentioned, the following key points outline and determine the grounds for further research within BIM-EED domain as presented in Figure 3.10 and summarised below:

1) The interpretative confusion of BIM as a practice and tool or BIM as the knowledge and process should be investigated and the associated reflections on BIM-EED need to be uncovered. The priority could be more given to the BIM as the process because of the dimensional appreciation of BIM implementation levels in EED.

- 2) A shift from lower levels to the higher levels of BIM adoption is imperative. Such adoption could be in line with the introduced classification of BIM-compatible, BIM-integrated and BIM-inherited EED in this study.
- 3) There are numerous metaphorical studies for BIM-compatible and BIM-integrated EED applications, yet, BIM-inherited EED tools such as Autodesk GBS®, Graphisoft EcoDesigner® and Bentley AECOsim® require comparative analysis amongst in order to demonstrate the functionality and performances of their energy simulators.
- 4) The available energy simulation packages, as discussed in the content analysis section, suffer from a broad spectrum of setbacks; ranging from lack of graphical user interface and unreliable data exchanges to the poor thermal engine. Therefore, researchers should still continue the research and development pathway to find more innovative ways of resolving the current issues.
- 5) The functions, comprehensiveness and data inclusion levels of the interoperability concept could be particularly set of paramount area for BIM-compatible EED. Poor data processing load denotes the lack of attention to the different rates of uncertainties and so the design simulation cannot be fully realistic.
- 6) Interoperability phenomenon, even if applying the improved data formats of IFC and gbXML, dictates restrictive circumstances on the EED development. Normally, these schemas are less robust than those of BIM aware applications and hence, it is recommended to focus on the inbuilt interoperability within BIM-inherited EED because of its automatically resolved interoperability problem.
- 7) LoD improvement; from *LoD 100* and *LoD 200* to *LoD 300* should be undertaken as a routine task in BIM-EED studies. It was observed that the overlooked LoDs lead to the superficial assessment of building energy performances.
- 8) It is required for capability investigations of full scale BIM models conversion and complex meshes along with their semantic and syntax using the interoperability formats of IFC and gbXML. However, this agenda of the research makes sense when the higher levels of LoD could be implemented.
- 9) An especially designated standard, guideline or specification is necessitated to detail the LoD and required information for energy efficient built environment. This protocol should be applicable for energy and building experts, practitioners and academics to be advised of the appropriate class of LoD for BIM-EED adoption categories.
- 10) The intelligence agent of BIM-EED should be built up. Substantial improvements such as active design decision making, advisory platforms and energy optimisation

- recommenders should be developed and embedded into BIM in order for assisting designers in choosing the most optimised options.
- 11) Data analytics and big data handling in the energy efficiency problems should be exploited for leveraging the parametric definition inherited in BIM. Henceforth, it seems that BIM-inherited EED is the best choice amongst for testing the inbuilt AI applications.
- 12) Large and industrial-scale surveys could be of benefit for the scientific community in terms of understanding the current gaps and future needs of BIM-EED.
- 13) The sheer volume of BIM-EED case study-based research studies should be established on theoretical frameworks to contribute positively to the body of knowledge.
- 14) Validating conceptual frameworks through applying proof of concept will reasonably raise the reliability of the theoretical knowledge of BIM-EED.
- 15) Last but not least, industrially verified tools and system prototypes open a new window of opportunity for BIM-EED in being widely applied and become more cost efficient for end use.

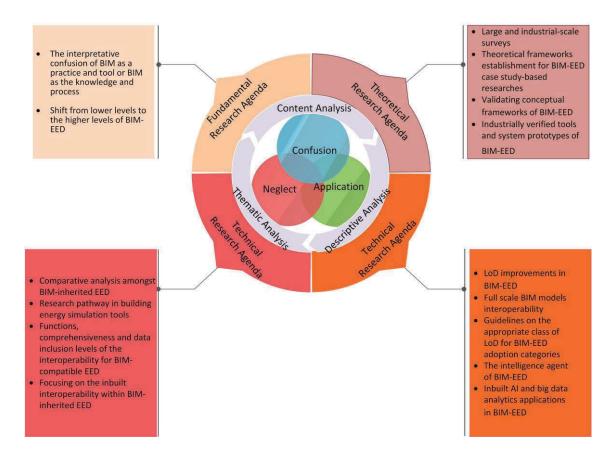


Figure 3.10. Future Research Agenda for BIM-EED

3.11. Implications for This PhD Study

In view of the conducted comprehensive literature review and future research agenda, the implications of such analytical and systematic review for this PhD study could be summarised as the below:

- BIM-inherited EED is of the particular focus for this research and framework development objective. As realised, BIM-inherited EED is on the highest level of the BIM adoption into the EED. Hence, in order to achieve the most out of the BIM potentials, the AI based active BIM will be developed on the BIM-EED basis.
- The thematic and research outcomes analysis of the literature indicated that a
 consolidated approach should be designated with BIM-EED research. This fact is in
 light of developing a conceptual framework and verifying its functionality through
 case study. Therefore, the study should comprise an established and robust
 combination of the theoretical background, framework development and framework
 validation via the case study.
- From BIM-inherited EED applications, Autodesk GBS-Revit® is the package to analyse and test the validity and reliability of the framework.
- To enhance the precision, depth and inclusion of BIM models in the framework, LoD 300 would be the target for the framework development and verification as the topmost LoD for the design stage.
- The parametric definition of BIM will be substantiated through AI algorithms to enable data analytics and energy optimisation in-built in BIM.

3.12. Summary

This chapter contributed to the body of the knowledge on BIM and energy efficient built environment and in particular; BIM-EED in several ways. First, the study identified and provided a shortcut to the previous reviews targeting energy efficient buildings for investigators interested in. Second, the chapter drew a picture of the current state of the art of BIM-EED adoption. It was then grounded on the systematic review, thematic and gap analysis frameworks to provide a view on the theme from a meta-perspective and give an identity to the available academic literature concentrating on the domain. This included identification of the descriptive trends such as the annual and regional distribution of the publications and their primary outlets. In addition, predominant research trends, preferences and potential concentration areas of the content including BIM-EED adoption levels, the simulation software, the interoperability and LoD of

BIM models were discussed. The chapter provided also evidence for anecdotal statements in previous studies with regard to the gaps within the body of the knowledge on the topic. On top of that, the established benchmarking framework provides a sound basis for future investigators. This helps in identifying the research themes, outcomes and spotting areas that are in the dire need of further research. Finally, the future research agenda clearly directed this research to strategically place the AI-enabled BIM-EED research and form a solid basis for sharing knowledge and collaboration in the area. The clear message is that the time has come to move beyond the current debates in the passive BIM-EED and shifting to the active BIM inherited EED to rectify the outlined drawbacks.

CHAPTER 4

Research Methodology

4.1. Introduction

The effectiveness of data collection is vital to the overall quality of research (Kumar & Phrommathed 2005). That means, poor quality data leads to poor quality research. Using the correct research method directly improves the validity and the quality of it (Kleinsasser 2000). This chapter is concerned with introducing the research methodology used in this study. It explains the methods employed to generate, validate and justify the outputs. After a brief description of relevant research methodologies, this section analyses the subject and structure of this research. References to the qualitative and the quantitative research methodologies are made.

4.2. Qualitative Research

Qualitative research techniques are effectively applied when the researchers need to gain insight into problems with complex and controversial issues and subjective nature (Alasuutari 1995). Some examples of these controversial subjects would be how people view topics like God and religion, human sexuality, the death penalty, or gun control. Gaining an understanding of underlying reasons, opinions and motivations lead to an insight toward a problem and assists in developing ideas or hypotheses for potential phenomena. For this reason, this method of research is often recommended for earlier stages of research (Berg, Lune & Lune 2004). By qualitative method, the design emerges as the study unfolds in which the data is in the form of words, pictures or objects. So, the inductive logic is used to deduce patterns or frameworks from observations to know the variables and constraints and the hypothetical relationships (Kothari 2011).

Number of strengths and weaknesses are stated in the literature regarding the qualitative research. One of the main advantages of this paradigm is its capability in keeping an open-mind with respect to the subject being investigated which can lead to complement the research elements during the investigation course (Taylor & Bogdan 1998). Therefore, the researcher can be more creative which in this case, fewer constraints may threat his/her observation. As the another strength, it allows the researcher to find issues that are often missed or neglected (such as subtleties and complexities) by the scientific and more positivistic enquiries (Denscombe 2014). In addition, another main advantage is to provide a communication between the researcher and

subject of the research. Such an interaction between observer and phenomenon opens a new window of opportunity for a better judgment about the research, instead of merely describing or evaluating it (Fowler Jr 2008).

However, one of the main limitations of qualitative research lies in its weakness in generating a generalised result further the investigated phenomenon. Thus, it does not necessarily indicate the extensive evidence (Berg, Lune & Lune 2004). Furthermore, lacking a theoretical foundation along with obtaining less reliable results may imply an inconclusive research. Another limitation is because of the time and costs involved in this type of method which generally does not allow for drawing samples from large-scale datasets (Rossi, Wright & Anderson 2013). The issue of adequate validity or reliability is another criticism as well. Due to the subjective nature of qualitative data and its source in single contexts, it is often hard to employ common techniques of reliability and validity. Therefore, it may not be that possible to replicate qualitative studies as the consequence of varied contexts, situations, events, conditions and interactions (McLeod 2017). These limitations and deficiencies can be minimised somewhat via utilising other approaches from different paradigms to validate and enhance the conclusions (Creswell 2013).

Qualitative studies have been used in the construction and built environment arena drawing upon the role of management and social sciences in it. Within BIM and EED as the established field of this PhD, qualitative approach has been generally applied to describe some fundamental questions of why and how BIM and EED could work and collaborate together. For instance, Hedges, Denzer and Asme (2008) investigated how the infusion of BIM as the process influences the design responses in architectural design studios. They applied qualitative method and especially participant observation technique on observing the opportunities to visualise energy performance concerned with architectural design. However, in line with the mentioned limitations for qualitative studies, the results of this research are difficult to replicate exactly due to the different context of participants with various backgrounds.

Thomas and Schlueter (2012) explored the variations in the EED space by a qualitative study of application of the Kepler scientific workflow system to experiment with the dynamic energy simulation system at an early design phase. Nevertheless, this research is limited in providing strong facts of the outcomes of applying Kepler workflow in the dynamic energy simulation of buildings. Jansson, Schade and Olofsson (2013) developed a framework of requirements management for the design of energy efficient buildings through qualitative method and applying unstructured interview techniques. They provided qualitative insights into how the proposed framework can contribute to a more structured requirements management of a

construction project with a focus on the energy-efficient design of buildings. But, it could be more conclusive by applying rigorous techniques in supporting with numerical evidences.

4.3. Qualitative Research Instruments

Researchers when using qualitative method usually apply different choices of data collection methods, ranging from interview and focus group to more advanced means like grounded theory and action research (Bryman 2012). This section is to give a brief overview of three most used qualitative methods of interview, focus group and Delphi in the built environment field (Fellows & Liu 2009).

4.3.1. Interview

Interview is an oral-verbal stimuli and reply technique that can be conducted through personal; face to face or telephone interviews. The data collection could be via the structured or semi-structured way. In a structured way, a set of predetermined questions and a recording method are employed. So, the interviewer needs to follow a rigid instruction in asking questions and fall to an ordered format (Bryman & Bell 2011). However, in the semi-structured interview, there is a flexibility in asking questions and the interviewer has more freedom to ask, omit and/or change the order of questions (Burnard 1991). But this type of flexibility leads to a lack of comparability among the interviews and as a result, the analysis procedure of semi-structured interviews becomes more time-consuming and burdensome than structured interviews (Kothari 2011).

Notwithstanding the variety in interview techniques, the merits of this method are asserted by Berg and Lune (2004). These are as obtaining more in-depth information, a greater flexibility in reorganising the questions; especially in the semi-structured interview and possibility in catch off-guard information. Moreover, it allows for controlling samples effectively and low rate of missing returns (Bryman & Bell 2015). However, Ritchie et al. (2013) mentioned some deficiencies for this instrument such as being very expensive and time-consuming method especially when large and geographically separated sample size is using. Furthermore, there is the possibility of bias such as the interviewer effect, personality and character which may differentiate the analysis and results of a research. It is also difficult in approaching important officials or people in high income groups (Bryman & Bell 2015).

Interview is one of the most common instruments in the qualitative research which has been frequently used in the construction and built environment studies (Fellows & Liu 2009). But,

in the focused area of BIM and EED, interview has not been much utilised due to the engineering origins of the field. In one of the rare cases of research with this instrument in the field, Attia et al. (2013) conducted interviews with 28 building energy optimisation experts on analysing users' needs and the gaps for integrating building performance optimisation tools in net zero energy buildings design. In line with the qualitative method role in investigating and scrutinising the context and background of a research, the referred study was intended to outline major criteria for optimisation tools selection, their capabilities and requirements specifications. The method used was appropriate to generate hypotheses from the population sample. However, there were some methodological limitations in which the lower number of the expert group made the statistical representations unavailable. Moreover, due to applying the prospective instead of purposive sampling, it is not possible to ensure that the experts represented a desired broad range of optimisation groups.

4.3.2. Focus Group

Focus group is a form of loose structured way of asking questions to obtain attitudes regarding a production, service, idea or theory (Kitzinger 1995). Groups usually consist of five to ten people recruited and brought together based on pre-specified qualifications. It is to concentrate on the experience of the informants and its effect. The facilitator is free to decide the manner and sequence of questions and explore reasons and motives (Hollway & Jefferson 2000). The main duty of the researcher is to narrow the respondents into discussing the issues which he/she investigates. Focus group is generally applied in developing hypothesis and constitutes a major of unstructured interview (Yin 2010).

One of the main advantages of focus group is that it enables researchers to run a more natural dialogue mode than generally conducts in a one-to-one interview. Besides, it costs less than survey method and the facilitator can get outcome faster. Another advantage is that it can be deemed as an opportunity for respondents to learn from each other through mutual interactions. So participants can feel this occasion as an enriching encounter (Kidd & Parshall 2000). On the other hand, observer dependency is the fundamental issue which has been argued by critiques (Ritchie et al. 2013). The researcher's own reading of the group discussion and/or his attitudes regarding the group may influence strongly the results which may question its validity (Yin 2010). In addition, the character of the researcher or facilitator can affect the opinions of participants. As an instance, if a prominent professor or a recognised expert held the group discussion, respondents may try to change their answers and conform to the facilitator's viewpoint. The lack of anonymity is also another criticism drawn by informants (Krueger 2009).

Among the relevant studies using the focus group instrument in the built environment, Sacks, Radosavljevic and Barak (2010) applied it in identifying and evaluating BIM-based lean production management system in construction. They held three focus group workshops including two in UK and one in Finland which each involved construction managers, trade team managers, and team leaders. Their developed BIM-lean prototype was demonstrated to the participants and they evaluated the interface and hands on interaction of the prototype based on some qualitative rating system. The research was ended up with a guideline on the evaluation of BIM-lean system. However, methodologically, different participants from different geographical backgrounds in each workshop could bring some inconsistency to the light in the results. The first workshop attracted 23 individuals from seven companies whereas, in the second workshop, another group of respondents including 10 people was recruited. More importantly, the third workshop was held with just 5 experts from Finland. This inconsistency in sampling method may reduce the consensus required for the results.

4.3.3. Delphi

Delphi method is an organised procedure to reach a consensus agreement among an expert panel through running frequent discussions in the form of interview or questionnaire (Kennedy 2004). The informants do not know each other and their discussion and communication are handled in a quite anonymous method. Running each round, the answers are analysed and based on the evaluations, the questionaries are developed, adjusted and sent to the experts for the subsequent round (Hsu & Sandford 2007). The iterative characteristic of this method provides the panel with the feedback and new information from different viewpoints. This opportunity allows them to revise and reconsider their based on the new comments. These rounds usually continue till fulfilling pre-determined criteria or pre-determined number of rounds (Mullen 2003).

Anonymity is one of the key features of Delphi that not only helps respondents in modifying the answers without publicly revealing it, but also assists them in examining any opinion based on its own value. It reduces any negative impact imposed by committee pressures and minimises the chance of winning certain views in order to reach valid results (Hollway & Jefferson 2000). Nevertheless, anonymity suffers from some weaknesses like lacking accountability for responses by the panel where the respondents' identities are not announced. It narrows the frontier of exploratory research and eliminates the synergy among the panel members (Mullen 2003). On the other hand, a unique opportunity of applying qualitative and quantitative approach can be offered by Delphi (Sourani & Sohail 2014). Generally, Delphi is considered as a qualitative method but since it facilitates utilising some quantitative instruments like Statistical

Group Response, some authors categorise it into mixed method approaches (MacCarthy & Atthirawong 2003; McEachern et al. 2005). Statistical Group Response typically indicates the panel responses through indices such as median together with minima, maxima and/or standard deviation (Pearl 2000). Finally, because of iterative process of feedback and re-evaluation of the responses, Delphi entails a self-validation procedure. According to Yeung et al. (2009, p. 66), "Delphi technique, by its inherent nature, serves as a self-validating mechanism. Each expert is given a chance to re-evaluate their scores with reference to the consolidated mean scores as assessed by other experts."

One major issue that could occur in using Delphi is to maintain the communication and response with informants over the whole subsequent rounds. Simplifying the procedural instructions and motivating the experts to take part from the incipient stage of the project should be implemented to secure the responses (Verhagen et al. 1998). Additionally, this approach is really time-consuming. Conducting all steps including questionnaires development, experts' sampling, convincing for willingness and commitment, questionaries distribution, follow up of non-respondents, results analysis and evaluation and re-developing of new questionaries are errorprone and time-consuming. Considering that the majority of these steps have to be done again for the subsequent rounds (Sourani & Sohail 2014).

In the narrowed down area of this PhD; BIM and EED, Delphi has not been much applied but in the construction and built environment arena, there are numerous studies using this instrument (Ameyaw et al. 2016). For example, Yeung and Chan (2009) used the Delphi method in developing a performance index for relationship-based construction projects in Australia. In this study, in the first round, an exploratory approach was taken through employing open-ended questions on the identification of performance indices. It was then structured in taking consequent rounds for identifying the level of importance and providing statistical data.

In one of the most recent studies, Hurmekoski et al. (2017) used Delphi in exploring long-term targets for GB, scoping toward the wood-frame multi-story construction in Finland. Two-round of Delphi study was broken down into employing a web-based questionnaire and a subsequent semi-structured interview. According to Robinson et al. (2011), combining interviews and a web-based questionnaire can generate a strong basis of data collection. Because the questionnaire creates an anonymous and "clinical" data which results in objective and statistically significant data. Interviews further create an open and socially warm platform where experts can give the comments and opinions in terms of different aspects and get feedbacks. Such approach heads to a more comprehensive arguments and discussion in the context.

4.4. Quantitative Research

The use of quantitative approaches remains predominant within construction management research (Knight & Ruddock 2009) and this fact reinforces the idea that the majority of researchers are still using a rationalist approach (Amaratunga et al. 2002). This is often attributed to the origins of construction management research lying in the engineering discipline (Carter & Fortune 2004). In this paradigm, the literature usually is used deductively as a core to evolve the research questions (Webster & Watson 2002). This is the approach that has been applied in this research in which a thorough survey of the literature used for identifying the knowledge gap. Quantitative approach commonly tries to find a cause and effect relationship between some variables and parameters and expresses it as hypothesis (Kumar & Phrommathed 2005). It quantifies the problem by way of generating numerical data or data that can be transformed into usable statistics (Amaratunga et al. 2002).

Survey, simulation and case study are typically applied to collect data from a population sample subjecting to the statistical analysis to test the hypothesis (Thomas 2008). Then, according to the hypothesis, broad generalisations can be made regarding the studied relationships through explanation or prediction. These generalisations are conducted for a large sample population or frequent aspects and circumstances with the adequate levels of reliability and validity via using rigorous methods in sampling and instrumenting the research design (Polit & Beck 2010). In this context, the reliability means the capability in providing consistent evaluations in equal conditions. While validity is the extent that the results correlate to what these results were supposed to be measured (Neuman & Neuman 2006).

One of the main positive sides of quantitative method is its scientific objectivity. A well-structured quantitative research has also the strength of delivering descriptive and inferential outcomes and generalisable information along with indications of significance in a reasonable manner (Vogt 2006). Quantitative data can be also interpreted with statistical techniques and since these techniques are based on the mathematical principles, the quantitative method is considered as a strong scientifically objective and rational approach (McLeod 2017). The accurate level of replication is another advantage of quantitative method. Numerical and statistical data are not that open to the vagueness in interpretation and so can be checked by the scientific community on the measured values (Kothari 2011).

In addition, quantitative method brings a very strong capability in testing and validating different hypotheses. In view of the numerical nature of collected data and their subsequent

statistical potential, constructed theories and hypotheses can be tested and validated via advanced statistical techniques (Creswell 2013). This virtue further indulges in the fast analysis of the findings in which statistical software packages eliminate much of the time and need for prolonged data analysis, particularly in cases which sheer volumes of data are involved (McLeod 2017).

However, this method has some limitations as well. The first limitation is the assumption that for the dependent variable or the outcome of the research, the independent variable which makes influence or cause is known. Therefore, the researcher might neglect observing phenomena due to the focus on testing a hypothesis instead of generating a hypothesis (Maxim 1999). It is also presumed that intervening parameters mediating between dependent and independent factor are known and can be managed. However, reaching to such accurate presumptions is difficult and very critical to validate findings of a study (Polit & Beck 2010). The second limitation is the presence of one scenario which can be studied objectively free of any background. It is presumed that the scenario approved by the analyst is correct and others have the same understanding of objectivity about it (Mugenda & Mugenda 1999). It is also presumed that the researcher has no bias in the analysis and backgrounds of people such as their life, experiences and his/her perceptions would not be influential on the responses. It is evident that these assumptions are not realistic (Kleinbaum & Kupper 1982). In analysing the quantitative studies, it is vital to interpret the outcomes and responses achieved from using surveys, experiments and simulations through a realistic context (Kumar & Phrommathed 2005).

The third limitation lies in not allowing participants to explain their choices or the meaning of the questions may have for those participants (Maxim 1999). So, there are some hidden types of biases which may affect the instrumenting and wording of questions and statements used in questionnaires. These biases may reduce the reliability and validity of the findings and may even impact on selecting and using non-representative samples (Collier 1995). Misdirected, ambiguous or those questions testing more than one relationship at a time may be negatively influential on the validity of results (Creswell 2013). Furthermore, accurate analysis of quantitative data requires adequate levels of researcher's expertise. Poor knowledge of the application of statistical analysis may negatively affect analysis and subsequent interpretation (McLeod 2017). Last but least, accurate analysis requires large sample size of data since the small sample may not be that reliable. Small sample influences the capability in generalising findings to the large group of observations (Denscombe 2014).

As mentioned in this section, quantitative methods have been largely used in the construction and built environment studies in view of their objective inferences. Likewise, this

approach has been widely applied within BIM and EED domain for mostly indicating the various technical aspects of BIM and their interactions with energy analysis packages. For example, Zhang (2014) put forward the BIM analysis technology and building energy consumption data integration through a quantitative method in which a large number of construction data information was collected through a BIM model and building energy consumption analysis was then run. However, this research suffers from a lack of a theoretical backbone of BIM and EED integration due to the limitations mentioned for the quantitative approach. Robert et al. (2015) further practiced a quantitative approach for connecting BIM authoring tools and energy simulation software where the IFC was used as a pivotal format to generate input data. The originality of this contribution lies in considering both building geometry and building energy systems while it doesn't elaborate the qualitative motivations of the overall approach implementation.

4.5. Quantitative Research Instruments

There are a wide range of quantitative research approaches especially when researchers want to utilise the statistical and measurement techniques. According to Fellows and Liu (2009), using questionnaire survey, doing simulation and running the engineering-based case study are among the most popular quantitative methods used in construction and built environment studies.

4.5.1. Questionnaire Survey

Questionnaire survey is one of the most popular data collection approaches particularly for big scale projects in the construction field of research (Holt 2014). Individuals, researchers, organisations and even public bodies adopt this method by preparing a sequential form of questions and distributing via post, email and/or online applications within their survey sample (Frazer & Lawley 2001). As maintained by Vogt (2006) for the advantages, this instrument is a low cost (especially when it is run via online) even if being applied for a large sample and there is usually adequate time for respondents to give their answers. Besides, people who are not conveniently accessible can be reached by online and internet facilities if applicable and if the required infrastructures become available (Holt 2014). Furthermore, since it allows to study over a wide spectrum and generate statistical data, the results may benefit from an acceptable level of generalisability and objective reliability.

However, there are also some critics against this method. Kothari (2011) stated that it is just applicable for educated people. Unforeseen bias is also inherited due to a low rate of return

in properly filled questionnaires. Moreover, as stipulated by Creswell (2013), once the questionnaire is sent, the researcher may lose the control over it. It has an inbuilt inflexibility and as the form sent; it is difficult to modify it. Last but not least, it is very time-consuming instrument especially when the sample size is large (Bryman & Bell 2015).

As mentioned, questionnaire survey is one of the most popular methods of data collection in the construction and built environment area however, this method has not been much applied in the field of BIM and EED. As one of the relevant instances, Attia, Beltrán, De Herde, et al. (2009) used questionnaire survey to make a comparison among ten different building performance simulation tools. In this study, 249 dully questionnaire forms were collected and the building performance tools were classified based on three criteria of usability and information management of interface, the integration of intelligent design knowledge-base and the interoperability of building models. This research summarised the key findings and underlined the major requirements for future improvement and development of building performance simulation tools. Nevertheless, the sampling approach was only concentrated on architects and designers and hence, the results are not generalisable for other construction and built environment experts.

4.5.2. Simulation

Simulation is to imitate a process or an action occurring in the real world. The simulation of something initially needs a model in which key characteristics or functions of the selected process or model be developed thoroughly (Gad-el-Hak 2010). The model illustrates the system while the simulation indicates the operation of the system overtime. Simulation is applied in various fields ranging from technology performance optimisation, safety engineering but mostly used in computer experiments (Sargent 2005). This method enables researchers to see and evaluate the eventual real effects or possible consequences of different conditions and courses of actions. Moreover, experts often use simulation in two conditions. First, when a system or process cannot be engaged due to being not accessible or it is unacceptable to be engaged. Second, when a system or process has been designed but it is not built or it does not exist (Prive & Errico 2016).

Acquiring validated sources of data regarding the key features of the model, facilitating the approximation and assumptions in the simulation and the reliability of the results are among the main requirements which should to be carefully addressed in this method (Sokolowski & Banks 2009). Figuring out the primary characteristics of the model and verifying the accurate values for them are vital in constructing a real model. Likewise, taking a balance between assuming some simplification strategies to approximate the model and considering a sufficient

set of configurations is another controversy that may overshadow the reliability of the simulation (Ripley 2009). Furthermore, the use of simulation necessitates an intensive and specialised training. The way of constructing a model, designating an accurate approach of configurations and interpreting its quantitative results require an exhaustive amount of practices (Sargent 2005).

Simulation is one of the most dominant research instruments in BIM and EED field. It is because of the overarching role of engineering-based studies along with the large share of technical applications of building performance simulation tools within (Noack et al. 2017). As discussed in full details in Sections of 2.6.2 and 3.7, the general routine of simulation method application in this research context is to first employ the simulation software i.e. EnergyPlus in Giannakis et al. (2015) and Jabi (2016), DOE-2.1E by Kim et al. (2013) and Kim et al. (2016), Ecotect in Song (2014) and Tan et al. (2015), Eco-designer in Tahmsaebi, Banihashemi and Hassanabadi (2011) and Kovacic et al. (2013), GBS by Inyim, Rivera and Zhu (2015) and Strobbe et al. (2015), IES in Gokce (2014) and Stundon et al. (2015), Modelica by Remmen et al. (2015) and Jeong et al. (2016) and DesignBuilder in Kim and Han (2012) and Agdas and Srinivasan (2015). Second, building facilities are modelled and simulated through these applications and quantitative data such as energy consumption and carbon emission are obtained. However, the inconsistency in the outcomes and functions of these tools (Raslan & Davies 2010), difficulty in the compliance checking of simulation procedure with energy efficient standards (Kavgic et al. 2010) and the significant time required for learning and achieving proficiency (Attia et al. 2013) are among the issues for applying this instrument in the BIM and EED studies.

4.5.3. Case Study

Case study is a research instrument to bring an understanding or knowledge of a complex issue, situation or object. It excels the ideas and experiences toward a thing which is already known through prior investigations. It extends a detailed and specific contextual analysis of events, objects, cases or conditions and their interrelationships (Algozzine & Hancock 2016). According to Yin (2013a), case study is an empirical inquiry to analyse a phenomenon within its real-life context by providing numerous sources of data and evidences. Case studies via using quantitative data include components of the empirical-analytical techniques. These types are then regarded antagonistic the qualitative approach of case studies (Mills, Durepos & Wiebe 2010). Application of quantitative analysis in case studies are contingent upon the type of the phenomenon under study, the research questions, the type of case study and the backgrounds and sources of the facts and evidences used (Algozzine & Hancock 2016).

In the literature, there are multiple case study research methods which have been applied in the various fields (Yin 2013a). Social science researchers have widely employed case study to explore the real-life examples of social situations and present a foundation for interpreting their concepts (Bryman 2012). In addition, in engineering disciplines, researchers have particularly applied case studies to test and examine the developed frameworks and prototypes in a real-life situation (Stake 2013). Although a carefully planned and designated case study provides strong outcomes of real-life issues and conditions, critics of this instrument postulate that studying a small number of cases may not establish a ground for reliability, validity and/or generalisability of a finding (Yin 2013b). In fact, in the case study, the aim is to achieve an analytical generalisation rather statistical generalisation to be able to generalise results to its broader theory (Mills, Durepos & Wiebe 2010). Therefore, case selection should be concentrated on realising a reflection of the diversity of the phenomena. Hence, the extreme or unique cases which are highly exceptional may not lead to the generalisation purposes (Yin 2013a).

In the BIM and EED field, case studies have been extensively applied to test and validate the functionality of the developed approaches and prototypes (Attia et al. 2013). Literally, case studies are often used jointly with the simulation instrument because each simulative study requires at least a model or case of a building facility (real-life or hypothetical) to be simulated. So, it enables the researcher to run the energy analysis (Nguyen, Reiter & Rigo 2014). Therefore, it can be stated that all studies in this research context which have employed simulation as the major research method, have also applied case study instrument to run it e.g. (Bank et al. 2010; Cemesova, Hopfe & McLeod 2015; Cemesova, Hopfe & Rezgui 2013; Gupta et al. 2014; Park et al. 2012a; Verstraeten et al. 2009).

4.6. Mixed Method

Following with the analysis of the qualitative method and its instruments of interview, focus group and Delphi, the quantitative method and instruments of questionnaire, simulation and case study and their applications in the context of BIM and EED, this section is dedicated to discuss the mixed method research. In principle, this is the type of the data and the research aim and objectives which determine the best methods and most effective instruments in research studies (Jackson 2009). Holistically, there are three options for collecting data in this research study and they are: qualitative alone; quantitative alone; or a combination of both in variable proportions (Punch 2005). Named the "third methodological movement" (Venkatesh, Brown & Bala 2013, p. 22), the mixed method approach is considered as one of the most effective methods

for conducting research in the interdisciplinary fields of management and engineering arenas through combining qualitative and quantitative methods (Jogulu & Pansiri 2011; Molina-Azorin 2012).

The crucial benefit of mixed method research is its methodological freedom and pluralism which often leads to the effectual research in comparison with single method research designs (Johnson & Onwuegbuzie 2004), along with delivering superior results (Molina-Azorin 2012). In fact, relying upon only one method for data collection may not seem sufficient. Since valuable findings are obtainable when they are drawn from various methods but converged into the ultimate aim of the research (Gillham 2007). Mixed methods pave the way of greater opportunities to implement research aims and objectives and advise researchers to assess the accuracy of their findings (Teddlie & Tashakkori 2003). The underlying reason is in combining qualitative and quantitative methods and enabling researchers to achieve the best out of both approaches by recouping for the drawbacks of each approach (Ahmed, Opoku & Akotia 2016; Creswell & Clark 2007; Punch 2005; Venkatesh, Brown & Bala 2013).

According to the seminal study of Tashakkori and Teddlie (1998), there are four major mixed methods design as the flowing:

- 1) Equal status mixed method design: In equal status mixed method designs, the researcher performs a research applying both the quantitative and the qualitative approaches equally to investigate the phenomenon under study.
- 2) Dominant-less Dominant mixed method design: In this approach, one research method and its instruments are dominant while a small part of the whole study is analysed through the alternative method and instruments.
- 3) Sequential Mixed Method Designs: In this approach, the investigator runs a qualitative phase of a study and then a separate quantitative phase, or vice versa. This approach allows the researcher to sufficiently develop the paradigm assumptions for each phase since the two phases are obviously separated. In the QUAN/QUAL sequence, the researcher begins with a quantitative method and then develops with a subsequent qualitative study. Whereas, in the QUAL/QUAN sequence, the researcher commences with qualitative data collection and analysis on a relatively unexplored and new topic and then proceeds to design the quantitative phase of the study. QUAL/QUAN is the popular type of sequencing because in most quantitative studies, the quantitative closed-ended instruments are conducted after exploratory qualitative instruments have been analysed.

4) Parallel/Simultaneous Mixed Method Designs: In this design, the quantitative and qualitative data are collected simultaneously and investigated in a complementary manner. Hence, quantitative and qualitative results do not necessarily confirm or associate together and in fact, most studies using this approach present numerical and narrative data which answer similar questions.

The construction and built environment field is one of the research arenas that has been recommended for applying mixed methods (Amaratunga et al. 2002). For instance, Dainty (2008) and Abowitz and Toole (2009) stated that mixing methods delivers enhanced understanding and compensates the defects of applying a mono-method of research in this field. In the same vein, Amaratunga et al. (2002, p. 23) highly recommended employing mixed methods by stressing that "a weakness in each single method will be compensated by the counter-balancing strength of another". Therefore, it can be inferred that using mixed methods generates clearer insight to inform theory and practice. Furthermore, the achieved findings could be more extrapolated (Ahmed, Opoku & Akotia 2016).

In the narrowed area of BIM and EED, as indicated in Chapter 3 and discussed so far, the majority of the studies fall to the quantitative method; applying mostly simulation and case study instruments combined. Likewise, the share of the mixed methods combining qualitative and quantitative ones are few. For instance, Niu and Pan (2016) developed a sequential mixed method to figure out technical characteristics of energy simulation tools that improve stakeholder collaboration on the EED. Following the literature review, semi-structured interviews of ten industry representatives were conducted to establish a theoretical basis for performing case studies on six state-of-the-art energy design tools. A comparative analysis was then conducted between academia research, industry perspectives, and technical practices to find out the technical and implementation gaps in the collaborative energy design technologies.

Conspicuous lack of an established mixed method approach in the field and concluding the stated remarks thus far, applying mixed methods for this research study was regarded justified. Nevertheless, "there is more to this issue of combining the two approaches than first meets the eye" (Punch 2005, p. 241). Hence, the type, process, mechanism and the design of mixing the two approaches should be explained and interpreted for the present study, as outlined in the next section.

4.7. Research Design

The technique of coupling qualitative and quantitative methods to reach a mixed methods study capitalises on the research context and functional approach within the research environment (Punch 2005). In designating the mixed methods study, plethora of designs and approaches are recommended by researchers (Teddlie & Tashakkori 2003). However, the most effective design can be reached by considering both the nature of the research questions and the objectives defined as the driving forces of a research. As indicated in the seminal study of Robson (2002), the design of any research study should establish a framework that connects research questions, objectives, methods and data collection strategies. In the present research, this has been considered as the basis for designing a mixed methods study as described below. Table 4.1 links the research aim, questions and objectives with the suitable research design based on the framework developed by Newman et al. (2003). In this work, the ultimate purposes for any research study were classified into nine holistic categories of:

- Prediction
- Adding to the body of knowledge
- Have an impact on a personal, social, institutional or organisational level
- Measuring change
- Understanding complicated phenomena
- Generating ideas
- Testing ideas
- Informing constituencies
- Examining the past

Table 4.1. The Framework of the Mixed Methods Approach

Research questions and o	Purposes, categories and effective methods, according to Newman et al. (2003)			
Research questions	Research purposes	Category of research purposes	Basic method	Complementar y method to form mixed methods
 What are the drawbacks of the current energy simulation and optimisation methods 	Examining the potential and challenges of BIM to	Understanding complicated phenomena	Qualitative	Qualitative
in buildings? How is BIM capable of optimizing the energy efficiency of buildings?	optimise energy efficiency in residential buildings	Generating ideas	Qualitative	Qualitative
What are the important variables playing key roles in energy	Identifying variables that play key roles	Understanding complicated phenomena	Qualitative	Quantitative
consumption of residential buildings?	in energy consumption of residential buildings	Adding to the body of knowledge	Qualitative	Quantitative
What types of AI algorithms are suitable for being used in BIM in terms of predicting and	bes of AI ms are suitable gused in BIM in predicting and ng energy Investigating the AI-based algorithms in energy ontimisation	Understanding complicated phenomena	Qualitative	Qualitative
optimising energy consumption?		Generating ideas	Qualitative	Quantitative
 How can an algorithm be linked to the BIM 	Developing a framework of AI application	Adding to the body of knowledge	Qualitative	Quantitative
packages? • What is the process of	in BIM in terms of energy	Generating ideas	Qualitative	Qualitative
optimisation for identified variables?	optimisation purposes and processes	Prediction	Quantitative	Quantitative
How can the body of knowledge be benefitted from the daysland from word? Assessing and validating the functionality	Measuring change	Quantitative	Quantitative	
developed framework? To what extent does this framework deliver energy efficient buildings? functionality of the framework using case studies		Testing ideas	Quantitative	Quantitative

Table 4.1 indicates that the qualitative approach is often the basic method for the different research purposes that is complemented by a quantitative approach to fulfil the required objectives. Such a mixed method approach falls to the $QUAL \rightarrow QUAN$ design (Morse 2003) through running a qualitative approach-driven project followed by a quantitative approach. This sequence was termed by Creswell et al. (2003, p. 225) as a "sequential exploratory design" in which narrative data are collected prior to collecting numerical data (Ahmed, Opoku & Akotia 2016).

The drawbacks of the mono-qualitative and mono-quantitative research methods as well as the nature of the research questions and objectives as identified in Table 4.1 justify using the mixed method; sequential exploratory design (i.e. $QUAL \rightarrow QUAN$). In fact, the theory testing and verification are mostly conducted by quantitative research while the theory generation and establishment are more directed toward the qualitative research (Punch 2005). Due to the lack of an established framework on BIM-based sustainability, building the initial stages of framework development on a qualitative method is defensible. It facilitates identifying the potentials, challenges, solutions, ideas and perceptions linked to the variables identification and AI based algorithms investigation.

This design is further substantiated when quantitative approach comes to the fore taking into consideration the study's objectives via using the deductive methods to quantify the variables, test and validate the framework. To be specific, as stated by Hyde (2000, p. 82) "... the findings of qualitative enquiry remain tentative as long as they are untested". Accordingly, a mixed method approach based on a $QUAL \rightarrow QUAN$ design was selected as the overarching approach for the present study. In case of qualitative methods precede quantitative methods in a mixed method study, the problem is quietly investigated and then, the findings could be construed to a larger samples, according to Creswell et al. (2003) and Ijasan and Ahmed (2016).

4.8. Research Implementation

Complementing the presented framework of the mixed method approach in Table 4.1 and in the previous section, Table 4.2 maps the discussed applicable research instruments to the research objectives and questions of this PhD. In principle, the designated mixed method of the $QUAL \rightarrow QUAN$ approach requires the application of the analysed research instruments to address the research questions and objectives via different research instruments. As indicated in Table 4.2, the objectives and questions relevant to the understanding of the phenomena, generating the preliminary ideas and adding to the body of the knowledge are mapped with the qualitative

instruments. On the other hand, the objectives and questions which were classified for measuring the change, prediction and testing ideas are correlated to the quantitative research instruments. Therefore, from the research implementation angle of this study, it can be concluded that more than one research instrument is required to fulfil the following steps:

- 1) Identifying and prioritising the variables that play key roles in energy consumption of residential buildings
- 2) Creating a comprehensive residential buildings dataset emphasising on covering the full range of identified variables
- 3) Developing AI-based algorithms using the collected database
- 4) Linking the developed algorithms to BIM application
- 5) Testing the workability of the procedure and evaluating its performance

Furthermore, each research study faces some challenges and limitations in its development process and this study is no exception to this rule. So, to define the scope of this research, the followings should be taken into consideration:

- 1) The design stage is on the focus of this research. Hence, the other phases of project lifecycle including construction and operation phases are excluded from this research.
- 2) The developed framework and algorithms are designed for the residential buildings only. Other types of building are excluded from the scope of this research but the developed framework can be equally applicable to other types of building with the modifications in parameters and dataset range.
- AI algorithms generally fall to two major functional categories of prediction and optimisation. So, two algorithms of ANN and DT for prediction and GA for optimisation were applied.
- 4) BIM has a wide range of applications from design to analysis, simulation and estimation. In this study, the focus would be on the Revit suite because of its popularity and parametric nature.
- 5) The developed procedure should be practical, realistic and conforms to present technical methods.

Table 4.2. Mapping the Applicable Research Instruments with Research Objectives and Questions

	Research Aim		Ap	plicable	Research	Instruments		
Research Objectives	Research Questions	Literature-based Exploratory Approach	Interview	Delphi	Focus Group	Questionnaire	Simulation	Case Study
Examining the potential and challenges of BIM to optimise energy efficiency in residential buildings	1) What are the drawbacks of the current energy simulation and optimisation methods in buildings? 2) How is BIM capable of optimising the energy efficiency of buildings?	✓	×	*	×	*	×	×
Identifying and prioritising variables that play key roles in energy consumption of residential buildings	What are the important variables playing key roles in energy consumption of residential buildings?	✓	✓	✓	✓	✓	×	×
Investigating the AI-based algorithms in energy optimisation	What types of AI algorithms are suitable for being used in BIM in terms of predicting and optimising energy consumption?	✓	×	*	×	*	✓	√
Developing a framework of AI application in BIM in terms of energy optimisation purposes and processes	1) How can an algorithm be linked to the BIM packages? 2) What is the process of optimisation for identified variables?	*	*	×	×	×	√	×
Assessing and validating the functionality of the framework using case studies	 How can academic community be benefitted from the developed framework? To what extent does this framework deliver energy efficient buildings? 	*	×	*	×	×	✓	√

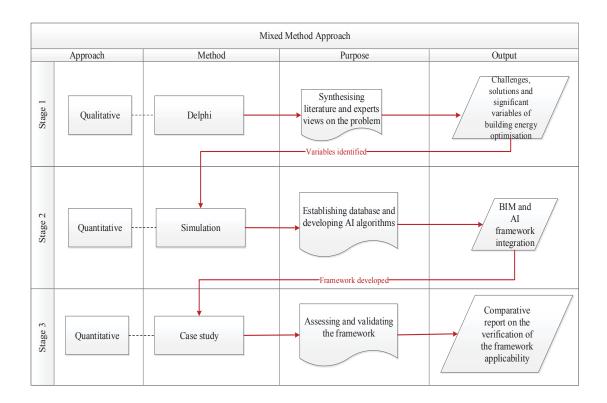


Figure 4.1. Mixed Method Research Implementation

Research implementation indicates the techniques, types and sequences of data collection and research conducting in a mixed methods study (Creswell et al. 2003). In view of the discussions presented above, the process and pace of the mixed method approach; sequential exploratory design for the present study, as illustrated in Figure 4.1, are divided into three consecutive stages of data collection.

The first stage falls to the qualitative phase and begins with the literature and Delphi study to find out and create a pool of the most relevant and significant variables that have a high impact on the energy consumption of residential buildings. As presented in Section 4.3, three applicable and dominant research instruments were discussed and their potentials and limitations were argued. Among interview, focus group and Delphi instruments, the last instrument; Delphi approach is selected to synthesise the literature. This choice is in view of the iterative nature in further reconsideration and refinement of the results, flexibility in grasping both qualitative and quantitative techniques such as statistical group response within its procedure and its self-validation mechanism (Ameyaw et al. 2016; Keeney, Hasson & McKenna 2011; Sourani & Sohail 2014).

This pool is, therefore, refined through running Delphi approach with energy and BIM experts to reach the final list of prioritised variables. In terms of the required number of rounds, it should be mentioned that this decision depends on the determined functions for each round (Ameyaw et al. 2016). Additionally, as asserted by Yeung and Chan (2009), conducting three rounds Delphi via online method usually enable researcher to obtain more meticulous results via a consensus agreement among the respondents. Thus, considering the functions required for each round and the statement of Yeung and Chan (2009), three rounds of Delphi is set. It is to, first, brainstorming about the building energy parameters and synthesisation with the literature, second, prioritising these parameters and, third, confirming the outcomes and the final list. In addition, the possible risks and challenges along with any innovative solution with regard to the AI application in BIM are discussed and analysed.

The next stage applies the quantitative method. Among the discussed quantitative instruments including questionnaire survey, simulation and case study in Section 4.5, the simulation is selected in this stage. Simulation is most fitted with the BIM and EED discipline and recommended to be applied in building performance analysis (Noack et al. 2017). Hence, it is employed to first, collect a reliable and verified data for the prioritised variables with an emphasis on covering the whole range of available values. These data are collected via simulating residential buildings within the energy and design software and applying parametric techniques as to reaching more reliability in data. Second, the AI algorithms need to be simulated using the created database. Two algorithms of ANN and DT are employed to predict an initial estimation of energy consumption of the buildings and the algorithm of GA is then utilised to optimise the estimated values. Therefore, three batches of algorithms composed from ANN, DT and ANN-DT are simulated in Matlab software. Then, the associated errors are calculated and the set with the least error and the highest applicability coupled with GA is identified as the best suite of optimisation algorithms for this research.

Simulation instrument comes again when the selected algorithm set should be linked and associated with BIM application to form the BIM and AI integration framework. Since Revit suit is the parametric software supporting its protocol of data exchange and the developed algorithm has a parametric nature too, the appropriate way lies in exploiting this capability. Hence, an iterative procedure is to be setup between two interfaces of BIM and AI in which the designed model in Revit is transformed through ODBC protocol into parametric values, these values could be optimised via the developed algorithm and finally the optimised database file could be

switched back into Revit. In the end, the model is updated automatically on the basis of optimised values.

Finally, the last instrument of the quantitative method; the case study is employed to test and verify the developed framework. It was inferred from the discussion on the quantitative instruments (Section 4.5.3) that the case study is one of the most appropriate instruments to test and verify the developed frameworks and prototypes resulting from simulation (Nguyen, Reiter & Rigo 2014). Thus, the functionality of the developed active BIM framework is tested and validated through implementing a pilot case study and comparing the results. Comparative deviation report between the current state (prior to framework application) and the applied state (after framework implementation) should be accounted in order to show the reliability and workability of the framework.

4.9. Sampling

Sampling is a significant requirement in conducting qualitative studies to identify the potential participants from the population of the study at hand (Rowley 2014). Population, here, refers to the group which is the target for respondents of the data collection (Punch 2005). Hence, sampling denotes the sample selection from the population of interest (Ritchie et al. 2013). With respect to the aim and objectives of this research, it could be mentioned that built environment people including architects, designers, building and energy experts, BIM experts, sustainability and energy engineers constitute the population target for this study. This decision is further corroborated by Attia et al. (2013) in setting up the population target for such studies. With this in mind, there are several techniques for choosing a sample among the population of interest. The selected method for this study is purposive sampling strategy which is a non-probability sample and is set according to pre-defined criteria and the objectives of the study (Robinson 2014).

Purposive sampling is both time and cost-effective and works well when there are limited number of primary data sources who can participate in the research (Robinson 2014). In addition, purposive sampling fits effectively to Delphi instrument since Delphi is the iterative study to find a consensus agreement among a relatively small sample of respondents (Ameyaw et al. 2016). In fact, arbitrary and random-based samplings are not usually applied for qualitative studies especially in cases of running Delphi methods (Merriam 2014). Purposive sampling assists researchers to achieve the aim and objectives of their study in the meanwhile of controlling the level of variations among respondents (Bazeley 2013). Therefore, in this study, architects, designers, BIM experts, energy and building experts and engineers are considered as the

population groups and members from each group are included as the respondents for data collection purposes. This strategy allows for representing each group of target experts in the collected sample (Preston 2009).

4.10. Data Analysis

With regard to the data analysis procedures, the relative importance technique is used for analysing the Delphi results and prioritising variables based on the respondents' opinions (Keeney, Hasson & McKenna 2011). Furthermore, once creating the database, the whole datasets should be normalised and stabilised against any excessive variance for improving their validity. By developing AI algorithms, based on the normalised data, the performance errors of the algorithm batches are calculated through Matlab software and the best one is selected. Finally, when the integration procedure of AI with BIM is implemented, the workability of the framework should be analysed by simulating case studies, running AI-based active BIM process and estimating the related energy consumption before and after optimisation. Accordingly, statistical and mathematical analyses are conducted to find the significant relationship between the results and confirm the reliability of the optimisation.

4.11. Summary

Chapter 4 has presented an overview of the major approaches of the research methods used, hence developing the research paradigm of this PhD study. Significantly, the application of the mixed method; the sequential exploratory design was discussed and affirmed in light of the research objectives and the arguments and counter-arguments of qualitative and quantitative techniques. Furthermore, the aspects of concerns and scrutinies in running the three stages of this approach were delivered. The outline of the data analysis and their primary statistical methods and purposes were introduced. The next chapters provide the full details of each stage in terms of collecting and analysing the findings.

CHAPTER 5

Data Collection and Analysis

5.1. Introduction

It is believed that drawing an applicable, relevant and coherent batch of variables is a fundamental tenet in the success of having an integrated BIM-based energy optimisation. However, in order to achieve a high level of usefulness, these variables need to be identified, refined and prioritised. Thus, this chapter is to first provide an overview on the building energy variables and investigate those variables which are of top priorities for energy optimisation of residential buildings in the design stage. Given the sequential exploratory approach, the literature and three-round Delphi study were then conducted to create a pool of variables, refine and prioritise them with energy and BIM experts to reach the final list of prioritised variables.

5.2. Building Energy Parameters

At the building level, when it is to design with the purpose of energy performance optimisation, large number of factors and variables can be considered. But some constraints like time, the scope of the project and the availability of resources and facilities may convince the researchers to narrow down the variables into a manageable number. The quest for optimum energy consumption requires a coherent implementation of factors that together optimise the performance of the whole building system (Radhi 2008). In the literature, huge amount of variables and parameters have been practiced and different types of categorisation have been introduced.

From the design perspective, the parameters influencing the energy consumption of buildings can be categorised into non-design factors and design factors (Clarke 2001). In this categorisation, occupant behaviour, climate and indoor environmental quality have been classified as the non-design factors and building layout, physical properties and HVAC related variables have been labelled as the design factors (Clarke 2001). In another categorisation by Park et al. (2012b), the factors have been classified based on the type of information they contain in which geometric information relates to the 3D form of the building. Semantic information implies the properties of components like u-values of walls and topological information describes the dependencies of these components (Park et al. 2012b).

Considering the different types of categorisations (Clarke 2001; Nemirovski et al. 2012; Park et al. 2012b), generally, the significant design and construction parameters influencing buildings energy consumption can be classified into 4 categories of (Nemirovski et al. 2012):

- i. Physical properties and building envelop
- ii. Building layout
- iii. Occupant behaviour
- iv. HVAC and Appliances

5.2.1. Physical Properties and Building Envelop

Building envelop is the key area where thermal losses happen and so is a very significant in the contribution to energy loss. It is a major path in thermal loss due to heat transfer in winter and an excessive solar heat gain area in summer (Nemirovski et al. 2012). For this reason, heating and cooling demand of the building is mostly dependent on design of the building envelop variables (Koo et al. 2014). Building envelopes are in the direct exposure to the external environment because of orientation and composition (Wong et al. 2010) and it is vital to identify the effects of their properties and optimise them in the early design phase. Moreover, they are responsible for more than half of the total heat gain in buildings (Utama & Gheewala 2009). The building envelop design contains the building configuration, shell and material related elements including walls, floors, roofs and windows (Banihashemi et al. 2015). These elements through thermo-physical properties represent the mechanisms of heat transfers or heat stores into the structure. Their geometries, construction materials and their level of insulation are essential in this stage (Bouchlaghem 2000).

U-value is the most important thermo-physical property which predominantly affects the rate of heat, transfer in and out of a building and consequently the air conditioning or heating energy requirements (Ekici & Aksoy 2011). This value reflects how many Watts will flow in one hour through one meter square of an entire building section when the temperature variance between hot and cold side is one degree Celsius (El Hjouji & Khaldoun 2013). Furthermore, the size and number of glazing of windows in a building will have a critical effect on both the heat gains and solar gains of a building. Because glazed areas have the highest heat gain per unit area and the major proportion of solar gains are also through windows (Urbikain & Sala 2009). The level of insulations also specifies the rate of heat conductivity and infiltrations the components of buildings may have (El Hjouji & Khaldoun 2013).

5.2.2. Building Layout

This category of variables mostly covers the design brief of the building such as the internal sub-division, number of rooms or the number of spaces requiring heating and cooling, size of the building and building orientation. Generally, a larger building will require more energy to heat and cool than a smaller building because of the larger of space to be cooled (Gong, Akashi & Sumiyoshi 2012). The question of whether a building needs less energy per unit volume or floor area is, however, a more complex one and still not completely resolved (Anastaselos et al. 2016). Many researchers take this view that larger buildings need less energy per unit size because of their smaller surface area per unit size and thus lower heat gain per unit size (Michalek, Choudhary & Papalambros 2002). Based on this perception, "the larger a building, and the nearer to spherical in shape, the less are its energy needs because of the simple reduction in the ration of surface area to volume" (Standard 2007, p. 10).

It can be stated that the architectural form for angular protrusions of buildings is an energy wasting form (Standard 2007). However, compact buildings cost more to erect and have higher energy running costs than sprawling ones and the quality of "compactness" in layout cannot be shown to be of paramount importance (Cao et al. 2017; Gros et al. 2016). According to the literature, the maximum volume with minimum external wall perimeter cannot be regarded as the most EED (Cao et al. 2017). So, due to the need for mechanical systems in providing interior comfort band, it may not even be the cheap design as well (Bucking, Zmeureanu & Athienitis 2014). As a whole, it is not possible to generalise or quantify the complex implications that planning and layout of spaces have on air conditioning and lighting requirements (Cao et al. 2017). Building orientation also affects significantly the energy consumption of buildings. It changes the air conditioning or heating energy requirements in two respects (Kibert 2012):

- i. Solar radiation and its heating effects on walls and rooms facing different directions
- ii. Ventilation effects associated with the relation between the directions of the prevailing winds and the orientation of the building.

5.2.3. Occupant Behaviour

Among various factors influencing building energy consumption, occupant behaviour plays essential roles in the energy performance. It is challenging in investigation due to the complicated characteristics and unpredictable personal behaviour (Yu, Haghighat, et al. 2011). The level of physical activity, the clothing worn, the duration of occupancy and age, size and

background and behaviour of the occupant influences the cooling/heating requirements (Soebarto & Bennetts 2014). For instance, a person wearing light clothes and doing light desk work seated will feel comfortable at 25°C while that person with a light business suit feels comfortable at 21°C (Böer 2012). This 4 degrees' difference can mean a 100% difference in the cooling or heating energy requirement of a room. In addition, the attitude of the occupants towards energy use has significant consequences (Delzendeh et al. 2017). They are influenced by the aims and goals of the users, the penalties and benefits to the user of conserving energy and expectations of the user. Even, users awareness of the relationship of their actions to the amount of air conditioning or heating energy used is another factor (Masoso & Grobler 2010).

Building operation is also an important factor. A clear understanding of the schedule of operation of the building is important to the overall accuracy of the energy estimation (Delzendeh et al. 2017). This includes information about when building occupancy begins and ends (time of the week, and seasonal variations), how many people are in the building and internal equipment operations schedules. The amount of energy used will generally be directly proportionate to the intensity of building occupancy (Amasyali & El-Gohary 2016). A building rented out for only half a year will obviously use half the energy of an equivalent building occupied throughout the year. Operating hours will be another normalising factor energy auditors must keep track of (Yu, Fung, et al. 2011a).

5.2.4. HVAC and Appliances

This category of variables includes the parameters related to heating, ventilation, air conditioning and electrical appliances within buildings (Jung et al. 2013b). Energy management of this category is a primary concern especially for commercial and office buildings since electricity has considerable share in HVAC among all building services installations and electric appliances (Bichiou & Krarti 2011). It is very complicated to model, simulate or optimise the energy consumption of these variables. Because, in addition to considering the thermal comfort and end users behaviour, the efficiency and product quality of HVAC devices and appliances are also playing major role in their energy consumption level (Pérez-Lombard et al. 2009). In fact, each appliance and device has its different production configuration with different energy efficiency index. Thus, in order for a precise modelling, these interrelationships need to be recognised as well (Capone et al. 2009).

Table 5.1 indicates the identified variables from the literature along with their respected categories and source of references which were discussed in Section 5.2. There are 22 variables which are screened and identified from 16 referenced sources.

Table 5.1. The Identified Variables from Literature

Variables	Physical Properties & Building Envelop	Building Layout	Occupant Behavior	HVAC	Reference
External wall material	✓				(Wong et al. 2010)
Internal wall material	✓				(Tuhus-Dubrow & Krarti 2010)
Roofing material	✓				(Wong et al. 2010)
Type of glazing in windows	✓				(Banihashemi et al. 2015)
Type of glazing in doors	✓				(Urbikain & Sala 2009)
Level of insulation	✓				(Ekici & Aksoy 2011)
External shading	✓				(Manzan & Pinto 2009)
Internal shading	✓				(Manzan & Pinto 2009)
Building orientation		✓			(Banihashemi et al. 2015)
Total number of rooms in the housing unit		✓			(Standard 2007)
Meter square of rooms heated		✓			(Korolija et al. 2011)
Meter square of rooms cooled		✓			(Korolija et al. 2011)
Glazing to wall ratio		✓			(Waldron et al. 2013)
Cross ventilation		✓			(Anastaselos et al. 2016)
Ceiling height		✓			(Gong, Akashi & Sumiyoshi 2012)
Operation schedule			✓		(Delzendeh et al. 2017)
Clothes type			✓		(Soebarto & Bennetts 2014)
Electrical appliance usage			✓		(Masoso & Grobler 2010)
Number of occupants			✓		(Amasyali & El- Gohary 2016)
Type of main space heating equipment used				✓	(Korolija et al. 2011)
Type of main space cooling equipment used				✓	(Korolija et al. 2011)
HVAC capacity				✓	(Bichiou & Krarti 2011)

5.3. Data Collection

Following with an overview on the building energy parameters and their respected categories and their summary in Table 5.1, according to the discussions in Chapters 1 and 4, the Delphi instrument comes to the fore in further identifying and prioritising building energy variables. This synthesised application of qualitative method (Merriam 2014) warrants that the research questions and findings remain linked to the literature and existing body of knowledge in the interim of creating new knowledge (Bazeley 2013).

The Delphi study is "a qualitative method used to combine expert knowledge and opinion to arrive at an informed group consensus on a complex problem" (Donohoe & Needham 2009, p. 2). As discussed in the Section 4.3.3, this method is not designed to collect random surveys of respondents but it is an iterative discussion method to obtain a consensus opinion from a relatively small sample of experts (Ameyaw et al. 2016). In the literature, Delphi has been used in different contexts with different techniques (refer to Section 4.3.3) however, the basics of this facilitated method for complicated issues are similar (Ameyaw et al. 2016):

- A possibility for respondents to convey their viewpoints on the topic
- A follow-up of feedbacks from respondents on their opinions
- Compiling the responses and analysing the group judgement
- A possibility for respondents to correct and/or modify their opinions according to the compiled responses
- An opportunity of consolidated agreement in anonymously

The complex problem targeted to this project is to compliment the literature to identify and prioritise the variables that play key roles in energy consumption of residential buildings. Hence, the problem for Delphi study was broken down into a series of smaller inquiries addressing:

- Brainstorming with regard to the main variables contributing to the energy consumption and optimisation of residential buildings in the design stage
- Prioritisation of the identified key variables
- Confirmation of the process

5.3.1. Participants

The knowledge areas required for this Delphi inquiry involve with architecture, BIM, building science and services and mechanical, energy and sustainability engineering. For this reason, it was intended to establish a survey sample via purposive sampling method in order to cover these expertise fields considering below recruitment criteria:

- The appropriate academic qualification: at least a bachelor degree in architecture, building science, sustainability engineering and mechanical engineering
- The recognised expertise and/or research background: at least 5 years of relevant work experience and/or conducting PhD level of research and development in the abovementioned areas

In light of the purposive sampling and for reaching the most consolidated results, only people fitting with the recruitment criteria were invited to the study. The recruitment procedure began with both word of mouth and their online resume screening. This practice was done through professional networks such as LinkedIn® and ResearchGate® profiles to identify people who match with the criteria. LinkedIn and ResearchGate allow users to present their professional and/or research skills and because of their public nature, they have become a reliable source for assessing experts' qualifications (Julie, Ben & Comila 2014). In principle, using social media for research and forming survey samples have many advantages including access to experts in distant locations, the ability to reach difficult to contact individuals, and more convenient automated data collection. These virtues significantly decrease the time and effort required for data collection along with having greater control on choosing and finding appropriate participants (Wright 2005). It should be also stated that in the online resume screening, the required academic qualifications, backgrounds and work experiences were set to the above-mentioned recruitment criteria and the profiles were browsed and searched (Brüggen, Van Den Brakel & Krosnick 2016). Total number of invited respondents was 50 people in which 8 people were asked face to face and the rest was sent the email invitation letter along with research ethics statement, research background and research aim and objectives.

Fortunately, the invited participants possessed a good variety of professional areas including BIM, architecture, building science, physics and services (energy and building), sustainability and HVAC engineering. This diversity of participation was not arbitrary and it was chosen on purpose (purposive sampling) in order to reflect a wide range of perspectives on inquires. It was then regarded that this diverse profile of the respondents and their varying levels

of profession and experience can provide the required depths of knowledge and experience as well as sufficient variation among participants to make comparisons possible. These notions are prerequisites for collecting high quality data in qualitative studies (Ochieng & Price 2010). 20 experts rejected the invitation due the reasons such as the lack of expertise and excessive workloads while 30 people accepted the invitation including 10 BIM experts, 16 energy and building experts and 4 engineers. Table 5.2 shows that 16 participants have equal or more than 7 years of work experience which confirms their appropriate level of professional expertise. In terms of academic qualifications, 19 participants have PhD degree evidencing their high profile research and development capabilities as well (Table 5.2).

Table 5.2. Respondents Profile

Expertise	BIM Experts	Energy and Building	Sustainability and	Total
		Experts	HVAC Engineer	
Academic Qualification				
Degree	3	2	-	5
Post-Graduate	3	2	1	6
PhD	4	12	3	19
Total	10	16	4	30
Work Experience				
5 Years	2	10	2	14
7 Years	5	1	1	7
More than 7 Years	3	5	1	9
Total	10	16	4	30

As stated by Sourani and Sohail (2014), presenting the background information of a research problem to respondents is a normal procedure during any Delphi study. Therefore, a document including the problem statement, research questions, aim, objectives and scope of this PhD study along with the research ethics statement were sent by email to the participants to brief them with the aim, objectives and the scope of this research.

5.3.2. Three Round Delphi

As discussed in the Section 4.8, this study comprised of three-round Delphi inquiries that was administered online through the Google Form platform² and distributed through email addresses of participants. The logic of doing 3 rounds of Delphi study is that it was intended to cover three main aspects of brainstorm, prioritisation and confirmation, respectively. So, as depicted in Figure 5.1, the first round was a brainstorming session, the second round was to analyse further and prioritise the opinions and the third round was to confirm the whole process. To ensure the anonymity of the participation, it was set to a login-required format in which respondents must log in to the form via their email address and input their responses into the system.

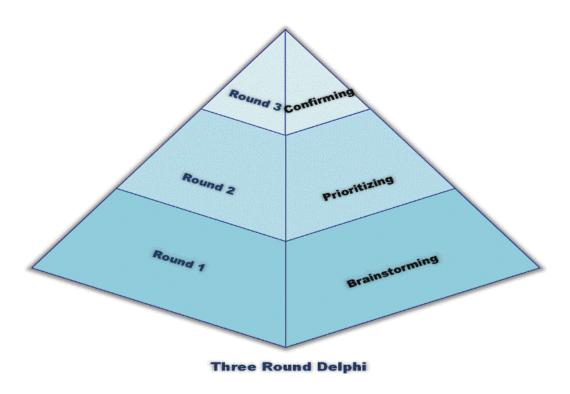


Figure 5.1. Three Round Processes in This Delphi Study

 $^2 https://docs.google.com/forms/d/16AZ90cBeop1HjhM0avqfJ2WEZ0lnktUDBjFM8fMmxyg/viewform$

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5.3.2.1. Round 1

The Round 1 was commenced on the first of October; 2015 and designed to provide a brainstorming session on the building energy variables in which the respondents were invited to answer open-ended questions as below:

- What are the main variables contributing to the energy consumption of residential buildings in the design stage? Please mention at least 10 variables with providing a brief reason for each.
- What are their implications toward the applicability of these variables to BIM, optimisation and design stage?

From the identified 30 people, only about half of them completed the questionnaires within the first 10 days. So, a reminder email along with the invitation letter was sent again on the 10th of October to the panel who had not yet returned the completed forms by the due time. Ultimately, 23 responses were collected until the 20th of October and the rest withdrew from participation due to the heavy commitment of their workloads. This sample size could be regarded sufficient as participants for a typical Delphi study generally range from 3 to 15 (Rowe & Wright 1999; Yeung, Chan & Chan 2009). Based on the 23 received responses from the survey sample, in the first step, 35 variables were extracted from the qualitative responses through a quick textual analysis method and summarised in Table 5.3. Frequency of these parameters was counted and it was observed that material with 10 times of referencing and water fitting, water heating, structural design, shape and roof attic space parameters with only one time of mentioning are the most and the least frequent variables, respectively.

Table 5.3. 35 Extracted Variables through a Quick Textual Analysis Method in Round 1

Variables	Reasons Mentioned by the Participants	Frequency
Space Heating & Cooling		1
Water Heating		1
Lighting		4
Material	Materials with different heat transfer coefficients are effective.	10
Shape		1
Morphology		4
Internal Walls Layout (Zones)		2
Windows Glazing Type	Solar Heat Gain per orientation needed, sized and location	9
Roofing Material Type		4
Ground Floor System		4
Structural and MEP Design		1
External Shading	Determines amount of sun/exposure to get the sun light in winter and block that solar radiation in summer	4
Orientation		8
Occupant Behavior	Different people with different cultures have different routine that affect the energy consumption.	8
Ceiling Height		5
Appliances and Equipment	Housewares with different energy labels result in different energy consumption.	2
Size of the Building		4
Size of the Opening		2
Insulation Type		9
Wall Thickness		4
Slab Insulation and Details		2
Air Distribution and Duct Design		2
Roof Attic Space		1
U-Value of the Building Envelop	Indicate how much heat is loss through the walls, roof, floor, windows, doors	1
Infiltration Rate		2
Window to Wall Ratio	Windows have a higher u-value than other thermal elements (e.g. the walls), so a greater source of potential heat loss	8
Daylighting Factor	Indicating what proportion of natural light can replace artificial light in the building.	3
HVAC System		6
Color of Façade	The color of the façade, its color, and heat absorption or reflection factor can be an affective factor on the engineering design which should be discussed with the architect.	2

Internal Shading Type	3
Floor Area	2
Water Fittings	1
Solar Heat Gain Coefficient (SHGC)	2

The most sensitive methodological issue with the Delphi method is the definition of a consensus among participants. The investigators must decide how agreement among participants will be measured and, if the agreement rate is used, what cut-off will be used to define a consensus. Then, in this study, through a normative assessment method; the comparison of each variable within its peers, only variables selected by 50% of experts or above were chosen to be analysed, according to Chan et al. (2001). This norm shows the indication of the relative importance of each criterion by the experts. In fact, those criteria which attracted 50% agreement or above are in the category of 'most important', 'very important' and 'important' in a unipolar Likert scale. Hence, all others receiving less than 50% of agreement were removed from the next round to maintain the consistency and significance of the results. Ultimately, they were ordered from a range of 10 to 3 most frequent ones resulting to 19 variables (Table 5.4). Around half of the parameters did not meet the 50% cut-off criterion and were not chosen for further study. The list of 19 variables in Table 5.4 is highly correlated with the outcome of literature-based study in the variables identification from Table 5.1. Generally, the occupant behaviour is in the detailed level in the literature but is holistic in respondents' perspective. The possible reason could be in view of the respondents' consideration of the design stage as the scope of this research. Furthermore, lighting and daylighting factors are mentioned by the respondents however, these two items are ignored in the literature-based study. All in all, it can be stated that synthesising the outcomes of the literature and the brainstorming round of Delphi can provide more solid and established results in the next rounds.

In addition to the cut-off rule, the derived 19 variables were checked as to the respondents' opinions on the second open-ended question of the Round 1 Delphi. With respect to the open-ended question on their implications for the applicability of variables for BIM, optimisation and design stage, the respondents gave very insightful ideas. In terms of BIM compatibility, it was stated that very generic variables cannot be considered in this study since the semantic values of very generic variables are not associated with the topological relationship within the BIM model. This idea is further supported with the literature where Kim and Anderson (2012) indicated the lack of appreciation of too generic variables in BIM environment. Therefore, a generic parameter of 'material' was divided into 'internal wall material', 'external wall material'

and 'roofing material' falling to the predefined ranges of BIM families. In addition, some of the experts mentioned that the variables with twofold effects need to be also omitted because BIM has not been yet equipped with intelligent fuzzy rules to identify the root causes of two-fold parameters. Therefore, these variables cannot be optimised and should be removed. Ladenhauf, Battisti, et al. (2016) confirmed this lack in their study on the role of computational geometries and intelligence in BIM interface.

Therefore, according to this concern raised by respondents and by virtue of the literature (Table 5.1), the variable of 'building size' was broken down into two variables of 'meter square of rooms heated' and 'meter square of rooms cooled' (Korolija et al. 2011). Additionally, in line with the two-fold notion, HVAC system was further divided into two variables of the 'type of main space heating equipment used' and 'type of main space cooling equipment used' in order for considering both cooling and heating loads applications (Korolija et al. 2011) (Table 5.1). Checking the subjectivity and objectivity of the variables was also another important task. Chong and Jun (2005) indicated that too subjective variables are serious hinders on the accurate energy estimation and simulation. Hence, the subjectivity and objectivity of the variables were controlled via their parametrisation and measurement capability in BIM. As a consequence, a too subjective variable; 'morphology' was omitted due to not being still parameterised and measured in BIM (Ladenhauf, Battisti, et al. 2016).

The respondents put forward their idea regarding the design stage as the scope of this PhD study and its reflection on the required variables. They stated that the variables relevant to the occupancy profile of buildings cannot be involved in the design-stage-focused study as these variables are within the operation phase of a building project lifecycle. This notion is further confirmed by the literature. It is widely believed that over the buildings projects lifecycle, design stage is the most promising phase in terms of EED as decisions here affect 60-70% of the lifecycle costs of the construction and operation (Stumpf et al., 2009, Kim et al., 2011). However, some variables seem to be more associated with the construction and operation phases. For example, occupant behaviour category of variables refers to the people and their occupancy profile and behavioural use over the operation phase (Yu et al., 2011a). In the design stage, it is difficult to predict the behaviour of occupants on the types of clothes worn, their schedule of building usage and their habits in using heating and cooling appliances (Yan et al. 2015).

In a nutshell, the strategies used in analysing and extracting variables from the 1st round can be mentioned as follow and indicated as the 'action column' in Table 5.4:

- 1- Textual analysis and identifying the keywords associated with any variables or parameters
- 2- Generic variables broken down into specific ones: for example, 'material' was divided into 'internal wall material', 'external wall material' and 'roofing material'.
- 3- Counting the frequency of words
- 4- Checking the subjectivity and objectivity of the variables: for example, a too subjective variable like Morphology was omitted as it is not measurable.
- 5- The variables with twofold effects were also broken down into their parts. For example, 'building size' was broken down into two variables of 'meter square of rooms heated' and 'meter square of rooms cooled'. 'HVAC system' was further divided into two variables of the 'type of main space heating equipment used' and 'type of main space cooling equipment used'.
- 6- Setting the variables with the scope of this PhD study: occupant behaviour was removed since the respondents pointed out its relevancy to the operation stage.

Table 5.4. Normative Assessment Results

Variables	Frequency	Action
Material	10	Broken down into 'external wall material', 'internal wall material' and 'roofing material' as being generic
Windows Glazing	9	
Insulation Type	9	
Building Orientation	8	
Occupant Behavior*	8	Removed as it is not in the scope of design stage and it goes to the operation stage.
Window to Wall Ratio	8	
HVAC System	6	Broken down into two variables of 'type of main space heating' and 'type of main space cooling'
Ceiling Height	5	
Lighting	4	
Morphology*	4	Removed as being too subjective
Roofing Material	4	
Building Size	4	Broken down into two variables of 'meter square of rooms heated' and 'meter square of rooms cooled'
Ground Floor System	4	
Wall Thickness	4	
Internal Shading	3	
Daylighting Factor	3	
External Shading	3	
Doors Glazing	3	

In the final stage of the analysis of the first round, 19 variables obtained from the Round 1 of this Delphi study were depicted in Figure 5.2 to illustrate their schematic view. It can be seen that there are wide range of variables which cover different aspects of buildings energy parameters. External wall materials, internal wall materials, wall thickness, insulation type, roofing materials, Ground floor system, window glazing types and doors glazing types cover the physical properties and building envelop (Nemirovski et al. 2012). There are parameters including ceiling height, meter square of rooms heated, meter square of rooms cooled, window to wall ratio and building orientation which belong to the architectural design and building layout aspects of the influential parameters (Cao et al. 2017). Variables such as lighting, daylighting, external and internal shading address the required considerations in designing for energy efficient lighting and solar exposure (Harish & Kumar 2016). Finally, the parameters of cooling space equipment used and heating space equipment used apply the HVAC system design significance (Jung et al. 2013b).

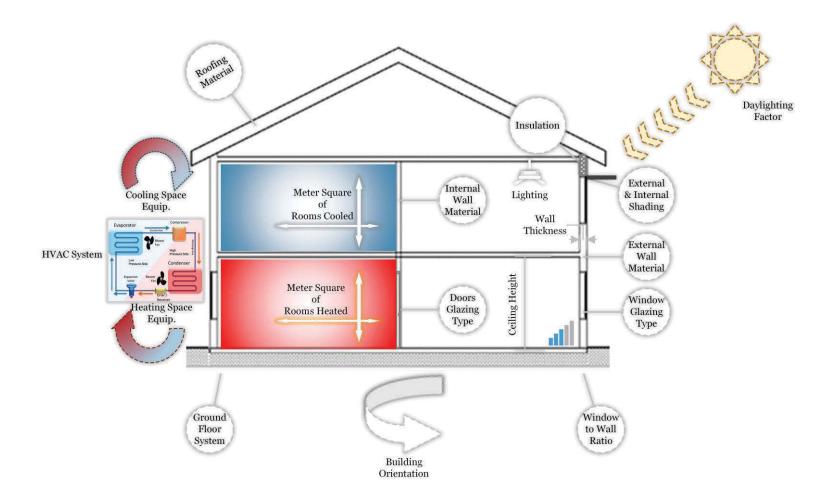


Figure 5.2. The Schematic Illustration of the Variables Resulted from the First Round

5.3.2.2. Round 2

Similar to the first round, the second round of this Delphi study, with the purpose of prioritisation of the variables list, was started on the 1st of November; 2015. The questionnaire forms together with the invitation and information letter were sent to the expert panel of 23 respondents from the previous round. This decision was made to keep the consistency and homogeneity of the participants and collected data which are very important factor for Delphi studies (Sourani & Sohail 2014). This round was designated to focus on the prioritising aspect and the experts were asked to prioritise the 19 variables derived from the first round. A five point Likert scale questionnaire form was developed and the experts were asked to rate the variables ranging from 1=least important, 2=slightly important, 3=important, 4=very important to 5=most important (Holt 2014). Its rationale is that the dimension for measuring these variables should be unipolar, referring to different degrees of the same attribute, but not bipolar, referring to the presence of opposite attributes (Schwarz 2014).

Among the survey sample of those 23 participants from Round 1, 10 people completed the questionnaires within the first 10 days. By sending the reminder email to the rest on the 10th of November, 18 responses, in total, were collected successfully within 20 days indicating a response rate of 78%. This response rate is again regarded sufficient (Rowe & Wright 1999; Yeung, Chan & Chan 2009). A statistical analysis was conducted on the 18 questionnaires received in which the Likert point averages for the 19 resultant variables were calculated. A preliminary series of weighted variables was developed based on the mean ratings advocated by the 18 experts using the following equation:

$$L_{vi} = \frac{\sum_{i=1}^{n} P_{vi}}{n} \tag{5.1}$$

Where L_{vi} stands for the Likert mean of each variable, P_{vi} is the point received for each variable (from 1 to 5) and n is the number of responses for each variable.

As a result of this round, the variables which received the L_{vi} equal to 3 or above were identified to be further analysed for the next round (Holt 2014; Perera et al. 2014). According to both Holt (2014) and Perera et al. (2014), in the unipolar type of Likert scale, the point of 3 indicates the middle value in the importance scale. So, the analysis is based upon this middle range to determine the required level of significance for the parameters. Therefore, the parameters which receive 3 or above are regarded significant and the parameters receiving the Likert point below 3 are determined as the insignificant ones (Holt 2014; Perera et al. 2014). Table 5.5 shows

the ranking of selected variables in the blue shaded and bold type which amounts to 13 variables. It reveals that insulation, roofing material, external wall material, windows glazing type and window to wall ratio are the top five items. On the other hand, external shading, wall thickness, doors glazing, daylighting, internal wall material and internal shading are the least important ones which will be ignored from additional considerations.

Table 5.5. Results of Round 2 Questionnaires

The Variables	Likert Points Mean (<i>Lvi</i>)	Rank
Insulation	4.29	1
Roofing Material	4.17	2
External Wall Material	4.11	3
Windows Glazing Type	4.00	4
Window to Wall Ratio	3.94	5
Ceiling Height	3.82	6
Lighting	3.58	7
Meter Square of Rooms Heated	3.58	7
Building Orientation	3.52	8
Meter Square of Rooms Cooled	3.52	8
Type of Main Space Heating	3.47	9
Type of Main Space Cooling	3.47	9
Ground floor System	3.41	10
External Shading	2.90	11
Wall Thickness	2.90	11
Doors Glazing	2.90	11
Daylighting	2.50	12
Internal Wall Material	2.29	13
Internal Shading	2.29	13

The findings so far indicate that respondents emphasised on the role of physical properties and building envelop in the energy consumption of residential buildings. The top three parameters of this ranking; insulation, roofing material and external wall material receive the average Likert points of +4. These belong to the physical properties and building envelop category of variables. The reasoning behind this fact is that it is widely accepted that building envelop has the direct

exposure to the external environment. It channels a major path in thermal loss due to the heat transfer in winter and an excessive solar heat gain area in summer (Koo et al. 2014). As a result, building envelop is responsible for more than half of the total heat gain in buildings (Utama & Gheewala 2009). The outcomes also conform to the major trend in the energy optimisation-based studies with respect to utilising the variables of three major categories of building envelop, building layout and HVAC systems in their simulation and analysis in the design stage (Foucquier et al. 2013; Machairas, Tsangrassoulis & Axarli 2014; Nguyen, Reiter & Rigo 2014). Merely, the significant variables identified through this Delphi cover a wide range of parameters involved in simulation and optimisation. Factors such as windows glazing, window to wall ratio and types of main space heating and cooling loads are affiliated with building envelop, building layout and HVAC, respectively.

All in all, through the journey from the brainstorming step in the Round 1 to the significant variables identification step via the Likert prioritisation in the Round 2, around half of the items were selected by more than two third of the experts. This fact implies that the majority of the participants were agreed upon the significant variables in this round. For the sake of providing a measure of consistency, a statistical analysis was performed to compute the Kendall's Coefficient of Concordance (*W*) (Kendall & Smith 1939), for the responses provided by the 18 experts. Kendall's *W* is a non-parametric test, running for the normalisation of Friedman statistic test, that can be used for assessing an agreement among participants. If the Kendall concordance coefficient equals to 1, all the survey scorers have been unanimous and they rate the variables identical. On the contrary, if the test results in 0, it means that there is no overall trend of unanimity among the assessors and they rank completely different (Corder & Foreman 2009).

For Kendall's W computation, S was first calculated from the row marginal sum of L_{vi} received by the variables:

$$S = \sum_{i=1}^{n} (L_{vi} - \overline{L_v})^2 \tag{5.2}$$

Where S is a sum of squares statistic over the sums of L_{vi} , L_{v} is the mean of the L_{vi} values and n is the number of variables. Following that, Kendall's W coefficient was obtained from the below formula:

$$W = \frac{12S}{m^2(n^3 - n)} \tag{5.3}$$

In which m is the number of respondents and n is the number of variables which in this round, there are 18 respondents and 13 variables.

In this case, the Kendall's W test produced a score of 0.149 at 10% significance level which is higher than zero and means a trend of unanimity and consistency on the responses (Corder & Foreman 2009) (Table 5.6).

Table 5.6. The Concordance Measurement for the Round 2

Variable	Likert Points Mean (Lvi)	Mean Rank	S
Insulation	4.29	10.50	38.56
Roofing Material	4.17	10.09	35.04
External Wall Material	4.11	10.24	37.57
Windows Glazing	4.00	9.38	28.94
Window to Wall Ratio	3.94	9.03	25.90
Ceiling Height	3.82	8.32	20.25
Lighting	3.58	7.56	15.84
Meter Square of Rooms Heated	3.58	7.18	12.96
Building Orientation	3.52	7.44	15.36
Meter Square of Rooms Cooled	3.52	7.18	13.39
Type of Main Space Heating	3.47	6.50	9.18
Type of Main Space Cooling	3.47	7.21	13.98
Ground floor System	3.41	6.62	10.30
Number of Variables (n)			13
Number of Respondents (m)			18
Kendall's Coefficient of Concordance (W)			0.149
Level of Significance			10%

5.3.2.3. Round 3

With regard to the third round of this Delphi which was devised to the confirmation purpose, the panel was provided with the results of the second round; those 13 significant variables along with their respected mean scores. The respondents were tasked with reconsidering their judgements in light of the mean scores received from their peers in the previous round. The questionnaires aiming at the confirmation process were sent via email on the first of December; 2015, to the same 18 people who had participated in the Round 2 and 10 answers were obtained in the first 10 days. A reminder email was sent again to the rest on the tenth of December and 5 more responses were collected in the next 10 days reaching to 15 completed questionnaires in the end of this round. This response rate was again deemed sufficient in view of the number of

respondents for a Delphi study which typically range from 3 to 15 people (Rowe & Wright 1999; Yeung, Chan & Chan 2009).

Table 5.7. Results of Round 3 Questionnaires

The Variables	Likert Points	Rank	Rank
	Mean (Lvi)		
		Round 3	Round 2
External Wall Material	4.46	1	3
Insulation	4.38	2	1
Roofing Material	4.15	3	2
Windows Glazing	4.00	4	4
Building Orientation	3.84	5	8
Window to Wall Ratio	3.76	6	5
Ceiling Height	3.61	7	6
Type of Main Space Heating	3.53	8	9
Type of Main Space Cooling	3.53	8	9
Meter Square of Rooms Heated	3.53	8	7
Meter Square of Rooms Cooled	3.30	9	8
Lighting	3.30	9	7
Ground floor System	3.23	10	10

Using equation (5.1), Table 5.7 shows that the majority of the experts had re-evaluated their rankings (Round 3 rankings in blue) in comparison with the previous round (Round 2 rankings in grey). External wall material was raised from the third to the top level while insulation and roofing material were lowered to the second and third rates, respectively. This implies that the building envelop has still caught the first consideration. Likewise the respondents have directed their particular attention to the external wall material because of its recognised effect on the heat transfer of building fabric (El Hjouji & Khaldoun 2013). Furthermore, lighting was dropped from 7th to 9th and on the other hand, type of main space heating was raised by 4 rankings. Interestingly, twin variables of meter square of rooms heated and cooled became convergent and took the places of 8^{th} and 9^{th} . It should be noted that the Likert Point Mean (L_{vi}) of all variables kept the score above three which confirms an appropriate congruence among the results (Holt 2014; Perera et al. 2014). In line with the previous round, the consistency of the survey was again calculated via Kendall's Coefficient of Concordance (W) using equations (5.2) and (5.3). It was revealed that the consistency was remarkably enhanced in the third round where it attained a number of 0.267 at 10% significance level pointing out 80% improvement in the reliability and consistency as compared to the second round (Table 5.8).

Table 5.8. The Concordance Measurement for the Round 3

Variable	Likert Points Mean (Lvi)	Mean Rank	S
External Wall Material	4.46	12.00	56.82
Insulation	4.38	11.19	46.31
Roofing Material	4.15	10.42	39.26
Windows Glazing	4.00	9.69	32.37
Building Orientation	3.84	9.00	26.56
Window to Wall Ratio	3.76	8.62	23.53
Ceiling Height	3.61	7.92	18.52
Type of Main Space Heating	3.53	7.23	13.62
Type of Main Space Cooling	3.53	7.35	14.52
Meter Square of Rooms Heated	3.53	7.35	14.52
Meter Square of Rooms Cooled	3.30	6.23	8.53
Lighting	3.30	6.23	8.53
Ground floor System	3.23	5.62	5.70
Number of Variables (n)			13
Number of Respondents (m)			15
Kendall's Coefficient of Concordance (W)			0.267
Level of Significance			10%

5.4. Summary

The current BIM does not sufficiently support decision making procedure to indicate a roadmap of energy optimisation of the significant variables of the design through the perspectives of BIM compatible variables. The identified variables in this Chapter could be the key asset for energy optimisation of buildings in the design stage if they are encapsulated through a unified approach in the BIM design process. To this end, the parametric definition inherited in the BIM technology should be focused. These variables are then required to be parametrised via the BIM development underlying approaches; AI such as machine learning and data transformation algorithms in order to be approachable in the BIM environment via securing the geometrical, topological and semantic associations (Figure 5.3). Integrated and parametric platform of BIM allows for the implementation of 'what if scenarios' so that the optimisation techniques and algorithms are run on these variables to find the most optimum values and minimise the energy consumption of buildings in the design stage.

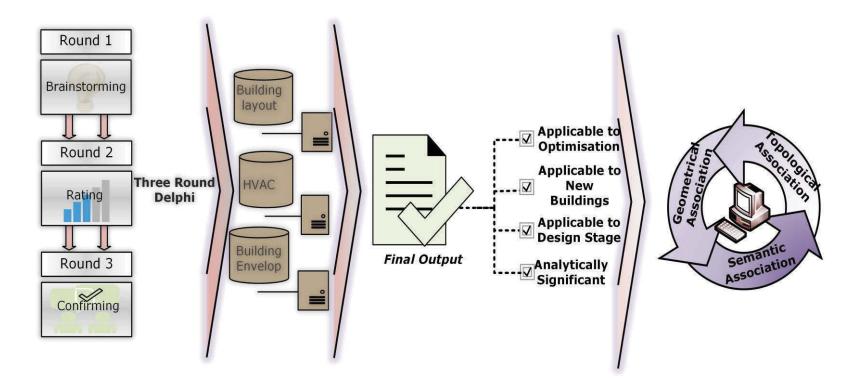


Figure 5.3. The Graphical Diagram of the Steps Leading to the Output

This chapter was intended to conduct data collection and analysis to identify the significant parameters of EED; scoped to the design stage and to be compatible with BIM according to the literature and experts' responses. The sequential exploratory research method was run by synthesising the literature and three-round Delphi. This procedure was ended up with the final matrix of 13 key parameters along with the rankings and mean scores, fulfilling a reliable concordance analysis and comprising major categories of physical properties and building envelop, building layout and HVAC.

CHAPTER 6

AI Algorithms Development

6.1. Introduction

This chapter aims to present the AI algorithms development from the outcomes of the previous chapter as the final list of variables for energy optimisation. The variables identified from the literature review and Delphi study laid the rigorous foundation to be considered in the energy simulation stage. The chapter commences by providing, as background, the dataset development procedure. Details of the operational aspects of conducting data size reduction are then discussed. Data interpretation techniques are further elaborated on the methods of data normalisation and regularisation. The main part of the chapter follows next with this allocated to developing AI algorithms; ANN as a prediction, DT as a classification and the Hybrid algorithms.

6.2. Dataset Generation

As discussed in Sections 4.5 and 4.8, the simulation method was selected in this stage to collect a reliable and verified data for the prioritised variables with an emphasis on covering the whole range of available values. These data are collected via building energy performance simulation. As outlined in one of the seminal studies by Karlsson and Roos (2003), there are four main methods to develop an energy simulation model:

- 1) Comparison based on the physical properties.
- 2) Using empirical coefficients based on the energy balance of components for different climatic conditions and building orientation.
- 3) Incorporating simple building properties to distinguish between different building types.
- 4) Performing a full scale simulation including climatic data, building layout, building envelop and physical properties.

Method 4 provides very accurate results (provided the simulation model is correct) as compared to the others since it includes wide range of parameters (Nguyen, Reiter & Rigo 2014). Nevertheless, it also requires experienced users, a lot of input data, which are not generally available, and huge computation for simulation (Nguyen, Reiter & Rigo 2014). Given the advantage of the accurate and comprehensive simulation in AI based research (Dounis 2010), this

study used the fourth method for generating a comprehensive dataset of energy relevant inputs and output in a broad context via considering the different climatic data.

However, in order to overcome the above-mentioned drawbacks of the fourth method, this study incorporated an approach in the size reduction of full factorial energy simulation by using metaheuristic method. Metaheuristic method assists to obviate the dataset development from numerous runs of simulations and limit the number of input data to those which were determined significant in the Delphi study (Shaikh et al. 2014). It is based on the fact that changing the values of variables in each run has direct impacts on the heating and cooling loads of building. This fact consequently affects the ultimate energy consumption of the simulated case (Nguyen, Reiter & Rigo 2014). To set the scope of the simulation, the following criteria were also taken into consideration:

- The simulated case should represent a typical residential building type in the considered climatic areas inclusive of the specifications complied with the well-known and international standard of ASHRAE (2007) in its building envelope.
- The simulation model should encompass main types of climatic conditions of temperate, tropical, hot-arid and cold (Kottek et al. 2006).

Considering all these, a five-story building consisting of four units per floor along with the parking lot in the ground floor was selected for simulation. Each level area is 320 m² summing up to the total area of 1600 m². The building was modelled in Rhino 5 and parameterised in Grasshopper software³ (elaborated in the next section). Figure 6.1 shows the typical layout of the floors and the perspective of the building. Table 6.1 lists the components and construction used in the simulation model which conforms to the variables resulted from the Delphi and their specifications set based on ASHRAE 90.1-2007.

³ Full details can be found in Section 6.3.2.



Figure 6.1. 3D Model and the Layout

For clarification of the simulation process and the construction specifications used, it should be mentioned that the model and its layout was constructed based on ASHRAE 90.1-2007 and using this standard to set the materials. The identified variables from Chapter 5 were corresponded to their required construction specifications in the standard and their respective climatic zones (Table 6.1). This procedure enabled the researcher to generate a baseline model according to the identified variables, their required specifications from ASHRAE standard and the climatic zones of temperate, tropical, cold and hot-arid. For building envelop and physical properties, available wall, roof, floor, insulation and glazing types for the selected climatic zones were extracted and input in the baseline model (see Table 6.1). Building orientation was also considered for its main 8 different degrees. Steam or hot water system, heat pump and built-in room heater was selected for different types of main space heating and central system and window to wall units were considered for the different types of main space cooling systems (ASHRAE 2007). Meter square of rooms heated and cooled were set for 10 and 15 meters and ceiling height was considered for a range of 3-3.5m which are applicable for each room in a residential unit (Michalek, Choudhary & Papalambros 2002). The window to wall ratio of 20-40% and lighting range of 1-40 lux were set as recommended by (ASHRAE 2007) (Table 6.1).

Table 6.1. Model Parameters Specifications based on ASHRAE 90.1-2007

Components	Spacifications	U Value
Components	Specifications	$(W/m^2.K)$
	ExtWall Mass Climatezone 1	0.7
	ExtWall Mass Climatezone Alt-Res 1	0.98
	ExtWall Metal Climatezone 1-6	0.7
	ExtWall Mass Climatezone 2	0.98
	ExtWall Mass Climatezone Alt-Res 2	0.77
Wall Tyra	ExtWall Mass Climatezone 3	0.77
Wall Type	ExtWall Mass Climatezone Alt-Res 3	0.64
	ExtWall Mass Climatezone 6	0.48
	ExtWall Mass Climatezone Alt-Res 6-7	0.42
	ExtWall Steel frame Climatezone 1-2	0.78
	ExtWall Wood frame Climatezone 1-4	0.54
	ExtWall Wood frame Climatezone 6-7	0.3
	ExtRoof lead Climatezone 1	0.37
Roof Type	ExtRoof lead Climatezone 2-8	0.28
	ExtRoof Metal Climatezone 1-7	0.38
Ingulation Type	ExtWall Insulation Layers 1-8	NA
Insulation Type	ExtRoof Insulation Layers 1-8	NA
Floor Type	Floor Climatezone 1-8	0.19
	Floor Climatezone 2-7	0.15
Glazing Types	Double Glazed Window	0.29
Chazing Types	Triple Glazed Window	0.28
Building Orientation	0, 45, 90, 135, 180, 225, 315	NA
T. CM: C	Steam or Hot Water System	NA
Type of Main Space Heating	Heat Pump	
	Built-in Room Heater	
Type of Main Space	Central System	
Cooling	Window/Wall Units	NA
Meter Square of	10 m^2	
Rooms Heated/Cooled	15 m ²	NA
	13 111	INA

C.1. H.14	3 m	NA
Ceiling Height	3.5 m	
Window/Wall Ratio	20%-40%	NA
Lighting	1-40 Lux Range	NA

Among various factors influencing residential building energy consumption, occupant behaviour plays an essential role and is difficult to investigate analytically due to its complicated characteristics (Yu, Fung, et al. 2011b). In Section 5.3.2.1, it was discussed that occupancy variables could not be considered for estimation and optimisation as the focus of this research is on the design stage. However, since Rhino and Grasshopper package utilises the EnergyPlus engine in its energy calculation procedure (Banihashemi, Tabadkani & Hosseini 2017), some basic occupancy parameters such as user profile should be selected by default to enable the software to proceed through the simulation processes. Hence, in order to facilitate this procedure, it was taken into account that the heating or cooling system in the building becomes active when the inside temperature goes higher or lower than the predefined comfort band.

For energy simulation in the EnergyPlus plugin, building calculation program was set to low-rise apartment; kitchen, bedroom, bathroom and dining room in each unit were defined as separate zones with their own thermal properties. This approach enables the thermal engine to precisely quantify adjacencies and inter-zonal connections (Shakouri & Banihashemi 2012). The thermostat was set between 18-26 °C (CIBSE 2006) to provide thermal comfort for occupants and activate HVAC devices below or above this range. Table 6.2 indicates the user profile of the zones for the units of the building. From Figure 6.1, it can also be seen that some units have 3 bedrooms and some units are single bedrooms.

Table 6.2. User Profile

Zone	Area (m ²)	Volume (m³)	Occupancy	Activity	Comfort Band
Living Room	19	57	4	Sedentary	18-26 °C
Kitchen	7	21	4	Cooking	NA
Bathroom	4	12	1	Sedentary	NA
Bedroom	10	30	2	Sedentary	18-26 °C

Using different climatic conditions in building energy performance simulation assists in generating the wide range of dataset and enhances the generalisability of the output and the framework developed for energy optimisation purposes (Gros et al. 2016). Therefore, considering the dominant climatic zones introduced by Kottek et al. (2006), four cities of Sydney, Moscow,

Kuala Lumpur and Phoenix were chosen as representatives of temperate, cold, tropical and hotarid climates, respectively. This wide range of climatic situations allows for generating more generalisable simulation dataset. Table 6.3 indicates the geographical coordination of these cities along with the dominant thermal systems required for each city (DOE 2014). The relevant EnergyPlus Weather format data were downloaded from EnergyPlus database (DOE 2014) and embedded in the simulation software indicating the climate zones of the four cities. These climatic data are in accordance with Typical Metrological Year (TMY) (Ebrahimpour & Maerefat 2010) concept in which data sets of hourly values of solar radiation and meteorological elements are recorded in a 12-year period of time and averaged for a 1-year timespan. Table 6.4 shows monthly mean values of climatic data for the selected cities including temperature, humidity, wind speed and solar radiation.

Table 6.3. Cities Chosen for Simulation

City	Latitude	Longitude	Climate	Dominant Thermal System
Sydney	33.86° S	151.2°E	Temperate	Cooling and Heating
Moscow	55.75°N	37.61°E	Cold	Heating
Kuala Lumpur	3.13° N	101.68°E	Tropical	Cooling
Phoenix	33.44° N	112.07° W	Hot-arid	Cooling and Heating

Source: Adapted from WMO (2016)

Table 6.4. Climatic Data of the Selected Cities

City	Month	Temperature (°C)	Humidity (%)	Wind Speed (k/h)	Average Daily Solar Radiation (MJ/m²)
	Jan	22.3	62	20	21.4
	Feb	22.3	64	25	19
	Mar	21.2	62	22	16.4
	Apr	18.5	59	20	12.9
>	May	15.5	57	8	10
Sydney	Jun	13.1	57	14	9.1
Syc	Jul	12.4	51	9	9.8
9 1	Aug	13.4	49	16	13
	Sep	15.5	51	12	16.7
	Oct	17.8	56	22	19.9
	Nov	19.5	58	22	21.3
	Dec	21.33	59	22	22.6
	Jan	-8	90	17	2.3
	Feb	-7	85 75	14	5.3
	Mar	-2	75 70	14 14	9.9 14.2
	Apr	6 13	70 70	14 14	18.1
WO	May Jun	18	70 75	14	18.8
Moscow	Jul	19	75 75	14	18.5
$\breve{\Xi}$	Aug	17	80	14	15.2
	Sep	12	85	16	9.4
	Oct	6	85	16	5.3
	Nov	-1	90	16	2.7
	Dec	-6	90	17	1.5
	Jan	27	80	9	15.6
	Feb	27	80	12	18.4
	Mar	27	80	6	18.9
Ħ	Apr	28	85	6	19.3
Kuala Lumpur	May	28	80	9	18.2
Cui	Jun	27	80	9	17.7
[a]	Jul	27	80	12	17.6
Kua	Aug	27	80	12	17.9
7	Sep	27	80	9	18.1
	Oct	27	85	8	17.4
	Nov	27	85	8	15.3
	Dec	27	85	6	13.7
	Jan Eab	13.6	45.6	8.2	11.7
	Feb Mor	15.4	43.9	9	14.8 19.9
	Mar	18.4	37.7 26.2	10.3 11.3	25.3
	Apr May	22.6 27.8	20.2	11.3	25.3 27.9
nix	Jun	32.7	20.0 17.9	10.8	28.1
Phoenix	Jul	34.9	29.1	11.3	25.1
Ph	Aug	34.2	34.6	10.8	22.4
	Sep	31.3	31.1	10.8	20.9
	Oct	24.8	31.4	8.9	16.7
	Nov	17.8	36.7	8	13.1
	Dec	13	46.2	7.7	10.8

Source: Adapted from WMO (2016)

6.3. Data Size Reduction

6.3.1. An Overview

The full factorial inclusion and all possible combinations of 13 parameters with each other and their respected values and ranges in the energy simulation for this study (see Table 6.1) requires huge number of simulation runs. It may require more than 6 billion of simulations⁴ that is completely infeasible to be conducted. As a solution, data size reduction techniques are commonly used in the whole building energy performance simulation (Shi et al. 2016). Not doing so in the studies which focuses on the annual aspects of energy and consists of high temporal resolution (seconds to hours) restricts the spatial resolution to a rough zonal discretisation (Seongchan & Jeong-Han 2011). In recent years, different approaches have been used to minimise the number of simulations required and simplify the building energy simulation procedures to glean precise but concise results (Jaffal, Inard & Ghiaus 2009; Pisello, Goretti & Cotana 2011; van Treeck & Rank 2007).

According to Eriksson et al. (2000), Design of Experiment is one of the most commonly applied approaches that can be used to design any information-oriented experiment especially where the variation and its observation is of high importance. It is a very efficient branch of parametric tests at evaluating the effects and possible interactions of several factors through its factorial design tool (Bailey 2008). The two-level-full factorial design in Design of Experiment relies on the approximation of the model by the polynomial expansion of 2^k possible combinations of the factors multiplied by the specified range of levels of values (Mara & Tarantola 2008). As an instance, Design of Experiment factorial design of a batch of 3 parameters with 2 levels for each factor will generate 8 runs of simulations. However, this method is specialised on continuous parameters and cannot handle categorical variables due to its numerical nature (Montgomery 2008). Therefore, in this research, a technique was applied via exploiting the parametric nature of Grasshopper software in incorporating generative design principles in the energy simulation development, as discussed below.

 $^{^4}$ 13 factorial simulations = (13*12*11*10*9*8*7*6*5*4*3*2*1) = 6,227,020,800 in the case that each parameter has only one attribute!

6.3.2. Metaheuristic-Parametric Approach in Data Size Reduction

Parametric modelling is a computational method, capable of delivering both generative and analytical model and streamlines a dramatic shift from modelling a designed object to the design's logic (Leach 2009). This method utilises the computational attributes in setting the design principles to provide a platform of design exploration and variations. In fact, different degrees of AI are applied upon the computational specifications such as rules, constraints, parametric dependencies and heuristic and meta-heuristic structures to encode data. It acts as a generator in order to yield a parametric-generative model (Bollmann & Bonfiglio 2013). The procedure of parametric-generative design constitutes three major elements of (Dino 2012):

- i. Start conditions and parameters (input)
- ii. A generative mechanism (rules, algorithms etc.)
- iii. The act of generation of the variants (output)

Each generative process starts with the inputs to establish the initial parameters which are then transformed through a generative mechanism toward the initial population of design. This mechanism is a finite set of instructions, rules and/or algorithms to fulfil a specific purpose in a finite number of steps. Upon the generation of variants; various design schema, a benchmarking or a selection procedure should be determined in the identification of the best variant and final output (Dino 2012). It is widely recognised that there is not a single and definite solution; rather an iterative divergence/convergence process is required to deliver the most comprehensive range of possibilities. This iteration helps explore, analyse and identify the best design option with regard to the desirable criteria (Liu, Chakrabarti & Bligh 2003).

In line with the underlying concept of generative design, as mentioned earlier, Rhino and Grasshopper software package were used as an integrated computer design tool with algorithmic method. Parametric modelling tools can simplify the widest possible range of concepts for design exploration by allowing the automatic generation of a group of alternative design solutions (Banihashemi, Tabadkani & Hosseini 2017). Rhino is a 3D modelling software where authorises the designer to link the layout to its underlying parameters by a plugin called Grasshopper. Grasshopper is also regarded as one of the most suitable parametric modelling platforms embedded in Rhino for developing the design variant algorithms in light of its powerful parametric programming capabilities (Abotaleb, Nassar & Hosny 2016). It is a graphical algorithm editor tightly integrated with Rhino 3D modelling tools which features an advanced user interface. The major interface of the algorithm development in Grasshopper applies the node-

based editor in which data is processed from a component by connecting wires. These wires always connect an output grip to an input grip where data can either be defined locally as a constant or imported as a variant parameter. Therefore, in this research, the following steps were taken into consideration:

- 1) The variables and their respected values and ranges were parameterised and linked to the building 3D model (See Table 6.1).
- 2) The selection procedure of construction details including wall, insulation, roof and floor for four cities was hinged on their respected climate zone, according to ASHRAE standard (ASHRAE 2007). That is an item index moves among the possible options of component categories and locks on the appropriate item which matches with the relevant climate zone. The number of moves depends on the size reduction rules set by heuristic principles (Figure 6.2).

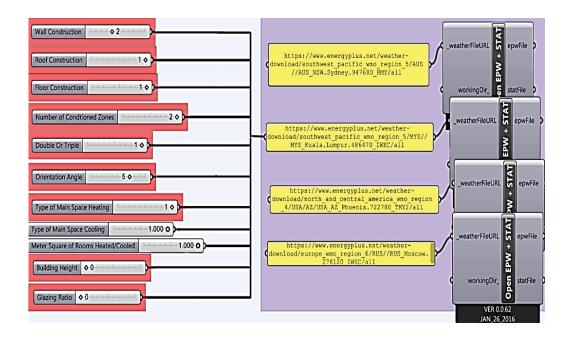


Figure 6.2. Parametric Setting of the Variables

3) The 'Holistic Cross Reference' command was used to set the back and forth iterative connections among all parameters and their values. This procedure imitates the full factorial simulation in the traditional approach. Figure 6.3 exemplifies this procedure in which 2 set elements of A, B, C and X, Y, Z are iterated equally to 9 times (3*3) and then crossed into each other creating 9 new members of AX, AY, AZ, BX, BY, BZ, CX, CY and CZ. (The cross referencing of these elements imitate the cross referencing the whole parameters used in the model simulation of this research).

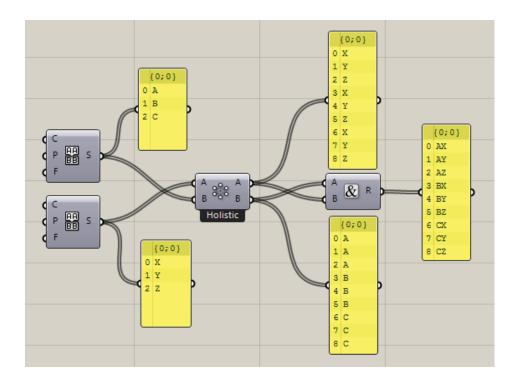


Figure 6.3. Holistic Cross Reference

- 4) Metaheuristic principles of evolutionary solver function were set upon the parameters in order to implement the virtual data size reduction and limit the full factorial simulation by using these rules:
 - Max stagnant was empirically fixed on 5 iterations for the initial population of 20 generations of genomes (13 parameters). This rule means if the fitness of 5 consecutive iterations comprising 20 generations of 13 genomes is kept fixed, the evolutionary solver function (energy simulation) is terminated.
 - To control the distance of genomes in each generation, the inbreeding rate was determined on 75% and the digital variant was maintained on 5%. This rule indicates how the relative offset of genomes (parameters) could be guided in distributing the mutation and crossing over of parameters for securing an appropriate functional handling in dataset generations. Figure 6.4 illustrates that next to the population generation arising from the previous steps, the genomes (simulation variables) are being mutated and crossed over. This is to cover the whole range of data and then, the presented metaheuristic rules pick the most optimums up.

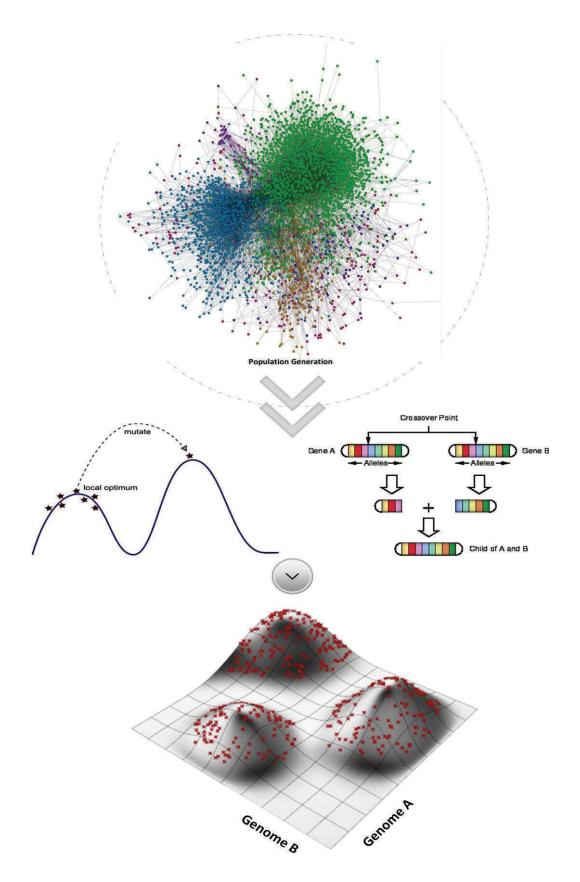


Figure 6.4. Conceptual Diagram of Heuristic Data Size Reduction Source: Adapted from Talbi (2009) and Gendreau & Potvin (2010)

6.4. Data Interpretation Approach

The procedures taken for the data generation were resulted in generating 4435 runs of simulation data including 13 inputs (the variables) leading to the output (annual energy consumption) consisting of 1053, 1138, 1114 and 1130 data for the four cities of Sydney, Phoenix, Kuala Lumpur and Moscow, respectively. The differences in the number of generated data are arisen from the metaheuristic data size reduction in light of their initial population generation and the number of iterations toward the convergence of the evolutionary solver function. For this reason, the solutions found are dependent on the set of random populations generated (Talbi 2009). To analyse the possible impacts of such randomness and obtain an overview about the generated dataset, descriptive statistics were performed for the whole dataset using Statistical Package for Social Science software on the measures of central tendency and dispersion (Weiss & Weiss 2012).

Different statistical measurements of minimum, maximum, range, mean, median, mode and standard deviation were computed to specify the probability distribution and the dispersion of the whole dataset (Table 6.5). This information demonstrates the status of generated data visà-vis the normal distribution state. Table 6.5 indicates that considering both continuous and categorical data, the generated output including all cities covers a wide range of distribution. This fact is of advantage for the optimisation purposes because it enables more precise optimisation (Neustadt 2015).

Table 6.5. Descriptive Statistics of the Developed Dataset (*Categorical Parameters)

Parameters	Range/	Minimum	Maximum	Mean	Std. Deviation	Median
	Number					
Wall type*	6.00	NA	NA	NA	NA	NA
Insulation type*	7.00	NA	NA	NA	NA	NA
Roofing material*	2.00	NA	NA	NA	NA	NA
Windows glazing type*	2.00	NA	NA	NA	NA	NA
Ground floor system*	2.00	NA	NA	NA	NA	NA
Type of main space heating*	3.00	NA	NA	NA	NA	NA
Type of main space cooling*	2.00	NA	NA	NA	NA	NA
Building orientation	315.00	0	315	102.98	87.02	90.00
Window to wall ratio	0.20	0.2	0.4	0.25	0.08	0.20
Ceiling height (m)	0.50	3.00	3.50	3.14	0.22	3.00
Meter square of rooms heated	5.00	10.00	15.00	11.77	2.39	10.00
Meter square of rooms cooled	5.00	10.00	15.00	12.39	2.49	10.00
Lighting (Lux)	39.00	0.00	40.00	2.39	2.58	2.00
Energy load (k.W.h)	10535.58	309.88	10845.45	2725.16	2015.30	2208.66

Matlab software was also applied to plot the observations with respect to the outputs; annual energy loads (Figure 6.5). It should be noted that the number of observations in this figure refers to each batch of inputs with 13 variables. This figure illustrates a relatively steady state from the first to the mid of the observation range where the annual energy loads of two cities of Sydney and Phoenix are depicted up to 2000 k.W.h. This monotonous trend is in view of the climatic conditions of these two cities (see Table 6.4) which refuse the excessive amount of energy consumption for keeping the comfort band. Though, for the other two cities; Kuala Lumpur and Moscow, a dramatic shift is occurred from the mid of the observations to the end and the annual energy loads are made at least double, reaching to more than 10,000 k.W.h at some occasions. Such an increase is quite normal as Kuala Lumpur and Moscow are in the extreme climatic regions; tropical and cold, respectively.

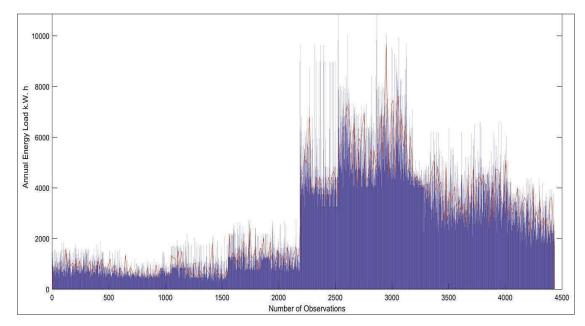


Figure 6.5. Annual Energy Load vs. Number of Observations⁵

6.5. AI Development

6.5.1. Introduction

The application of metaheuristic size reduction coupled with the data interpretation and interpolation approach was ended up with the interpolated dataset. The well-fitted dataset is now prepared for being used in developing the optimisation algorithm. But it should be noted that each optimisation algorithm requires specific objective function as its fundamental unit to model the parameters and minimise the values. Developing the most appropriate objective function is a critical task as much as the reliable dataset generation particularly where, both types of qualitative and quantitative data are involved with the optimisation solver (Neustadt 2015). It was revealed in Chapter 2 that wide range of AI algorithms has been applied for prediction, classification or optimisation of buildings energy consumption.

However, there is a salient gap in the literature on the investigation of hybrid objective function development for energy optimisation problems including qualitative and quantitative datasets in their constructs. It is widely believed that two types of machine learning algorithms; namely prediction and classification are run for continuous and discrete parameters of building energy consumption, respectively (Machairas, Tsangrassoulis & Axarli 2014). In some cases,

⁵ Number of observations refer to each batch of inputs with 13 variables.

transformation techniques are also utilised for converting the continuous and discrete variables into each other but some shortcomings such as losing integrity or randomness may be arisen (Blum & Roli 2003). Therefore, in this stage, two well-known algorithms of ANN and DT were developed separately and integrally upon the datasets in order to find the best solution for energy optimisation functions. Section 2.6.3 presented the discussion on the common predictive methods in building energy performance including CDA, SVM and ANN. From these discussions and the pros and cons of different methods, ANN was chosen for being used in this study in view of its fast computing capability, great level of accuracy, handling large number of data and its wide application in building energy prediction (Demuth et al. 2014; Machairas, Tsangrassoulis & Axarli 2014; Yuce, Rezgui & Mourshed 2016).

Furthermore, among the different classification algorithms, DT is one of the most effective supervised classifiers which works very well with both continuous and categorical data (Iqbal et al. 2014). Comparing DT with SVM as one of the other powerful classifiers, DT takes less time in the computation time and runs effectively on the nonlinear data (Ahmed et al. 2011). Besides, Caruana and Niculescu (2006) analysed 10 different classification algorithms on eleven different data sets and compared the results on 8 different performance metrics. Results indicated the superior performance of DT as compared to the others such as SVM, random forest and Naïve Bayes.

6.5.2. Artificial Neural Network

Artificial Neural Network (ANN) is a mathematical or computational model that tries to simulate the structure or functional aspects of biological neural networks (Demuth et al. 2014). One of the applications of ANN in engineering field is to predict the outcome of non-linear statistical problems and is usually utilised to model complex relationships between inputs and outputs or to find patterns in datasets (Flores 2011). The thermal equations used to analyse and calculate energy loads are complex, making ANN a good platform to be used for this purpose (Nguyen, Reiter & Rigo 2014). In this form, the network was presented with datasets obtained from simulations and the values of inputs were fed into each neuron or nod. The weights were then adjusted through learning algorithms iteratively until a suitable output was produced (Machairas, Tsangrassoulis & Axarli 2014). A suitable output, in this case, suitable predicted annual energy load is the one which is as close as to the simulation results.

One of the most popular and efficient network structures for an ANN model is the multilayer perceptron (MLP). MLP consists of identical interconnected neurons that are organised

in layers (Demuth et al. 2014). These layers are also connected in which outputs of a layer act as the inputs of subsequent layers. Data flow starts from the input layer and ends in the output layer (Kruse et al. 2013). Through this journey, data pass through one or multiple hidden layers which recode or provide a representation for the inputs. In this study, due to the large number of variables and existing non-linearity among them, MLP network was used to model significant relationship between the inputs and the output and predict the data-driven energy performance.

6.5.2.1. ANN Model Configuration and Performance Analysis

This study constructed a three-layer ANN model of feed-forward type with one output neuron. There are 13 neurons in the input layer for the 13 input variables in the model and one neuron in the output layer. In ANN modelling, the data are divided into three groups of training, testing and validating. The best configuration of ANN models usually depends on some elements such as the number of neurons in the hidden layer, the type of learning algorithm and the training-testing proportion of data (Yuce, Rezgui & Mourshed 2016). The identification of the best configuration is a trial and error process which requires different experiments to find the best architecture and optimal performance (Demuth et al. 2014).

Therefore, this process was commenced with the best architecture identification for this ANN model. When using multilayer neural networks for solving a problem, number of neurons in the hidden layers is one of the most important issues. It is known that insufficient number of neurons in the hidden layers leads to the inability of neural networks to solve the problem (Demuth et al. 2014). On the other hand, too many neurons lead to over fitting and decreasing of network generalisation capabilities due to increasing of freedom of network more than it is required (Flores 2011).

Although the selection of architecture for ANN comes down to trial and error but the best number of neurons for the hidden layers could be experimented with a few heuristic rules given as follow (Shahidehpour, Yamin & li 2002):

- The number of hidden layer neurons is equal to the number of neurons in the input layer, or
- The number of hidden layer neurons is equal to two times the number of input layer neurons plus one, or
- The number of hidden layer neurons is equal to the number of input layer neurons plus number of output layer neurons, or

• The number of hidden layer neurons is equal to sum of the number of input layer neurons and the number of output layer neurons divided by two.

Therefore, four different numbers of 13, 7, 14 and 27 neurons for one hidden layer, considering the default types of Matlab software package for learning algorithm (Levenberg-Marquardt), transfer functions of hyperbolic tangent and sigmoid and 1000 number of iterations were tested. Consequently, number of 7 neurons was found to be the most optimum number for the hidden layer neurons. Best performance of the model was measured based on the error produced by the ANN model, which in this case, Mean Square Error (MSE) was used as a performance indicator. MSE can give a quantitative indication of the model error in terms of a dimensional quantity (Ramedani, Omid & Keyhani 2012). MSE equal to zero indicates a perfect match between the observed and predicted values and is calculated by the following equation:

$$MSE = \frac{\sum_{i=1}^{N} (E_p - E_a)^2}{N}$$
 (6.3)

Where E_a is the actual energy value, E_p is the predicted energy value and N is total number of datasets (Flores 2011). The model including 7, 13, 14 and 27 hidden neurons resulted in, respectively, 0.048, 0.061, 0.058 and 0.073 errors. Thus, the optimum number of neurons was found to be 7. The conceptual structure of this ANN model is visualised in Figure 6.6.

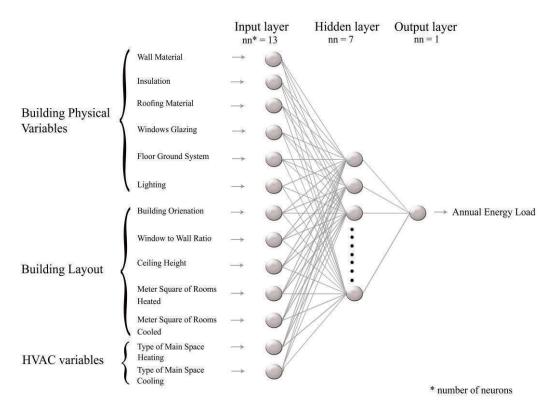


Figure 6.6. The Conceptual Architecture of the Developed ANN

In the ANN conceptual architecture, the information flow starts at the input layer, ending in the output layer and this happens through the hidden layer (Flores 2011). Subsequent to the model architecture identification, the best configuration selection was followed with the optimum training algorithm. Hence, six different types of training algorithms with a bias toward the back propagation category as the most efficient ones for MLP (Alsmadi, Omar & Noah 2009) were tested. This test was run via 7 hidden neurons, the default transfer functions of hyperbolic tangent and sigmoid and 1000 iterations and their performance errors were calculated (Table 6.6). Back propagation is a method which feeds back the size of the error into the calculation for the weight changes (Zhang et al. 2007). According to Table 6.7, the Levenberg-Marquardt Back propagation algorithm was found to have the least algorithm error (0.0029) vis-à-vis the benchmark error (0.005) asserted by Flores (2011). So, Levenberg-Marquardt Back propagation algorithm was used as a method to fit the weights during the learning process starting at the output layer and through the input layer (Table 6.7).

Table 6.6. ANN Training Algorithms Applied

Number	Function ID	Algorithm Name	Seminal References
1	Trainbr	Bayesian regularisation backpropagation	(MacKay 1992)
2	Trainscg	Scaled conjugate gradient backpropagation	(Møller 1993)
3	Trainlm	Levenberg-Marquardt backpropagation	(Levenberg 1944)
4	Trainoss	One-step secant backpropagation	(Battiti 1992)
5	Trainrp	Resilient backpropagation	(Riedmiller & Braun 1993)
6	Traingd	Gradient descent backpropagation	(Baldi 1995)

Table 6.7. Different Training Algorithms Performance

Number	Function ID	Benchmark Error	Algorithm Error	Number of Iterations
1	Trainbr	0.005	0.0043	1000
2	Trainscg	0.005	0.0062	1000
3	Trainlm	0.005	0.0029	1000
4	Trainoss	0.005	0.0038	1000
5	Trainrp	0.005	0.0057	1000
6	Traingd	0.005	0.0047	1000

To find the optimum percentage of dataset⁶ to be trained, tested and validated, test 1 with 60% training-20% testing-20% validating, test 2 with 70% training-15% testing-15% validating and test 3 with 80% training-10% testing-10% validating were performed, as recommended by Shahidehpour, Yamin and Li (2002). The observations were randomly used for training, testing and validating since the random observations in ANN design and development is imperative to avoid biases and evaluate ANN performance more robust (Demuth et al. 2014). Based on the results, the lowest MSE for training, testing and validating with the values of 0.011 and 0.008 were achieved by test 2 when 70%, 15% and 15% of the dataset were used for training, testing and validating, respectively (Figure 6.7). Furthermore, it can be stated that this batch of percentage is deemed appropriate in terms of providing sufficient number of cases for a proper procedure of training, testing and validating. This is according to the seminal reviews of similar studies in the literature (Ahmad et al. 2014; Evins 2013; Foucquier et al. 2013; Shaikh et al. 2014).

⁶ 4435 datasets including 13 inputs (the variables) leading to the output (annual energy consumption) consisting of 1053, 1138, 1114 and 1130 data for the cities of Sydney, Phoenix, Kuala Lumpur and Moscow, respectively.

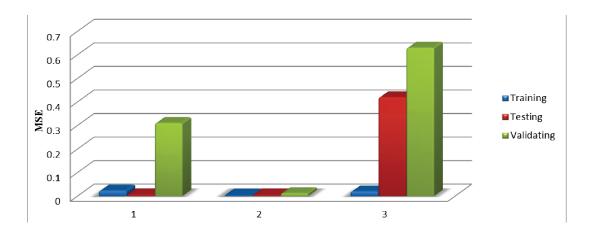


Figure 6.7. Different Training, Testing and Validating Percentage Performances

6.5.2.2. Final ANN Model

Given the identification of the best architecture and configurations for ANN model so far, the final run of ANN with 13, 7 and 1 neurons in input, hidden and output layers were started including 70% training, 15% testing and 15% validating. Hyperbolic tangent function was the activation function chosen for the input layer, sigmoid transfer function was applied between the hidden layer and the output layer and the Levenberg-Marquardt Back propagation algorithm was set as the learning algorithm. The program was then instructed to run for 1,000 iterations as maintained by Demuth et al. (2014) and Shahidehpour, Yamin and Li (2002) and the error for each run of iteration was measured. In this model, 1,000 iterations were found to be adequate for the optimal training process.

The iteration should be terminated when no obvious change and/or improvement is observed. Hence, in order to avoid overtraining, it was intended that training to be stopped when the error remains unchanged for 6 iterations (Rawat, Patel & Manry 2013). Overtraining has more popular meaning in ANN structure design. If too many hidden layer neurons are used, ANN is trained to keep too much details of the training data, and so, it performs much worse in the testing data (Demuth et al. 2014). Figure 6.8 illustrates that the minimum gradient and the MSE for training data was recorded at the 32nd epoch. This amount of epoch and the respected error were deemed acceptable in comparison with the literature (Cohen & Feigenbaum 2014; Flores 2011).

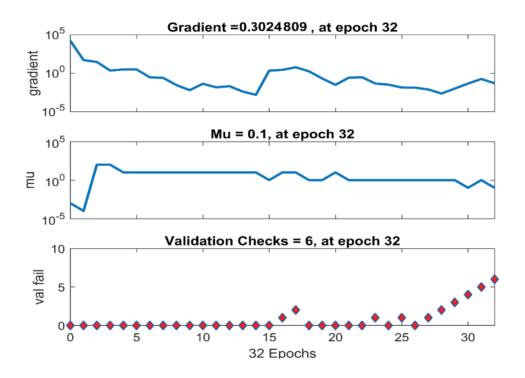


Figure 6.8. ANN Training State

As the training stops after six consecutive increases in the validation error, the best performance was taken from the 26th epoch with the lowest validation error (Figure 6.9). Furthermore, graphically demonstrating the model performance, the correlation coefficient graph (R) indicates how much close predicted energy loads fit to the actual loads. Closer R value to 1 shows that predicted values are closer to the actual results (Lebart 2013). Figure 6.10 illustrates that the overall R value of the developed ANN was calculated at 0.81186. This number presents a strong performance as an objective function in the optimisation problem in comparison with the statistical perfection of 1. This achievement is also remarkable as compared to the similar studies in the literature (Ahmad et al. 2014; Foucquier et al. 2013; Shakouri & Banihashemi 2012).

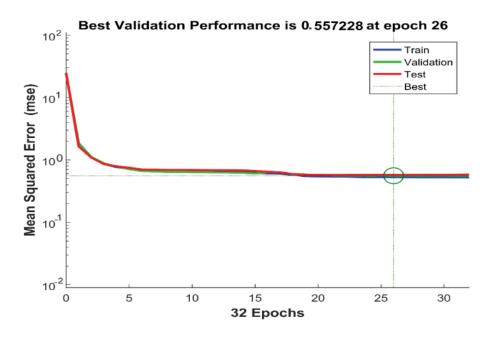


Figure 6.9. Best Validation Performance

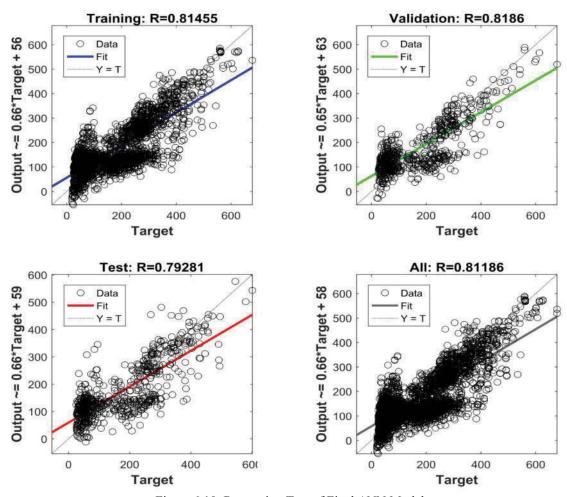


Figure 6.10. Regression Test of Final ANN Model

6.5.3. Decision Tree

6.5.3.1. An Overview

In Section 6.5.1, it was discussed that because of including both continuous and categorical data in the current dataset, it is of priority in running two major categories of machine learning applications on prediction and classification algorithms, separately and integrally. Thus, next to the application of ANN prediction on the whole dataset in Section 6.5.2, this section is to apply the classification algorithm; Decision Tree (DT) on the whole dataset. It is further followed with Section 6.5.4 to apply the combination of these two algorithms on the same dataset. This investigation may facilitate the knowledge for finding more proper solution with the better performance and the lower error.

DT is one of the most applied types of machine learning algorithms in classification problems (Iqbal et al. 2014; Kotsiantis, Zaharakis & Pintelas 2007). The reputation of this algorithm is largely hinged to its interpretability and accuracy in delivering classification models with understandable structure which generates useful information on the corresponding domain. In addition, DT is capable of processing both numerical and categorical parameters (Lebart 2013). However, it should be considered that this method is more appropriate and accurate in handling the categorical parameters rather than numerical data (Yu et al. 2010). There are different types of DT algorithms including Simple Tree, Medium Tree, Complex Tree and Bagged Trees which follow the similar fundamental principles but different degrees of complexity in combining Trees. It applies a flowchart like tree structure to separate the dataset into different predetermined categories for presenting the interpretation, categorisation and generalisation on data (Kotsiantis 2013).

The tree-based logical model of the algorithm denotes the process of target (dependent variable) prediction and classification via the values of a batch of independent parameters. A Tree algorithm consists of three basic components of Root Node, Branch and Leaf (Kohavi & Quinlan 2002):

- A root node evaluates a specific attribute
- Branches are assigned to the node according to the available values for each attribute
- A leaf shows a class and when an item attains a leaf, the leaf's class will be designated to the item.

Root node and branches indicate a binary split test on a specific attribute whereas leaf node presents the result of the classification and holds the categorical label.

6.5.3.2. DT Model Configuration and Performance Analysis

Generally, DT generation follows three steps as suggested by Muniyandi, Rajeswari and Rajaram (2012):

- 1) Learning the data
- 2) Attribute selection
- 3) Optimum DT architectural configuration

With regard to the first step; learning the data, the energy dataset (as a result of dataset generation; Section 6.2) should be prepared for using as a training data. Hence, first, the continuous parameters were assigned with the classes based on the integer numbers and the output was classified considering the classes set to the continuous parameters. The target variable for this DT is the annual energy load with four potential states being classified as Low, Medium, High and Excessive energy consumption as recommended by Yu et al. (2010). This means that the algorithm is going to be fully developed in order to identify the appropriate output ranges for this subjective classifications. Similar to ANN, in learning DT, data should be divided into two subsets of training and testing in which a majority is usually employed for training and the rest for testing. However, unlike ANN, the proportion of training and testing in DT depends on the algorithm which takes them to learn and this element is not controlled by the user. The underlying DT generation algorithm is ID3 (Quinlan 1986) which was further developed and extended to C4.5 algorithm (Quinlan 2014) and its flexibility and applicability in dealing with different data types were improved. It adopts the training dataset as the input and delivers the decision structure.

C4.5 algorithm is a top-down and greedy search through the space of possible branches with no backtracking. It iteratively splits a partition by choosing a split attribute to well separate the target class values. This process is initiated with grouping the training data into a single partition. In each iteration, a predictor attribute is selected by the algorithm which can best split the target class values in that partition. Following with the predictor attribute selection; C4.5 algorithm separates the partition into child partitions in a way that each child partition consists of the same value of the selected attribute. Iteratively splitting the partitions, the learning algorithm terminates when one of the below circumstances are met (Yu et al. 2010):

- 1) All data within a partition features the same target class value. As a result, the class label of the leaf node is the target class value; or
- 2) Further splitting a partition is not feasible due to running out of all remained predictors. So, the leaf node is labelled with the majority target class values; or
- 3) No data are available for a particular value of a predictor variable. Thus, a leaf node is created with the majority class value in the parent partition.

In building a DT, the second step is to choose an attribute (as a node) and then divide it (branching). Since C4.5 partitions the data into subsets that should contain instances with similar values. This homogeneity should be calculated in a structured manner (Iqbal et al. 2014). Therefore, the concept of entropy as maintained by Shannon and Weaver (2015) is usually used to assess the homogeneity of the data samples in DT. If the sample is quietly homogenous, the entropy would be zero and if the sample is an equally separated it will have the entropy of one.

$$E(D) = E(P_1, P_2, \dots, P_n) = \sum_{i=1}^{n} -P_i \log_2 P_i$$
(6.4)

Where E and D denote the entropy and the energy dataset, n indicates the number of values that the final classes can take (4 values of low, medium, high and excessive) and P_i is the partition of the dataset (D) ranging from one to four. The Information-Gain is computed based on the decrease in entropy after a dataset is split on an attribute. Building a DT completely falls to find an attribute which delivers the highest Information-Gain or the most homogenous branches. Thus far, subsequent to calculating entropy for different branches using Equation (6.4), they are accumulated to obtain the total entropy for the splits and the Information-Gain could then be estimated via the following equation:

$$IG(D,A) = E(D) - \sum_{v \in Values(A)} \frac{|D_v|}{|D|} E(D_v)$$

$$(6.5)$$

Where IG and A are Information-Gain and attribute, D_v is the subset of D (dataset) with A = v and Values (A) is the set of all possible values of A. The attribute with the largest Information-Gain is selected as the split attribute for each tree node but this metric is biased toward the attributes consisting of large number of domain values. Normalisation of the Information-Gain by a split information value is a solution to minimise such a bias which could be considered in C4.5 algorithm structure as the below (Han, Pei & Kamber 2011):

$$GainRatio(D,A) = \frac{IG(D,A)}{SplitInfo(D,A)}$$
(6.6)

Where

$$SplitInfo(D,A) = \sum_{i=1}^{n} \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|}$$
 (6.7)

Ultimately, a branch with entropy of zero is set as a leaf node and branches with more than zero require further splitting. C4.5 is run recursively on the non-leaf branches until no critical observation can be found on information gain or gain ratio in further splitting. In this case, it means that all data are classified (Tang, Alelyani & Liu 2014).

Similar to ANN model development, the configuration of DT algorithm also falls to the trial and error process (Kotsiantis 2013). Therefore, it is reasonable to test different tree structures and find the best performance amongst. Applying learning the data and attribute selection, Classification Learner Toolbox of Matlab software package was then used on developing the various types of DT and the generated outcomes were recorded. All possible types of DT including Simple Tree, Medium Tree, Complex Tree and Bagged Tree (Ensemble Trees) algorithms (Quinlan 2014) were developed using the energy dataset in which the architecture of Simple Tree (Figure 6.11), Medium Tree (Figure 6.12) and Complex Tree (Figure 6.13) were visualised. It is worth mentioning that the architecture of Bagged Tree is not possible to be demonstrated due to the massive interactions of more than 100 complex trees with each other.

The root node and starting point of the classification algorithms for all types of DTs is the type of main space heating parameter, determined by the Equation 6.4. Using the Equations 6.5 and 6.6 in the developed trees, decision rules can be utilised starting from the root node and falling through branches to the leaf nodes. For instance, in Figure 6.11, it can be seen that the Simple Tree via choosing Steam or Hot Water System as the type of main space heating is classified as the excessive energy consumption category. This tree could reach the medium level of energy consumption by selecting the Steel Frame R6 and Window to Wall Unit as the insulation and main space cooling type, respectively.

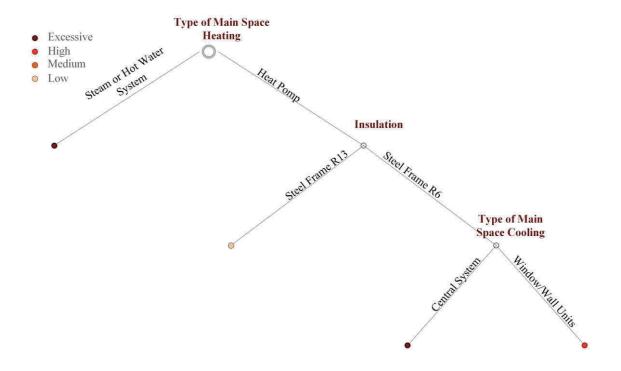


Figure 6.11. Simple Tree

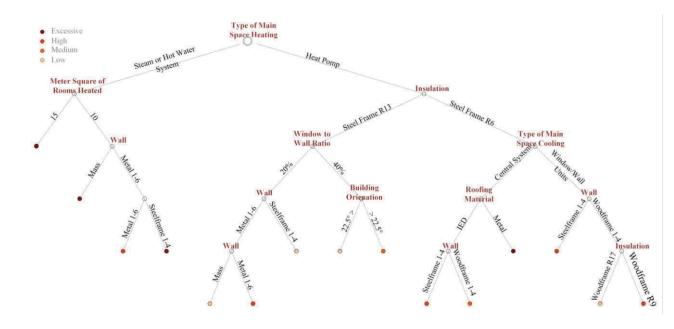


Figure 6.12. Medium Tree

Such decision becomes more informed when Medium Tree is applied and more parameters come to the fore. As depicted in Figure 6.12, in addition to the type of main space heating parameter which is the root node of the algorithm, 4 layers of branches consisting of 7 unique leaf nodes (parameters) are added. Consequently, extracting diverse decision rules allows

for more precise classification. For example, heat pomp of main space heating in combination with Steel Frame R13 (insulation), Window to Wall ratio of 20% and steel-frame 1-4 (wall) could lead to the low energy consumption of residential buildings.

The more complicated tree is developed; the more conscious decisions will be made (Tang, Alelyani & Liu 2014). Figure 6.13 illustrates the complex tree that comprises 9 layers of branches and all 13 parameters of the energy dataset. As mentioned earlier, the interpretative capability of DT distinguishes this algorithm from its counterparts. Valuable information can be obtained from this DT model that provides a blueprint for energy consumption pattern and its optimisation objective functions (Iqbal et al. 2014). For instance, different variables are automatically chosen as the precursors for classifying the energy consumption level. These variables are selected to split the nodes of DT and their distance from the root node implies their significance and the number of records influenced by. Particularly, the visualised complex tree covers a wide range of attributes for all parameters and traversing across the branches and leaf nodes result in different decision rules. Hence, by exploring the tree nodes, the level of strength of the variables and their ranks which specify the building energy demand profile can be extracted.

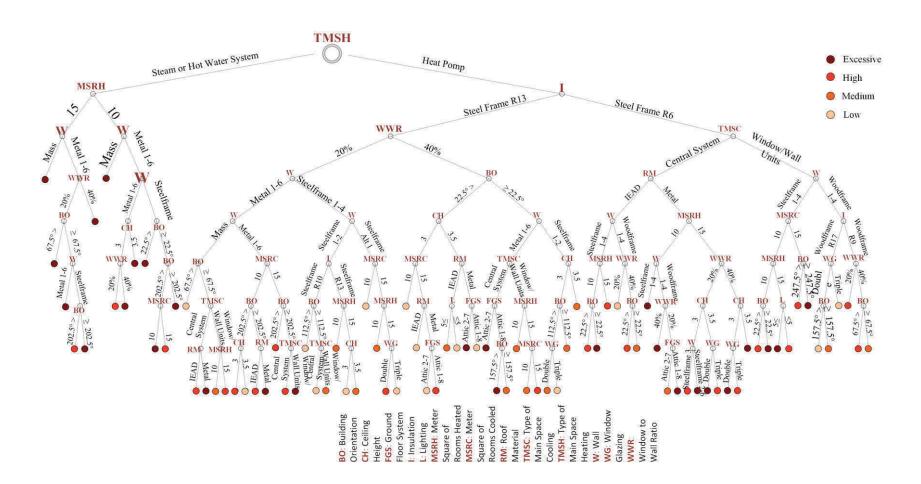


Figure 6.13. Complex Tree

The fourth type of DT; Bagged Tree is an ensemble learning method using bootstrap aggregation which bags a weak learner such as a complex DT on the dataset. It generates many bootstrap replicas of this dataset and grows decision trees on these replicas (Breiman 2001). Bagging works by training learners on multiple-complex DTs on the dataset. In addition, every tree in the ensemble can randomly select predictors for decision splits that improve immensely the accuracy of the bagged trees. The optimum number of complex DTs that should be bagged and aggregated is dependent on the classification error, generated through testing and cross-validation processes (Tang, Alelyani & Liu 2014).

Hence, 200 complex trees were aggregated and bagged and the produced errors in testing and cross-validating states were displayed in Figure 6.14. This figure shows that the performance of the algorithm is perfectly satisfactory in the cross-validation state vis-à-vis the testing condition (Iqbal et al. 2014). The reason behind this fact is that in the cross-validation procedure, bagged tree crosses the trained complex DTs, integrates their overlapped branches and nodes and analyses accumulatively their performance (Tang, Alelyani & Liu 2014). Such collective approach enhances competitively the bagged tree performance over the testing state. This is a condition in which the performance of the trained complex DTs is computed in the standalone manner and arithmetically averaged. The pattern of red dots also reflects an interesting trend in the training and learning of the bagged tree performance. The classification error has dropped sharply from the first DT training to the middle, reaching to the minimum at the 90th tree and then trivially increased with a monotonous regularity to the end. As a result, it can be inferred that 90 complex trees are sufficient and learning more leads to an overtraining problem.

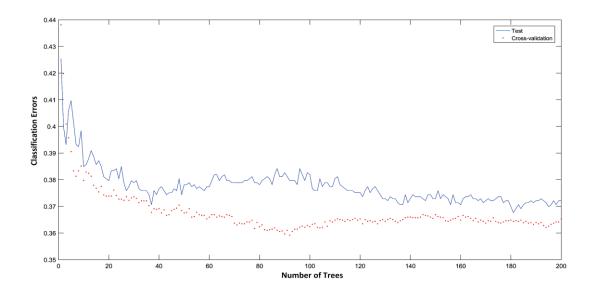


Figure 6.14. Classification Errors of the Trained Bagged Tree

Developing four types of DTs, the accuracy of the developed classification algorithms is assessed via running predictions on the testing dataset. Generally, accuracy is the most significant element in comparing various algorithms since this feature represents the functionality of the learning schema in the identification of the correct classes (Tang, Alelyani & Liu 2014). It is evaluated by contrasting the predicted classes of the test data with their counterparts in the actual data. If the accuracy is found reliable, the DT could be utilised for classification, prediction or objective function development for optimisation purposes. Otherwise, the problem should be investigated and diagonal activities should be adopted (Iqbal et al. 2014).

Therefore, first, confusion matrix plots were depicted to understand how the developed classifiers performed in each class (Figure 6.15). The confusion matrix assists in identifying the areas where the classifier has performed strongly or poorly. For each confusion matrix, the rows show the true (actual) classes and the columns show the predicted classes (Roiger 2017). The diagonal cells show where the true classes and predicted classes match. If these cells are green and display high percentages, the classifier has performed well and classified observations of this true class correctly. On the contrary, the red cells point to the misclassified match between the true class and the predicted class (Rokach & Maimon 2014).

The confusion matrix for Simple Tree shows a good performance for 'Low' and a relative performance for 'Excessive' classes whereas it performs very poor for classifying high energy consumption class and zero performance for 'Medium' class. This observation is understandable since the developed tree was very limited and could not travers to the medium leaf nodes (see Figure 6.11). Medium and Complex Trees indicate a gradual growth in the classification performance, yet, far from the acceptable level. According to Yu et al. (2010), the accuracy of higher than 80% indicates an acceptable level of reliability for a classification algorithm. Bagged Tree, in this research, classified the energy dataset with the accuracy of 83%, 87%, 89% and 90% for the classes of Medium, Low, High and Excessive.

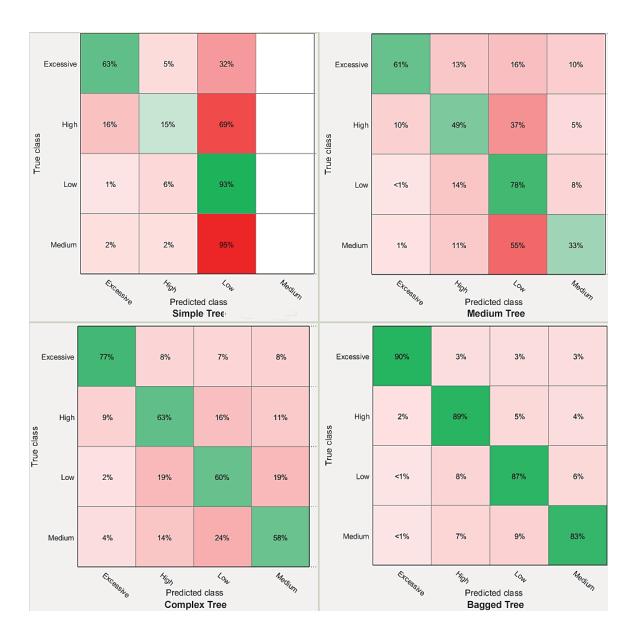


Figure 6.15. The Confusion Matrix for Four Developed DTs

Table 6.8. Performance Summary for the Classification Algorithms

No.	Decision Tree Algorithm Types	Prediction Speed	Training Time	Accuracy
		(OBS/Sec)	(Sec)	
1	Simple Tree	~810000	0.40035	43%
2	Medium Tree	~1000000	0.21317	55.00%
3	Complex Tree	~930000	0.22943	64.50%
4	Bagged Tree	~36000	2.4256	87.30%

Table 6.9. Number of Observations and Data Ranges for Each Class

No. of Observations for Each Class		Predicted				Data Ranges	
		Low	Medium	High	Excessive	(k.W.h)	
	Low	959	89	65	37	0-888	
	Medium	61	841	45	38	888-2208	
Actual	High	84	74	1073	37	2208-4244	
	Excessive	4	5	26	997	4244-Inf.	

Table 6.8 presents an average of classification performance for all DTs along with the prediction speed and training time required for learning each algorithm. It is clearly deduced that the Bagged Tree outperforms significantly the other classifiers with the average accuracy of 87.30%. However, with respect to the time and speed criteria, this algorithm holds the last rank. This result seems to be reasonable due to the highly complicated and integrated structure of the Bagged Tree as compared to the competitors (Rokach & Maimon 2014). If the functionality of this algorithm is concerned, having a look on Table 6.9, this classifier can address the energy-wise decision making for the number of observations ranging from 800 to more than 1000 in seconds. It should be also acknowledged that there are some misclassified observations (Table 6.9) but these are altogether less than 15% of the observations which is acceptable based on the similar studies in the literature (Dounis 2010; Iqbal et al. 2014; Yu et al. 2010). Therefore, the developed Bagged Tree, composing from an integrated bag of 90 Complex Trees was proven to be the first classifier for the energy dataset.

6.5.4. Hybrid Objective Function Development

As mentioned in Sections of 6.5.1 and 6.5.3.1, single model objective functions are widely applied in the structures of prediction and classification algorithms for energy optimisations. Nevertheless, developing a unified objective function which is capable of handling both continuous and discrete datasets perfectly could alleviate the issue of qualitative and quantitative variables inclusion in a dataset. Therefore, the procedure of hybrid objective function development was started with running ANN and DT on the continuous and discrete parameters. The configurations of these algorithms were obtained from the previous Sections; 6.5.2 & 6.5.3. The procedure was then followed with the weighted averaging the output of these two separately trained models in a hybrid function (Merkwirth, Wichard & Ogorzałek 2007).

$$\bar{f}(\vec{x}) = \sum_{k} w_k f_k \vec{x} \tag{6.8}$$

Where k is the index for each algorithm and w denotes the weight of f(x) for each objective function.

C4.5 algorithm, according to the concept of entropy, was used to construct the Bagged Tree including the 7 discrete variables of wall, insulation roof and floor materials, glazing type and the types of main space heating and cooling systems. Progressively, the generic configuration of the algorithm is similar to the bagged DT developed for the whole dataset in the previous section. However, based on the weighted average output of the hybrid function (Equation 6.8), the final result of each function should be the same. On one hand, results falling to the classified level of energy consumption of buildings such as low, medium, high and excessive could not be arithmetically averaged with the results of ANN model which are numerical and continuous. On the other hand, using transformation techniques may lead to the randomness or losing integrity (Lebart 2013). Furthermore, with respect to the energy optimisation purposes, since optimisation algorithms generally work better with numerical outputs (Delgarm et al. 2016), it is of high priority to obtain the actual-numerical level of energy consumption from the hybrid objective function.

Hence, taking advantage of the flexibility of C4.5 in handling numerical outputs, it was intended to apply standard deviation reduction instead of Information-Gain to calculate the homogeneity of the splits of DT (Tso & Yau 2007). In this method, standard deviation is zero if the splits of DTs are completely homogenous. In fact, the decrease in standard deviation after a dataset is split on an attribute shapes the process of DT construction.

$$SP(X) = \sum_{D \in X} A(D) S(D) \tag{6.9}$$

Where *SP* (*X*) indicates the split of data based on the attribute (A) of standard deviation of D, based on the below.

$$S(D) = \sqrt{\frac{\sum (x-\mu)^2}{n}} \tag{6.10}$$

Likewise, the attribute with the largest standard deviation reduction is selected as the split attribute for each tree node. Considering the optimum configuration of DTs obtained from the classification section, the algorithm was set to train 100 complex trees and the test errors and cross-validation errors were computed (Figure 6.16).

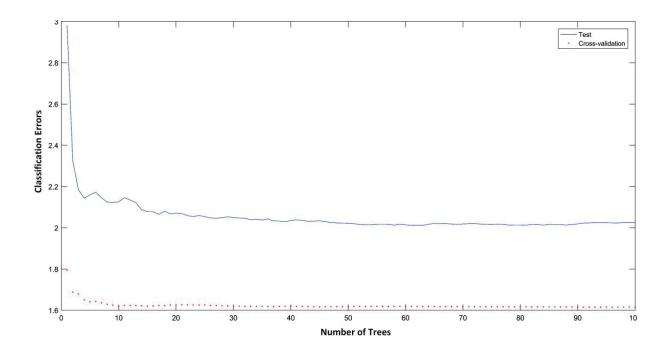


Figure 6.16. Performance Error of the Trained Bagged Tree in Hybrid Model

It can be seen in Figure 6.16 that the Bagged Tree performs well in the cross-validation state as compared to the testing condition. The red trend shows the lowest error around 1.6 from the tenth complex tree on, without a significant fluctuation toward the end of the training trees. However, this performance is noticeably weaker than that of Bagged Tree conducted for the whole dataset (see Figure 6.16) where the lowest error was 0.36. This observation may be in light of the decrease in the number of parameters from 13 to 7⁷. Overall, AI algorithms deliver greater results when are benefitted from more variables in prediction and classification (Gandomi et al. 2013). Henceforth, this gap should be filled with the advanced techniques of machine learning to enhance the accuracy in the meanwhile of the reduction in the number of parameters.

With this respect, applying the standard deviation in the structure of the Bagged Tree opens a new window of opportunity in using ensemble regularisation technique. It is a process of removing weak learners from the DT structure and improve the performance in a way that fewer number of trees are required to train the algorithm (Tang, Alelyani & Liu 2014). This feature is also a significant achievement in the hybrid function as the time of the training could be

⁷ In line with the consideration of 7 categorical parameters in DT and the 6 continuous parameters in ANN

considerably reduced, raising the speed of optimisation engine. The regularisation procedure specifies a well-trained learner weights that could minimise the errors in the below Equation:

$$Reg \ DT = \sum_{n=1}^{N} W_n g\left(\left(\sum_{t=1}^{T} \alpha_t \ h_t(x_n)\right), y_n\right) + \lambda \sum_{t=1}^{T} |\alpha_t|$$
 (6.11)

Where α_t is the optimal set of learner weights, $\lambda \ge 0$ is the lasso parameter, h_t is a weak learner in the ensemble trained on N observations with predictors of x_n , responses of y_n , and weights of w_n and $g(f,y) = (f-y)^2$ is the squared error. The below matrix indicates a trade-off between λ and the trained weights (w_n) .

According to the above matrix, the fifth element (0.111) was found to be the smallest in the flat range and the ensemble was reduced using the shrink method through the weighted average of the fifth element. The minimised α_t could be achieved with minimising MSE of the above equation. Usually an optimal range could be found in which the accuracy of the regularised ensemble is better or comparable to that of the full ensemble without regularisation. In this process, if a learner's weight α_t is calculated to be 0, this learner is excluded from the regularised ensemble. In the end, an ensemble with improved accuracy and fewer learners (in comparison with unregularised ensemble) is obtained. As a result, the reduced Bagged Tree contained 16 complex trees in its structure along with generating approximately 0.8 cross-validated MSE (Figure 6.17). This reduced ensemble gives low loss while using many fewer trees.

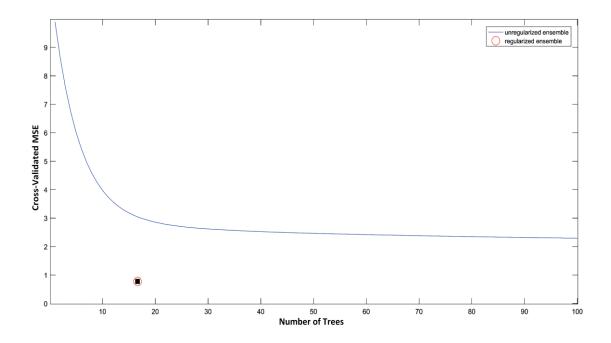


Figure 6.17. Regularised vs. Unregularised Ensemble in the Hybrid Model

Similar to DT model development for qualitative data (categorical parameters), ANN model was also developed upon quantitative data (continuous parameters) of the ceiling height, building orientation, lighting, window to wall ratio and meter square of rooms heated and cooled. It was made based on the configurations of ANN, identified from Section 6.5.2. Therefore, this ANN was structured with 6, 7 and 1 neurons in the input, hidden and output layers by comprising of 70%, 15% and 15% of data for training, testing and validating, respectively. Hyperbolic tangent function was the activation function chosen for the input layer. Sigmoid transfer function was applied between the hidden layer and the output layer and the Levenberg-Marquardt Back propagation algorithm was set as the learning algorithm. The model was set again to 1,000 iterations and the best validation performance was recorded at the 109th iteration with MSE of 0.40974 (Figure 6.18).

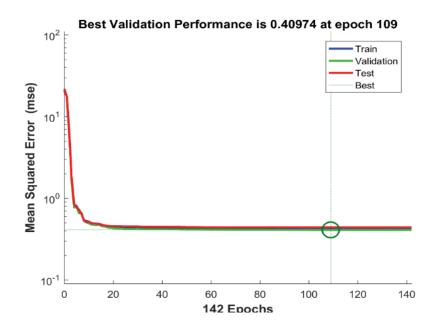


Figure 6.18. Validation Performance of ANN in the Hybrid Model

This ANN model was trained up to 142 epochs and stopped on the rule of 6 consecutive runs without any decrease in the performance error. In addition, Figure 6.19 depicts the regression performance of this ANN for the different batches of training, validation, test and the overall states. These R models with the figures higher than 0.75 also justify the significant correlation of the predicted outputs with the actual values. It is worth mentioning that the training models of DA and ANN are followed based on their own procedures. However, it should be acknowledged that this is a kind of limitation in developing the hybrid model. Because, the simultaneous training of all data may influence each other and this influence may even be significant. Whereas, this fact has not been considered in this research as to its sophistication.

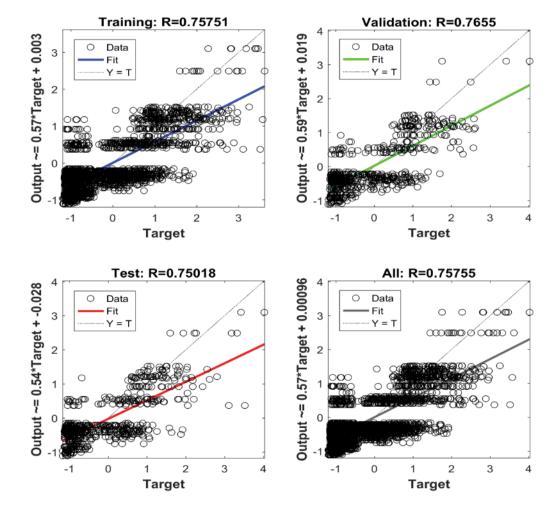


Figure 6.19. Regression Test of Hybrid ANN

Ultimately, referring to the Equation (6.8), the hybrid model was composed from the ensemble of Bagged Tree and ANN model covering both continuous and discrete parameters in one objective function (Figure 6.20). Since algorithms generation, MSE was considered as the main accuracy driver, this criterion was also employed in demonstrating the improved accuracy of the hybrid model. The MSE of the hybrid model was computed approximately at 0.6 which is very low in the error rates (Tao, Zhang & Laili 2014). In order for validating the improved performance of the Hybrid Model against single objective models, first, the normalised values of the predictions of single ANN were figured out upon the whole dataset. Second, the performance error of single DT on the whole dataset was plotted. Finally, the associated results along with the performance of Hybrid Models were illustrated vis-à-vis the normalised actual outputs of energy consumption indicating the comparative performance of each model. As shown in Figure 6.21, the approximate linear trend-line of the normalised values predicted by the Hybrid Model matches better with the equality state in comparison with that of single ANN and DT models. This

observation confirms the superior performance of the hybrid model in generating the predictive data as close as to the baseline data and provides more robust objective function.

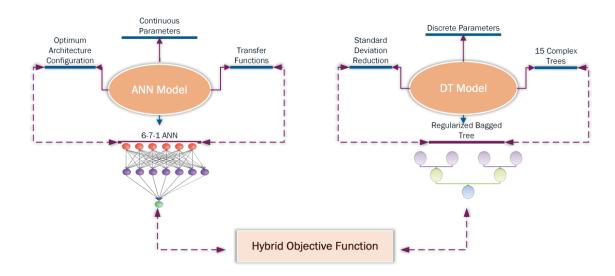


Figure 6.20. Conceptual Structure of Hybrid Model

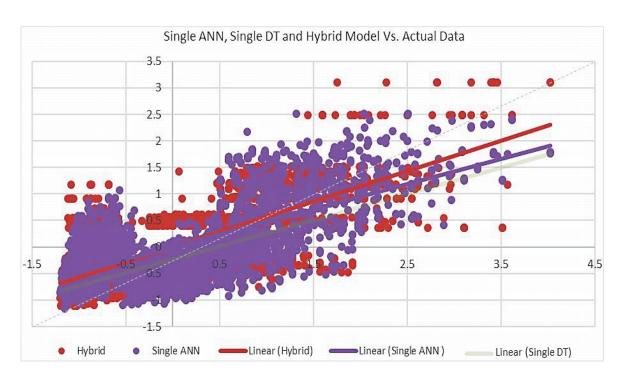


Figure 6.21. Normalised Predictive Performance of Single ANN, DT and Hybrid Model vs.

Normalised Actual Energy Data

6.6. Summary

This chapter provided the efforts in fulfilling one of the very crucial objectives of this research project in developing AI algorithms of building energy prediction and classification. Driven by the literature and Delphi study in Chapter 5 with regard to identifying the significant parameters of building energy consumption, a comprehensive dataset including discrete and continuous parameters were generated via the techniques of parametric simulation and further normalised through metaheuristic data size reduction. Prediction and classification algorithms; ANN and DT were run separately and integrally on the dataset and a homogenous objective function model was successfully developed. As a result, a hybrid algorithm of prediction and classification was established for generating energy consumption prediction with the very low error and the high accuracy. This paves the way of presenting a powerful engine for building energy optimisation. The outcome is an integrated objective function containing both qualitative and quantitative variables of building energy consumption without affecting data consistency or requiring any data transformation procedures.

CHAPTER 7

BIM-inherited EED Framework Development and Verification

7.1. Introduction

Hybrid objective function of ANN and DT, obtained from the combination of both continuous and discrete variables, resulted in a reliable objective function that can now be used for the optimisation and framework development purposes. This chapter is to address three main parts of the results of this research including the optimisation procedure of the developed algorithms, the key stages of BIM and AI integration framework (BIM-inherited EED) and verification and validation of the framework performance.

7.2. Optimisation Procedure

Optimisation procedure in this research commenced with identifying the 13 parameters as the optimisation variables (see Table 6.1) and the hybrid objective as the fitness function for optimisation. As discussed in previous Sections; 2.6.10 and 4.8, GA (Genetic Algorithm) was selected for optimisation in this research. This is in light of its superior flexibility in handling such hybrid objective function, reliability and precision in finding the optimum values, fast reaction for big datasets and its popularity among the scientific community (Tuhus-Dubrow & Krarti 2010). GA operator initiates the optimisation procedure by corresponding the variables and their values with chromosomes in Matlab. GA changes the values of parameters into the binary codes and then randomly generates the initial population (Cohen & Feigenbaum 2014). The distances of chromosomes in the initial population from each other are calculated and checked through the minimisation criterion. This algorithm iteratively improves the solutions via generating more populations by getting learned from the previous iterations (Sarker & Newton 2007). The most widely applied stopping criteria in GA optimisation is to check the convergence of populations into the single solution (Tao, Zhang & Laili 2014).

The algorithm can also be terminated when there is not any improvement in finding the best solution over the number of generations. In this condition and as illustrated in Figure 7.1, two important strategies of crossing over and mutation were implemented for minimising the risk of early termination without reaching the best response (Sumathi & Paneerselvam 2010). Crossing over creates one or more children from some selected parent chromosomes and the resulted offspring are placed into the population to cover the new range of population. Mutation

alters a percentage of chromosomes to explore the full solutions and prevent GA from converging too quick prior to sampling the entire surface (Rao & Rao 2009).

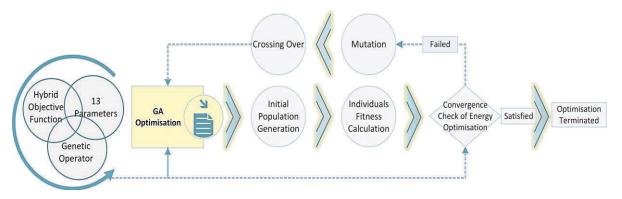


Figure 7.1. Optimisation Procedure Diagram

According to the depicted diagram (Figure 7.1), GA worked toward the satisfied convergence of energy optimisation goal. Figure 7.2 confirms the performance of GA in reaching the perfect convergence below 80 generations. A sharp drop could be seen during the first 20 generations of GA where the GA gets better over the time and it then reaches to a gradual plateau. The minimum of approximately -750 gets constant after around 20 generations and then, strategies of mutation and crossing over are run to mock up all the available solutions. So, as it can be inferred, the height of the generation bars diminishes progressively. The trend after around 30 generations is monotonous till the complete stoppage of GA below 80 generations which indicates the perfect convergence of GA and its great performance in the fast track.

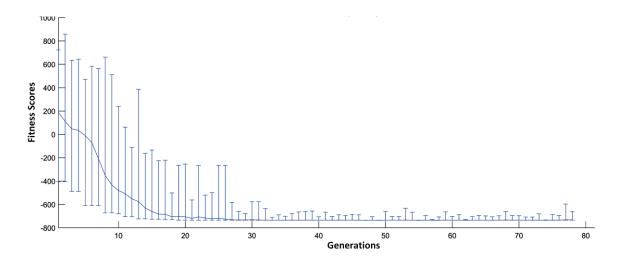


Figure 7.2. Convergence Performance of GA

The average distance between individuals is also presented vis-à-vis the generations in Figure 7.3. This plot specifies how the populations are diversely scattered during the optimisation (Sumathi & Paneerselvam 2010). A population has high diversity if the average distance is large; otherwise it has low diversity. Diversity is essential to GA because it enables the algorithm to search a larger region of the space (Sarker & Newton 2007). As depicted in Figure 7.3, there are higher levels of diversity among the first 30 generations and then it is diminishingly scattered toward the convergence in the end. This fact implies that wide range of solutions have led to the uniform result, confirming again the great performance of the optimisation algorithm.

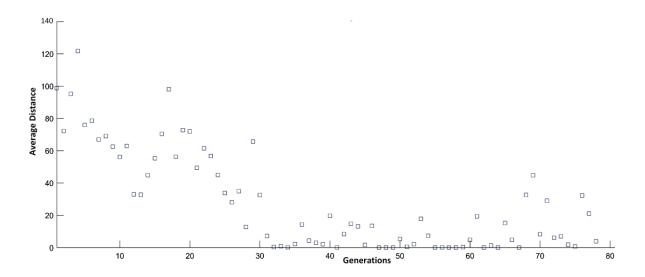


Figure 7.3. Average Distance between Individual Results

7.3. Integration Framework

This section is to develop the framework of AI-enabled BIM-inherited EED; the package of AI (i.e. ANN, DT and GA) including prediction, classification and optimisation algorithms inbuilt in BIM. This is to present a promising solution to the data integration problems and contextualise the BIM-inherited EED which is effectively equipped with AI. The bottom line of the integration framework lies in a method built up on the dexterous capability in minimising the reinterpretation and conversion of data. The key here is keeping data in the native format as much as possible by attempting to adapt them from different sources of information and maintain the homogeneity of the optimised data. Therefore, the integration workflow of this framework was structured on five major stages of database development, database exchange, database optimisation, database switch back and database updating, as illustrated in Figure 7.4 and discussed in the following.

Integration Framework of AI and BIM AI Enabled BIM

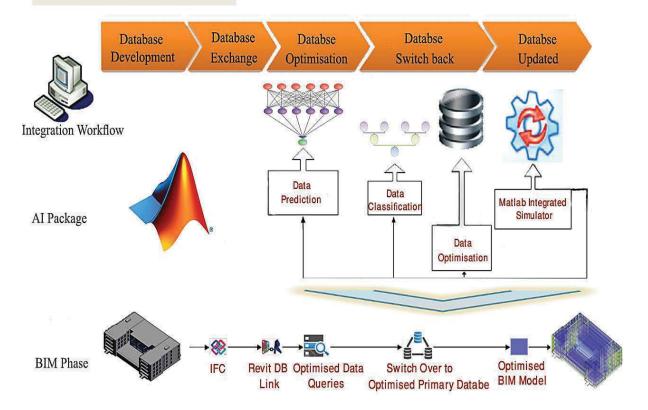


Figure 7.4. AI and BIM Integration Framework (AI-enabled BIM-inherited EED)

7.3.1. Database Development

The first stage; database development denotes the modelling strategies and the standard of information which should be implemented in this framework (Figure 7.4). Modelling here means to represent the real condition of the 'model elements' in the most representative and accurate manner (Kensek & Noble 2014). As discussed in Section 3.7.4, the Model Elements are the components included within the model which contain the quantity, size, shape, location and orientation to represent the particular object, system or assembly (buildings in this study). Assembling these Model Elements together results in the model federation. Federation process is to combine the various disciplines outputs such as fabric, structure, lighting, mechanical, electrical and plumbing services and, generally, all AEC deliverables into one model (Mordue, Swaddle & Philp 2015). However, in order to see the impact of design, orientation and engineering decisions on the energy optimisation, non-graphic information such as semantic and project information should also be attached to the Model Elements.

BIM is especially regarded as the model-based technology linked with a database of project information. It integrates semantically rich information related to the facility, including all geometric, non-geometric and functional properties during the whole lifecycle in a collection of smart model elements (Teicholz, Sacks & Liston 2011). Therefore, beyond consisting of a high level of accurate geometric information, and forming an advanced 3D graphical representation of the project, *LoD 300* (see Section 3.7.4) should be dealt with the priority in the database development stage. The reason on targeting this LoD is to bring the model to the construction documentation level for paving the way of the detailed energy estimation and optimisation. It further alleviates the risk of generic variables inclusion and the disassociation between the semantic values with the topological relationship. *LoD 300* positively affects the building performance analysis and optimisation quality in the database development process. It also dictates the minimum dimensional, spatial, quantitative, qualitative and other data included in a Model Element (NATSPEC 2013).

As the last but not least consideration in this stage, the authorised uses of *LoD 300* in the database development should be exerted in covering the wide range of values by BIM families. In other words, parametric change engine of the BIM authoring tools; Revit, should be matched with the data ranges that have been already established in the optimisation algorithms. This is to secure the semantic association with the geometrical and topological configurations of data enrichment in BIM modelling elements and families. This notion further ensures that once a change is made to a family or a model element in BIM model, it is propagated throughout the database. This propagation acts according to the defined level of information in view of their compatibility with three BIM-based data enrichment criteria of topological, geometrical and semantic associations.

7.3.2. Database Exchange

Database exchange constitutes the second major stage of the framework and is run by two consecutive steps of information export with IFC format and Revit Database (DB) link. For information export, a pre-defined series of data drops are specified in the database exchange protocol to identify the required exchange schema (Figure 7.5). However, as a non-proprietary schema, the interoperability can't be solely provided with IFC; rather, it requires a platform to interfacing with it. Through DBLink which is a tool for Revit projects to be exported into a Database, the exchanged database of the BIM Model can be explored easily as the *mdb* file and can be read with the external applications. In particular, database exchange here is to represent

the full interoperability of the BIM database and to keep its competency to talk to multiple software products.

Practically, in this stage, first, the project information including building layout, HVAC and physical properties and building envelope parameters are extracted in IFC format. Afterwards, property sets are assigned with entity class definitions for interrogating BIM design solutions and building knowledge ontologies. As the last step of specified data drops, the entity class definitions are standardised and structured based on IFC schema as to the enhancement of data export accuracy for a strict regime of Model Elements classification. Conducting all specified data drops tasks, Revit DBLink is applied to synthesise the IFC database to a readable one. The challenge in using IFC is to find a method to manipulate the database in a transparent format so that the AI package could be implemented on the database. Therefore, Revit DBlink is utilised to associate the database with Matlab via Open Database Connectivity (ODBC) which is an open standard Application Programming Interface (API) for accessing a database. By using ODBC statements in a program, the database can be accessed in a number of different formats via calling APIs for different applications such as Matlab, Access, dBase, Excel, and Text (Yang, Shiau & Lo 2017). Hence, an industry-wide, open, and neutral data format that is fast becoming the defacto standard for rich data exchange is created by an ad hoc linking database and is accessible via Matlab (See Figure 7.5).

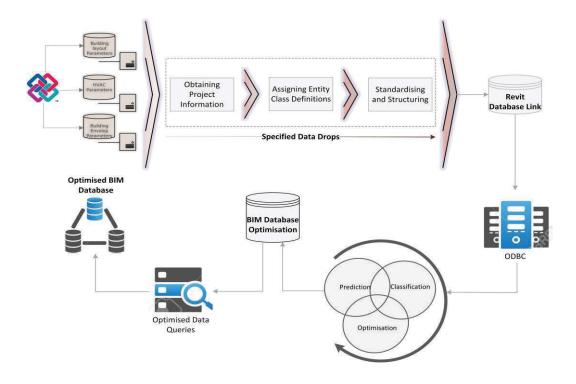


Figure 7.5. Database Exchange, Optimisation and Switching Back Process

7.3.3. Database Optimisation

Database optimisation conceptualises the third stage of the integration framework and is particularly designated to pinpoint the workflow of optimising the database arising from ODBC. The exchanged database presents a mixture of semantic, topological and geometric entities which are classified based on ontology query-able format. So, it should be primarily instantiated with available values of AI package in Matlab environment, as depicted in Figure 7.6. For this reason, the open database is cohered with the parameter placeholders embedded in the Matlab Integrated Simulator (see Figure 7.4) which, in turn, develops the verified property fields. This achievement results in a prompt reaction of Matlab Integrated Simulator on calling the package of prediction, classification and optimisation algorithms. The mechanism of calling is based on the IFC property sets and entity classifications to quickly find the 13 building parameters that are the target of AI.

Highlighting the target parameters and the respected values from a long list of project information, first, the hybrid objective function is activated. This is to operate on the parameters by dividing them to the continuous and categorical variables. This momentum is done via the entity classifications introduced in the database exchange section. ANN and DT algorithms work on the continuous and categorical data, respectively, and then, hybrid objective function aggregates and sends the results (energy estimation) to the optimisation algorithm. GA, as the optimisation engine, further processes data to the optimised level by finding the best combination of the parameters which could minimise the energy estimation value (the results coming from the hybrid objective function). Accordingly, Matlab integrated simulator saves the outcomes in their respected entities and creates a new database called BIM database optimisation (see Figure 7.5).

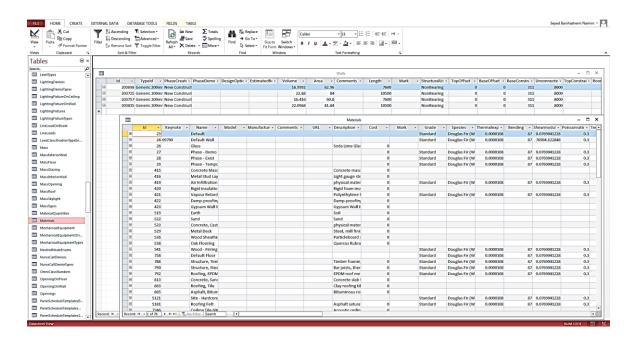


Figure 7.6. ODBC Database Structure

7.3.4. Database Switchback

The fourth stage of the integration framework; database switchback ensures that this is not a one-time static export and all entities and parameters modification, outside of BIM environment, must be switched back into BIM (see Figure 7.4). It means that the changes in the values of Model Elements that are occurred as the result of the database optimisation stage should be automatically corresponded to their counterparts in the BIM model. Hereby, ODBC comes again to fore by linking dynamically the optimised DB with the existing query-able entities of the database. It should also be noted that some new fields of values can be added to the database and linked to the BIM model as the shared parameters. Though, they are not optimisable due to being out of the realm of the target parameters.

The significant technical element of the database switch back is the optimised data query command which provides control over the stored data in the optimised database, as depicted in Figure 7.5. This mechanism distinguishes the optimised parameters from the rest based on their defined entity classes and sets their Boolean property editor to 'on'. Query tab is then launched to glean all verified instances with the 'on' conditions and send back the data to the BIM database. Among the original features, there is the possibility to associate the query-able data to different objects of the original IFC database which transforms the numerical BIM model elements into a powerful navigation interface in the project construction database. This feature allows for the framework to save considerable time in browsing and understanding complex database

switchback structure. This stage incorporates a mechanism for BIM to plug-in the variations of the model database to its updated version.

7.3.5. Database Updated

By running the database switch back, the primary BIM model is updated with the optimised values and hence, the last stage of the integration framework; database updated is completed, as indicated in Figure 7.1. The technical approach here starts with overwriting the optimised values of the target parameters, which are inferred from the previous stages, with their initial values (database development stage). With respect to the suited BIM database content management, the whole data are merged into a single entity and are recorded in the Revit file format. Once the database is successfully overwritten, Revit generates a report to specify the modified values and parameters.

This stage enables the object mapping between two states (pre- and post-optimisation) of BIM database via object-oriented modelling concept. When object oriented programming is considered in updating the database, it effectively facilitates natural object mapping between Revit and all external database applications such as DB and ODBC. Therefore, once the required instances are populated from the prototype, the updated values are encapsulated in model elements instances. Finally, object-oriented nature of Revit allows to automatically update the BIM model in any design view (Figure 7.7).

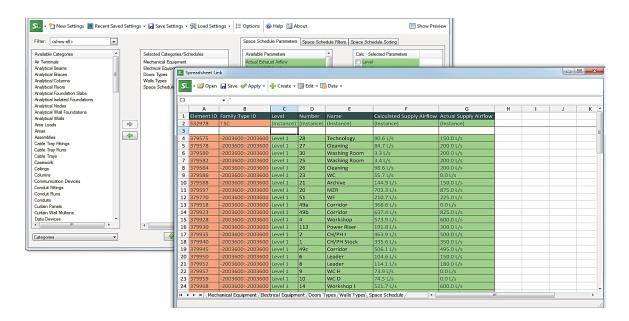


Figure 7.7. The Database Update Process

The developed framework presents an integration method for conducting BIM-inherited EED; AI enabled BIM which optimises the BIM model database via AI algorithms. Via this framework, the interdisciplinary data interoperability between the architectural and construction model with EED is made in CDE and the seamless environment of BIM model elements. This fact leverages the consistency in utilising building layout, physical properties, building envelop and HVAC parameters without simulating them in external applications manually. Data reuse from BIM model minimises the manual efforts in developing input data, removes the error prone process and enables the system interface with the better accuracy. However, the functionality of the framework should be tested to prove its performance.

7.4. Testing and Validation

The last part of the data analysis in this study is to present a proof of concept on the reliability and workability of the developed AI algorithms and the framework of their integration (BIM-inherited EED) in optimising the energy consumption of residential buildings. For this reason and according to the adopted methodology, a case study was chosen to be analysed in its existing (baseline) and optimised states in order to indicate a statistically significant transformation.

7.4.1. Case Study

The baseline case study⁸ chosen for the verification objective is a three-story building consisting of four units on each floor which represents the conventional type of mid-rise residential apartments in Australia. Each level area is 820 m² summing up to the total area of 2460 m². The case is a real-life example of a residential building which is located on Sydney and was modelled in the BIM authoring tool; Autodesk Revit software with *LoD 300*. Figure 7.8 shows the BIM model rendering and Figure 7.9 depicts the layout plan of the baseline case. Table 7.1 also shows the construction of the model and their specifications.

⁸ This case study is different from the building case which was used for generating energy simulation datasets in Section 6.2.



Figure 7.8. BIM Model of the Baseline Case Study

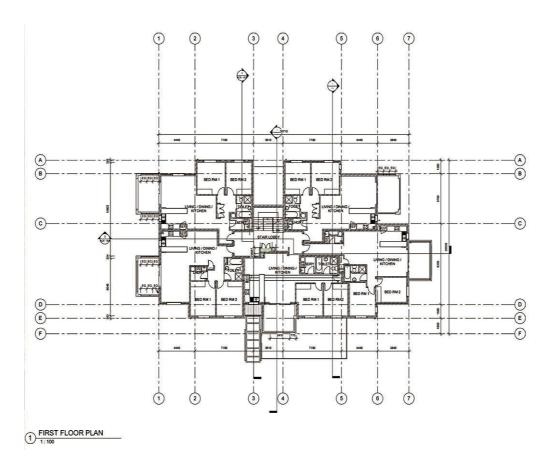


Figure 7.9. Layout of the Baseline Case Study

Table 7.1. Baseline Case Study Specifications

Construction Component	Specification	Thickness
External Wall	Double Brick Wall	270 mm
	Masonry	110 mm
	Thermal Air	50 mm
	Masonry	110 mm
	Cement Render	12 mm
Insulation	Air Terminal	50 mm
Roof	Roofing Pitched	70 mm
	Concrete Roof Tile	100 mm
	Timber Roof Truss	30 mm
Floor	Reinforced Concrete Floor	170 mm
Windows	Single Glazed	NA
Orientation	45°	NA
Ceiling Height	3000 mm	NA
Area of Rooms Cooled	725 m ²	NA
Area of Rooms Heated	725 m^2	NA
Type of Main Space Heating	Heat pump	NA
Type of Main Space Cooling	Cooling Fan	NA
Lighting	4.84 W/m^2	NA
Window to Wall Ratio	15% NA	

7.4.2. Energy Simulation

For energy simulation of the baseline case in its existing state, GBS which uses the EnergyPlus engine and is effectively inherited in Revit was employed. Although the focus in on the design stage, some parameters such as preliminary schedules for occupancy should be taken for granted to enable the software to proceed through simulation. Hence, the model was defined as the analytical surfaces to calculate the kitchen, bedroom, bathroom and living room as the zones and their adjacencies and inter-zonal relations. For providing the thermal comfort inside the units, the thermostat was fixed between 18-26 °C (CIBSE 2006) and HVAC devices were set to be activated below or above this range. Table 7.2 indicates the user profile of the zones in the building.

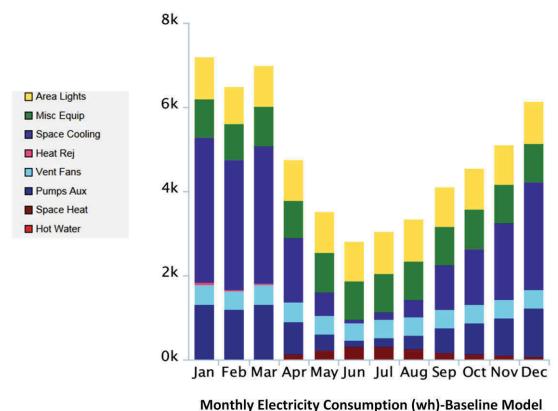
Table 7.2. User Profile

Zone	Area (m²)	Volume (m³)	Occupancy	Activity	Comfort Band
Living Room	19	57	4	Sedentary	18-26 °C
Kitchen	10	30	4	Cooking	NA
Bathroom	4	12	1	Sedentary	NA
Bedroom	12	36	2	Sedentary	18-26 °C

With respect to the specifications of the simulation of the baseline case (Table 7.1), double brick construction has been used for walls having the U value of 1.5 W/m²K. Concrete roof tiles with 100 mm thickness, covered with the pitched roofing with 70 mm thickness and 30 mm of timber roof truss and the total U value of 1.61 W/m²K has been applied for the roof of the case. Besides, a single glazed window with metal frame and the U value of 6 W/m²K has been used as the typical materials used in residential buildings in Australia. With respect to the context of the baseline case, Sydney is the most populous city of Australia and is located on -33.86° latitude and 151.2° longitude (See Table 6.3). It enjoys a temperate climate with a mild winter, and has about 104 sunny days a year (WMO 2016). Since Sydney never experiences extremely hot or cold days throughout of a year, the loads that the designer should consider while designing for air conditioning systems are not that extreme too (Bambrook, Sproul & Jacob 2011). The climatic data of Sydney can be found in Table 6.4 as well.

7.4.3. Baseline Case Simulation Results

The simulation was run for the baseline model in Sydney and the results were recorded as depicted in Figures 7.10 and 7.11. Figure 7.10 illustrates the monthly electricity consumption and Figure 7.11 indicates the total energy consumption including electricity, hot water and gas for heat pump application. As a holistic view on Figures 7.10 and 7.11, it is inferred that space cooling and heating loads have the largest share of the energy consumption drivers amongst for the baseline model, as expected. However, the former is the most influential element for electricity consumption (Figure 7.10) and the latter plays the key role in the total energy consumption estimation (Figure 7.11). The reason is that for cooling space, cooling fans are used in the case and these items work by electricity power. But for heating space, the heat pump system has been employed which uses another source of power; gas. This fact also causes two completely different trends for electricity and total energy consumption (i.e. electricity and gas) in which, the former has a U-shaped (Figure 7.10) but the latter experiences a relatively n-shaped (Figure 7.11).



monthly Electricity consumption (mily Eusenine most

Figure 7.10. Monthly Electricity Consumption (wh) for Baseline Model

Cooling load is the rate at which electricity is consumed at the cooling coil that serves one or more conditioned spaces in any cooling system such as A/C and fans. The total building cooling load consists of sensible and latent loads. The former includes the heat transferred through the building envelope such as walls, roof, floor, windows, doors etc. and the latter encompasses the heat generated by occupants, equipment, and lights (Sørensen 2011). As illustrated in Figure 7.10, in the first three months, the electricity consumption amounts to over 6,000wh per each month and then decreases by 1500wh to 2000wh for the end of September. It then increases to around 6,000wh for the last three months. These ups and downs align well with the climatic condition of Sydney and its summer-winter cycles. For the electricity consumption, there are other elements of area lights, miscellaneous equipment, vent fans, pump auxiliary and space heating which have the minor impacts and do not experience remarkable variations.

For the total monthly energy consumption as depicted in Figure 7.11, the peak is recorded at the over 10,000wh in June and July months. The significant element of the total energy consumption is the space heating load which is the amount of the energy required for maintaining the space in the comfort band and includes both latent and sensible loads. The plotted graph (Figure 7.11) experiences a stable trend from Jan. to April with the amount of 7500wh and then,

increases gradually to reach the peak. This consumption diminishes in the last four months. In the total energy consumption calculation, in addition to the heating and cooling loads, the other elements of area lights, miscellaneous equipment, vent fans, pump auxiliary and hot water have been again estimated, as the same as monthly electricity consumption. Since these items are more relevant to the occupancy profile and their estimation are based on the fixed assumptions (Table 7.2), their effects are not that considerable and fluctuating.

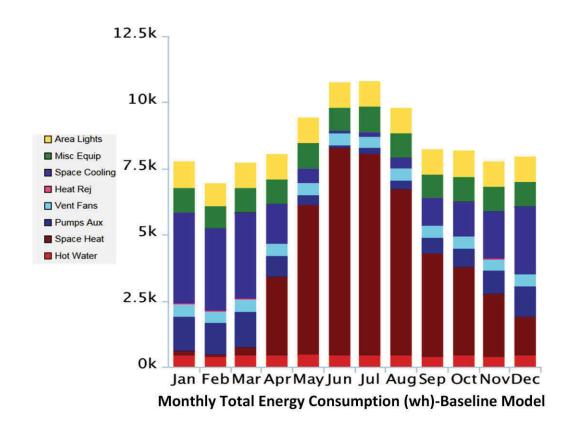


Figure 7.11. Monthly Total Energy Consumption (wh) for Baseline Model

7.4.4. Case Optimisation Procedure

Given the simulation results for the baseline case model and according to the developed AI and BIM integration framework in Section 7.2, the optimisation procedure started with identifying the model elements and their current specifications of the model (see Table 7.1). This task was done through making schedule queries of data and federating the data from multiple disciplines of the case including architectural, structural and mechanical elements. The reason for such federation is that the targeted 13 variables of optimisation belong to these case disciplines. The data schedules were then propagated via IFC and proceeded with Revit DBlink application

in order to synthesise the data into Microsoft Access and Excel formats; readable by the external software of Matlab (Figure 7.12).

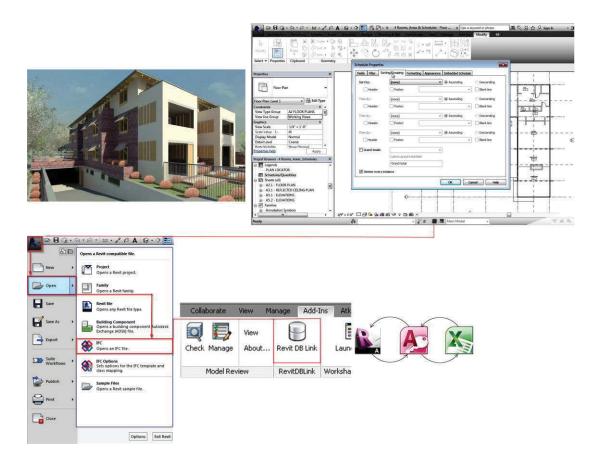


Figure 7.12 Database Development and Exchange Processes of the Case Study

Upon getting the database accessible by Matlab, the entity classifications of the database could be interpreted by the Matlab integrated simulator as the target variables. The continuous and categorical parameters were then differentiated and operated by ANN and DT algorithms under the hybrid objective function. Once operation of the algorithms, a preliminary energy estimation resultant from the hybrid objective function was aggregated and minimised by GA optimisation algorithm in order to reveal the optimised values for the target variables, as illustrated in Figure 7.13.

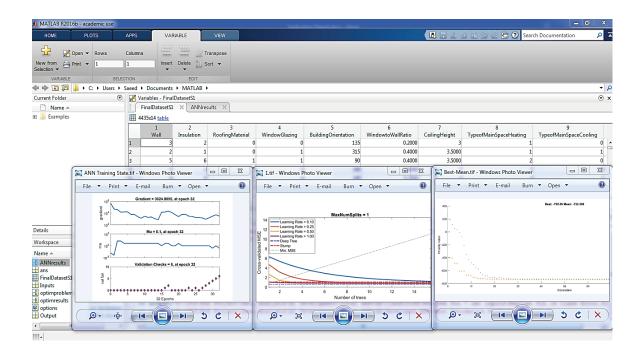


Figure 7.13. Matlab Interface during the Operation Process

7.4.5. Case Optimisation Results

The optimised values of the model were found in Table 7.3. As it can be seen, there are significant changes in the model elements of the target variables. External wall material was set to the wood framed wall with the U-value of 0.54 W/m².K and 1.2 cm air film as the insulation layer. Roof, floor and window glazing were optimised to the metal roof, RC floor and triple-glazed (for all orientations) with the U values of 0.388, 0.199 and 0.66, respectively. The model was further oriented with 20 degrees toward the North which is evidently the most suitable orientation for the mild and temperate climates like Sydney by providing the daytime heating and cool sleeping required (Bambrook, Sproul & Jacob 2011).

This orientation receives the passive heating of living areas during the day and cooler, southerly sleeping areas. In winter, the wood framed wall separates the zones and transfers solar warmth to sleeping areas since it has the poor thermal mass and so, has the higher level of thermal transfer. In summer, passively shaded clerestory windows along the spine would allow hot air to escape from bedrooms in summer while allowing in a small amount of winter sun. The ceiling height decreased to 2.7 meters however, the areas of rooms cooled and heated were not considerably changed. The reason behind this observation may be due to the intensity of the other components optimisation and the lower capability of the current BIM application in changing the layout of the design. The current BIM is fully powerful with the potential in tweaking building

envelop and physical properties, HVAC and as a whole, geometrical and semantic attributes. Nevertheless, it lags behind in the building layout association with the topological attributes (Gerrish et al. 2017). Furthermore, types of main space heating and cooling were transformed to the Steam/Hot water system and window/wall unit, respectively. Lighting intensity decreased to 4.16 W/m² but window to wall ratio increased to 38%.

Table 7.3. Optimised Baseline Construction Specifications

Construction Component	Specification	U-Value (W/m².K)
External Wall	ASHRAE 90.1-2007 Wood Framed Wall	0.54
Insulation	Air Film	0.209
Roof	ASHRAE 90.1-2007 Roof Metal	0.388
Floor	ASHRAE 189.1-2009 Floor	0.199
Windows	Triple Glazed	0.66
Orientation	240°	
Ceiling Height	2700 mm	
Area of Rooms Cooled	718 m ²	
Area of Rooms Heated	729 m^2	
Type of Main Space Heating	Steam/Hot Water System	
Type of Main Space Cooling	Window/Wall Unit	
Lighting	4.16 W/m^2	
Window to Wall Ratio	38%	

Updating the baseline model with the resulted specifications from the optimisation process, the energy simulation was again conducted for obtaining the energy estimation by Revit-GBS simulation. Figures 7.14 and 7.15 indicate the monthly electricity and total energy consumption for the optimised model, respectively. Figure 7.14 shows that the electricity energy consumption has almost reduced by half and reached to its minimum level from April to December. In the first three months, the electricity consumption is around 3,000wh per month and then decreases by 500wh till the end of year. For the total energy consumption, as indicated in Figure 7.15, although the same peak is occurred again around 10,000wh in June and July months, the amount of the energy consumption for the other months were reduced significantly too. The graph of the monthly total energy consumption (Figure 7.15) indicates the monotonous trend from Jan. to April. with the amount of 3000wh (less than half of the baseline model performance). It, then, rises to the maximum in June while the peak is diminished again to the least by getting to the end.

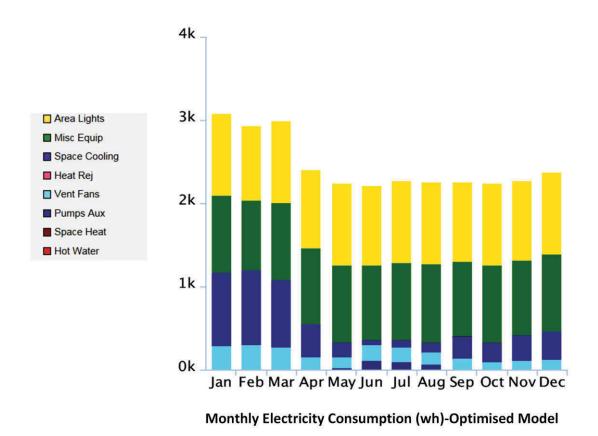


Figure 7.14. Monthly Electricity Consumption (wh) for Optimised Model

Visually comparing the energy consumption graphs of the optimised model (Figures 7.14 and 7.15) and baseline model (Figures 7.10 and 7.11), it can be stated that the electricity consumption has been completely changed in light of its significant reduction. Whereas, the trend of the total energy consumption is to some extent similar. This observation could be because of the fact that the optimisation was more focused toward the parameters that have direct effect on the electricity consumption aspects of residential buildings. In fact, the target parameters of energy optimisation resulting from the Delphi study are more inclined to the electricity energy plan rather than the other aspects like fuel consumption. Routinely, the other elements of energy consumption such as area lights, miscellaneous equipment, vent fans, pump auxiliary and hot water were also considered in the simulation.

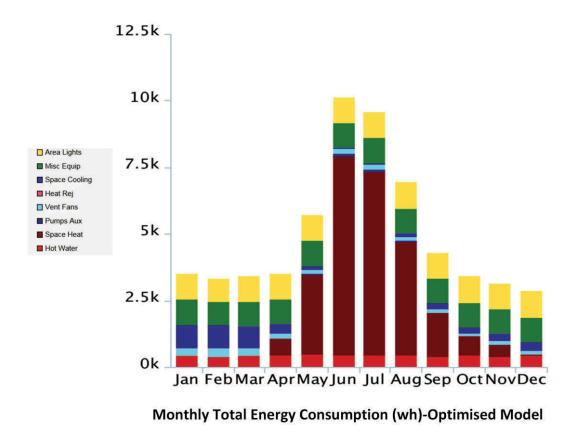


Figure 7.15. Monthly Total Energy Consumption (wh) for Optimised Model

For providing a holistic view on the validation procedure and results thus far, Figure 7.16 summarises the steps and outcomes of the case study. This figure presents five consecutive steps of using the case study, considering the simulation parameters, BIM simulation results for the existing and baseline model, framework operation and energy optimised results. The critical simulation parameters were categorised into the project information, building program, model elements, project variables and climatic condition along with 2 significant scrutinies of LoD 300 and design stage. Progressively, three crucial outcomes of the annual electricity consumption, annual fuel consumption (gas) and annual peak demand were obtained (aggregation of the monthly estimations for the baseline model) with the quantities of 58,001 kWh, 164,195 MJ and 15.3 kW, respectively. These figures are within the range of the average household energy consumption released by Australian Energy Regulator in March 2015 (Regulator 2015).

Through the next step, the BIM-inherited EED integration framework was activated and AI enabled BIM was operated by three major operators of database development, database exchange and database optimisation and the energy estimations were then delivered for the optimised model. As mentioned, a significant decline can be observed in the energy consumption

level of the optimised model in which the annual electricity consumption has been almost cut by half reaching to 29,531 kWh. Such a finding is more corroborated with the remarkable descend in the annual fuel consumption (gas) and annual peak demand by the records of 109,076 MJ and 14.0 kW, respectively (Figure 7.16). According to the Australian Green Building Council, these figures are within the range of the highest ratings for the energy category of residential buildings; five to six stars, audited by this body (GBCA 2013) which puts more highlight on the reliability of the framework.

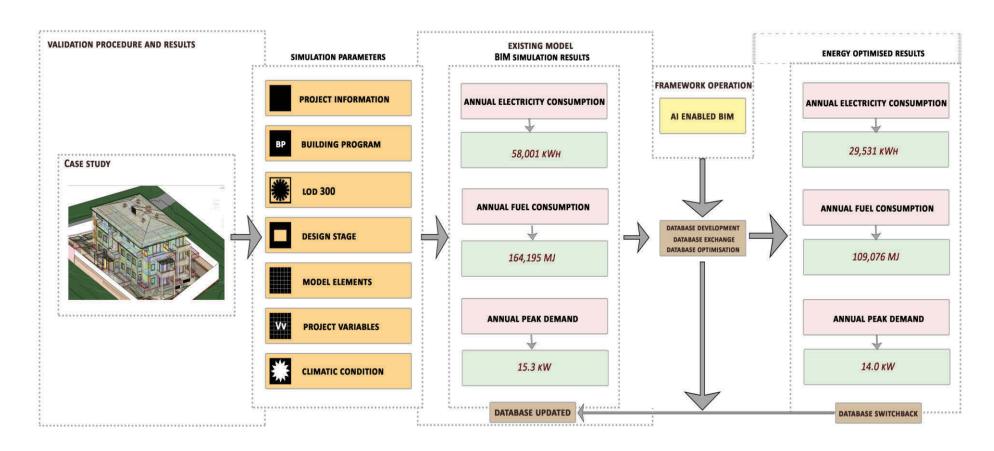


Figure 7.16. Validation Procedure and Results

7.4.6. Optimisation Reliability Tests

The last section of the validation and verification stage is to test the result-oriented reliability of the optimisation runs and the significance of the results delivered by the framework. The optimisation engine used in the framework is GA which, as discussed in Section 7.2, has an impeccable performance in exploring and exploiting the solution realm simultaneously. Growing amount of theoretical justifications and successful applications to real-world problems confirms such robust and decent optimisation technique. However, as to its heuristic nature, it could be of paramount to find the threshold of the approximate performance guarantee for the algorithm (Williamson & Shmoys 2011). As depicted in Figure 7.17, the goal here is to find a circled ratio of the minimum and maximum values for the optimisation problem that the algorithm is supposed to handle in terms of the feasibility and reliability. In other words, in this method, an acceptable threshold should be first set for the below and upper boundaries of an optimisation problem. In the second step, the result of the optimisation should be investigated to realise whether the result is within the boundary or out of that.

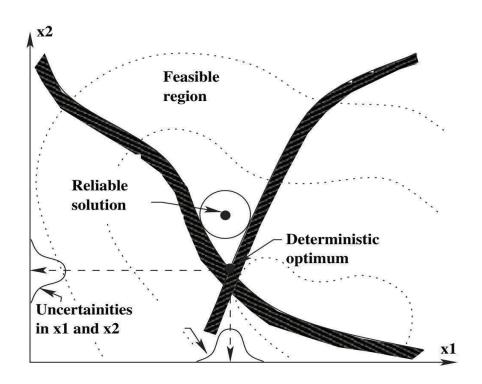


Figure 7.17. Concept of Reliability Threshold Source: Williamson & Shmoys (2011)

Therefore, the solution space; the generations that GA algorithm produced as the energy estimations based on the input variables was first converted into a first-order approximation

hyper-surface (p) to create its circular boundary. A reliability threshold should then be set as the constraints to determine the boundary for the solutions space $(\beta_{i,j})$. To do so, the Australian Green Building Council guideline on the minimum and maximum of energy savings from 4 to 6 green star rating, amounting to 42% to 72%, was applied as the reliability threshold (GBCA 2013). In this step, the optimisation result should correspond to the reliability threshold where makes the first order approximation of $p = \theta$ ($\beta_{i,j}$). Figure 7.18 illustrates this approach hypothetically to depict the probabilistic constraint in the solution space (U-space), the corresponding constraints of 42% and 72% and the feasible region. Hence, minimisation of the solutions space from 58,001 kWh to 29,531 kWh was found to be encompassed within the boundary and considered to be satisfactory.

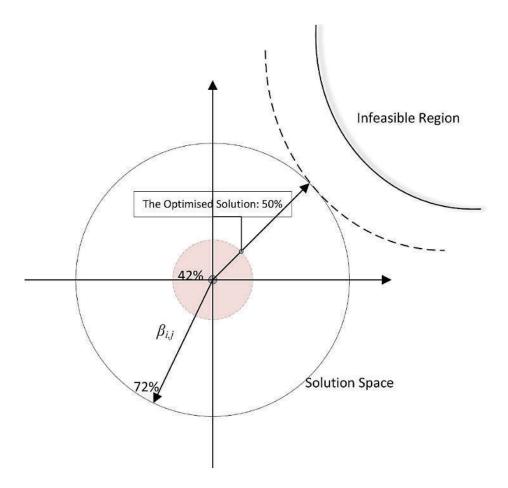


Figure 7.18. Optimisation Reliability Test

The second test is to prove that the arising difference between the results of the baseline and optimised model is statistically significant. Since there are two sets of quantitative results for the same procedure of the energy estimation, 2 paired sample t-Test was selected (Corder & Foreman 2009). The underlying concept is simply to calculate the average difference between the

measurements. Then, it is to determine whether there is a statistical evidence that the mean difference between paired observations on the outcome is significantly different from zero or not. The calculation formula are as the below:

$$t = \frac{\bar{x}_{diff} - 0}{s_{\bar{z}}} \tag{7.1}$$

$$S_{\bar{x}} = \frac{s_{diff}}{\sqrt{N}} \tag{7.2}$$

Where X_{diff} is the sample mean of the differences, N denotes the sample size (the number of compared cases), S_{diff} indicates the ample standard deviation of the differences and S_x refers to the estimated standard error of the mean (s/sqrt(n)). The calculated t value is then compared to the critical t value with df = N - 1 from the t distribution table for a chosen confidence level. If the calculated t value is greater than the critical t value, it is concluded that the means are significantly different. Accordingly, the resulted quantities of the annual electricity and fuel consumption along with the peak demand of the case study were considered for the test. Table 7.4 indicates the calculation outcomes for these data. Evidently, there are 3 paired data for the baseline and optimised models (N=3) which results in 1.499 as the t Value and 9 as the standard deviation (df). This table shows that the results of baseline and optimised models are significantly different from zero by 0.168 at 95% of confidence interval which further verifies the statistical significance of the optimisation performance and validates the applicability of the framework.

Table 7.4. Paired Sample T-Test Calculations

Model / Observations	Annual Electricity Consumption (kWh) Annual Fuel Consumption (MJ)		Annual Peak Demand (kW)	
Baseline	58,001 164,195		15.3	
Optimised	29,531	29,531 109,076		
N (Number of samples)	3			
t Value	1.499			
df (Standard Deviation)	9			
Statistical Significance	0.168			

7.5. Sensitivity Analysis

Sensitivity analysis is an effective method to find out how mathematical models, machine learning packages or resultant frameworks react to a range of uncertainties. It is a technical procedure over the re-calculation of the outcomes in view of various assumptions made to assess the impact of independent variables on the dependent factor (Hopfe 2009). Sensitivity analysis

can be applied for different purposes such as evaluating the validity of the results, better view toward relation between inputs and outputs, identifying model errors and reducing uncertainty via focusing on the significant factors (Tian 2013). Therefore, in this section, sensitivity analysis test was run to understand how sensitive the framework is and how some possible uncertainties impact on the framework including missing data and noise interferences.

This approach was started with establishing the framework and its dataset in Matlab and setting rules of data manipulations. According to Yeung et al. (2010), machine learning-based models could be approximated with Regression batches so that their sensitivity can be assessed through regression performance criteria such as MSE, R and MAE as introduced in Chapter 6. Furthermore, it is recommended to consider the random data eliminations of 10%, 20%, 30% and 50% from all variables involved in case of large datasets. Moreover, data noises were involved via automatic noise toolbox of Matlab to model possible errors of regression approximation. Hence, these rules were capitalised on the platform and performed to activate regression analysis and the outcomes record. Full dataset regression was first run to create the baseline model leading to be compared with 4 uncertainty scenarios. Figure 7.19 indicates the data records and regression test for the full dataset as its baseline model. Analysing the current strength of the baseline regression in Table 7.5, MSE, R and MAE records of 1020, 0.76 and 776.18 confirm a significant correlation with the full dataset performance.

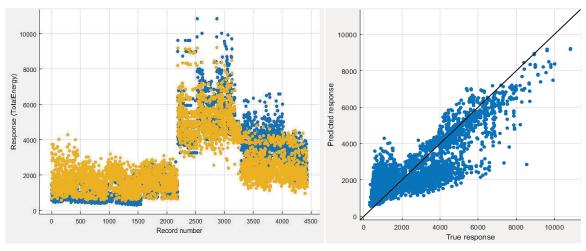


Figure 7.19. Regression of the Baseline Model

Subsequently, 4 sensitivity analysis scenarios were conducted to assist with comparative evaluation of regression values and reveal any significant discrepancy arisen from exposing to uncertainties. Figure 7.20 illustrates the regression tests which were run for the 10%, 20%, 30% and 50% scenarios. As mentioned throughout this section, these scenarios were composed from

randomly eliminating data from the dataset of 13 variables along with the automatic noise interference to the data to identify possible impacts of regression approximation.

Schematically, the plots show a good performance of agreement with the steady trend line. In spite of gradually random dataset reductions from full to 50%, the overall trends of the regressions were almost kept fixed and reliable. Analytically, Table 7.5 indicates the figures of the regression performance criteria for uncertainty scenarios. It can be inferred from this table that the framework performs well and maintains the homogeneity and consistency up to 30% of data reductions and noise interferences with the R values of 0.76, 0.75 and 0.75 for 10%, 20% and 30% scenarios, respectively. However, the sensitivity of the framework is a bit intensified in the 50% scenario; the very extreme uncertainty which is applicable for very large datasets and few number of parameters. The R value slightly dropped to 0.72 and MSE and MAE increased to 1060 and 803.

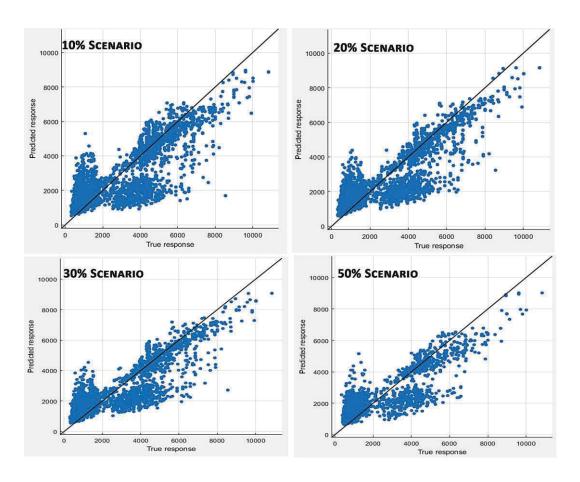


Figure 7.20. Regression Sensitivity of Different Scenarios

Table 7.5. Regression Results of Baseline vs. Sensitivity Analysis Scenarios

	Baseline Model	10%	20%	30%	50%
R	0.76	0.76	0.75	0.75	0.72
MSE	1020	1032	1043	1042	1060
MAE	776.18	779	795	798	803

All in all, considering the conducted sensitivity analyses, it can be mentioned that the framework is valid and secured against the uncertainties of random data missing and noises up to 50% of its database asset. This achievement is superiorly remarkable as compared to the similar studies in the literature (Nourani & Fard 2012; Tian 2013).

7.6. Summary

This chapter presented the last part of the analysis and results of this research on four major sections of optimisation process, BIM-inherited EED framework development, testing and validation of the developed framework and sensitivity analysis. It was revealed that GA algorithm was performed well on the hybrid objective function and converged into the optimum solution quickly and properly. This achievement finalised AI algorithms stage and grounded a stepping stone for developing the framework of AI-enabled active BIM. Database development, database optimisation, database exchange, database switchback and database update constituted five key elements of BIM-inherited EED framework which were established in series and processed integrally. This framework was tested through using a real residential building located in Sydney and via running comparative energy simulation pre and post-framework application (baseline and optimised case). The outcomes indicated around 50% reduction in the electricity energy consumption and 66% saving in the annual fuel consumption of the case study. This performance was verified by optimisation reliability test and paired sample t-Test for statistical significance. The framework was further analysed against different uncertainty scenarios and found to be secured and reliable for the data reduction and noise interferences up to 50%.

CHAPTER 8

Conclusion

8.1. Introduction

The last chapter of this thesis comprises three major sections. The first section is dedicated to summarise the research background, problem and aim, the key findings of the research objectives and underline the interactions and patterns amongst. It is followed with evidencing the contributions to the body of knowledge vis-à-vis the limitations mentioned and derived from the literature. Implications for Practice are also the components of the section four to assert the practical implications which emerged and linked to the findings from this study. Finally, the limitations of the research and recommendations toward improving and extending the acknowledged gaps are presented in the third section of this chapter.

8.2. Review of Research Background, Problem, Aim and Method

GB is being promoted in the construction industry in order to minimise the detrimental impacts of massive upsurge of construction activities, resource depletion, waste generation, energy consumption, carbon emission etc. (Alwaer & Clements-Croome 2010). It entails integrating principles of sustainability into building design and construction activities throughout the whole lifecycle of a building facility. This can include every actor and action involved in a project being committed and responsible for undertaking sustainable practices (Venkatarama Reddy & Jagadish 2003). Despite this strategic focus, challenges such as the lack of the whole system thinking, construction process complexity, lack of communication and coordination among parties involved, unavailability of innovative approaches and tools and lack of integrated design methods hamper the proposed shift towards GB practices (Häkkinen & Belloni 2011). The problem of translating these strategic objectives into concrete actions at the EED level has particularly remained unresolved as well (UNEP 2014).

Therefore, the construction industry has attempted to tackle a wide range of abovementioned challenges and their unsustainable impacts such as excessive energy consumption by harnessing the capabilities of BIM (Kibert 2016). Of these, connecting the often fragmented processes of a building design through automated, integrated and streamlined communication has remained the main application. While, efficiency gains with digitised and

standardised energy simulation procedures is another benefit (Zanni, Soetanto & Ruikar 2014). BIM process has the potential of offering some advantages in energy consumption estimation. It represents the building as an integrated database of coordinated information and can expedite the EED process through providing the opportunity of testing and assessing different design alternatives and materials' impacts on the building energy consumption (Azhar et al. 2011). In spite of such great potentials, EED still lags in fully embracing BIM (Kibert 2012).

The passiveness of BIM in endorsing the intelligent decision making platforms, the lack of ideal interoperability between BIM and energy analysis software packages, the dearth of inbuilt practices of calculative, predictive, simulative and optimisation methods of EED in BIM and the need for more inputs and technical specifications in improving the semantic-rich content of BIM models hinder the full diffusion of BIM into EED (BIM-EED). This premise has triggered a new research direction known as the introduction, inclusion and integration of AI into BIM-EED. This research arena focuses on developing, facilitating and optimising the EED in an integrated manner by means of BIM and AI. It represents an alternative solution for building design and construction projects to embrace sustainability. This assertion seems a workable way of introducing BIM and AI on the EED. However, very little is known about the methods through which this could be achieved. In essence, research on the interface between BIM-EED and AI is very limited. Particularly, not much explicit body of knowledge from the built environment context has been developed to investigate the integrated effects of AI and BIM on the EED.

AI facilitates access to transparent information, enhances accountability, increases accuracy of data, enables automation and integration of activities in BIM, elevates the level of agility and generates insights for better decision making and optimisation of EED processes. It handles the problem of interoperability by shifting the current post-design routine of energy analysis and optimisation in using the external software into the inbuilt EED in BIM. AI further drives 'what if' scenario analysis for choosing various design parameters by applying prediction, classification and optimisation algorithms on the operational energy of building model in the design stage. Moreover, the issue of consistency and homogeneity of the EED data can be mitigated, based on the integrated platforms of AI and BIM. Therefore, this study was aimed to develop an AI-based algorithm to optimise energy efficiency at an early design stage in BIM. It is to obtain an initial estimate of energy consumption of residential buildings and optimise the estimated value through recommending changes in design elements and variables. This aim was pursued through the below objectives:

- i. Examining the potential and challenges of BIM to optimise energy efficiency in residential buildings
- ii. Identifying variables that play key roles in energy consumption of residential buildings
- iii. Investigating the AI-based algorithms in energy optimisation
- iv. Developing a framework of AI application in BIM in terms of energy optimisation purposes and processes
- v. Assessing and validating the functionality of the framework using case studies

In order to achieve the stated aim and objectives, a mixed method approach following a design of $QUAL \rightarrow QUAN$ was designated for this study in which it entailed conducting a preliminary qualitative data collection method to serve the subsequent quantitative phase. This sequential exploratory approach was started with the application of qualitative instruments to the exploratory tasks of objectives one and two. It included examination of the potential and challenges of BIM and EED and identification of the significant variables in the energy consumption of residential buildings via literature study and Delphi approach. It was then factualised with quantitative instruments to address the third to the fifth objectives where the simulation method was used to generate the building energy datasets and simulate AI algorithms to investigate their functionality for energy optimisation. It was then followed with developing the integration framework of AI and BIM and, finally, validating the framework through case study verification.

8.3. Review of Research Processes and Findings

As mentioned, the aim of this study was to develop an AI-based algorithm to optimise energy efficiency at an early design stage in active BIM in order to obtain an initial estimate of energy consumption of residential buildings and optimise the estimated value through recommending changes in design elements and variables. Hence, the key processes and findings of the research aim for this study which flows through conducting its 5 research objectives, presented in Section 1.5 of Chapter 1, are discussed as the following.

8.3.1. Objective 1: Examining the potential and challenges of BIM to optimise energy efficiency in residential buildings

This objective was primarily fulfilled through reviewing an overarching theoretical framework of three theories of sustainability, information and optimisation (see Section 2.2). It was revealed that the definition by Brundtland (1987, p. 42); "...development that meets the needs of the present without compromising the ability of future generations to meet their own needs" formed the basis for this study. So, developing the knowledge at interdisciplinary levels and efforts of modelling and evaluating the sustainability were among the actions that could positively contribute toward this definition. This procedure is a cycle of endless development and adjustment which indicated the interaction of sustainability, information and optimisation theories requiring continues supervision and analysis for finding an intelligent decision based on CDE. It was disclosed that the cutting-edge scientific discoveries in information theory together with computer-aided algorithms in optimisation theory can facilitate managing the scale and spectrum of sustainability issues and allow for the smooth evolution of data.

It was then presented that the information theory and its functional driver; informatics works on the information process toward the sustainability (see Section 2.2.4). This momentum can be significantly conducted when CDE as the single source of information could be applied to drive BS1192 information management implementation. Via this virtue, this batch of information is being optimised through optimisation theory paradigms via setting objective function, mixing continuous and integer variables and convex function for reaching the maximised effectiveness of sustainability. Therefore, such a theoretical integration sets the journey to the downstream and practical level which should be elaborated in the construction field. However, it was realised that these concepts are mostly applied isolated in the construction industry and an interdisciplinary attempt should be made to build the inextricable link toward their functional approaches for addressing the aim of this study.

Hence, sustainability was narrowed down into the sustainable construction drivers (Section 2.3). BIM, then, came to the fore as the representative of informatics, CDE and BS1192 applications in the construction industry to store, transmit and process the optimised information (Section 2.4). The optimised information is the one which is optimised through AI as the practical machine of optimisation theory paradigms to convex them (Section 2.5). Through this setting, the integration of three fundamental theories of sustainability, information and optimisation was built on CDE and linked to their three functional drivers of sustainable construction, BIM and AI and established a theoretical framework for the aim of this research.

It was also identified that there are two important concepts of the passive and active BIM which are opposed to each other (Section 2.4). Passive BIM lacks an intelligent decision making and cannot sufficiently provide sustainability analysis data. However, active BIM is the AI-enabled BIM which supports the intelligent decision making frameworks in its structure and contributes to the sustainable construction by streamlining design optimisation capabilities. This fact consequently underlined trilateral interactions of sustainable construction drivers, BIM and AI by discussing the calculative, predictive, simulative and optimisation methods in the common ground of EED.

Performing the Objective 1 was followed with a comprehensive review on BIM-EED in light of BIM diffusion stages into EED (Chapter 3). The available literature on the topic was identified and verified through a systematic review methodology, BIM-EED were categorised into three stages of BIM-compatible, BIM-integrated and BIM-inherited EEDs and their state of the art were reviewed. In principle, BIM-compatible EED referred to the first level of BIM adoption and indicated the central role of the data exchange between BIM and a first generation of energy simulation software (Section 3.4.1). One step ahead, BIM-integrated EED underscored the direct integration of BIM and a second generation of energy applications as to the maturity of the intelligence growth from data to the information level (Section 3.4.2). The third level of the BIM diffusion into the EED; BIM-inherited EED denoted the internal interoperability and inbuilt function of the third generation of energy simulation in the homogeneous platform of BIM (Section 3.4.3).

BIM-EED classifications were further examined under the different sub-groups of review taxonomy such as descriptive (Section 3.6), content (Section 3.7), thematic (Section 3.8) and gap analysis (Section 3.9). It was indicated that although BIM-inherited studies constitute the least share of the publications, there is a shift from lower to the higher levels of BIM implementation in EED. This observation is also imperative for a move to the upper levels of interoperability and LoD in this area. Thematic analysis showed that case study based-analytical, tool/prototype development and conceptual studies are in the first to the third rank of target for researchers. Hence, it was concluded that conceptual frameworks should be validated through case studies in order to generate more reliable prototypes of BIM-EED. Gaps were highlighted according to three major categories of confusion, neglect and application in the extant literature.

Confusion spotting indicated a gap in interpreting BIM as a process or as a tool. This observation was corroborated by competing interpretations due to the BIM-EED adoption confusion. The second category; neglect was found to be the biggest part of gap spots where it

included three subgroups of overlooked, under-researched and lack of empirical support. Analysing this gap demonstrated that interoperability and LoD are mostly overlooked. Furthermore, AI, machine learning and data analytics are under-researched areas in BIM-EED and the majority of conceptual studies suffer from the lack of empirical support via a proof of concept. Finally, it was concluded that BIM-EED are overwhelmed with the application gap; focusing on the sole application of energy simulation and the dominance of technology-oriented view toward BIM.

Conducting Objective 1 was resulted in the significant achievements and implications for being applied in this study. It was recognised that considering the three theories of sustainability, information and optimisation and their integration path narrowed into the EED, BIM and AI lead to the BIM-inherited EED, as the active BIM and based on CDE concept. It was found to be the particular focus for this research and framework development objective. BIM-inherited EED was attributed on the highest level of the BIM adoption into the EED and hence, in order to achieve the most out of the BIM potentials, the AI based active BIM was developed on the BIM-EED basis. The parametric definition of BIM was further substantiated through AI algorithms to enable data analytics and energy optimisation in-built in BIM.

The thematic and research outcomes analysis of the literature showed that an established approach should be designed with BIM-EED research in order for developing a conceptual framework and verifying its functionality. Therefore, the study was designated to comprise a consolidated combination of the theoretical background, simulation-based framework development and framework validation via the case study. In addition, the scrutiny of BIM-inherited EED applications determined the package of Autodesk GBS-Revit® to analyse and test the validity and reliability of the framework. Finally, to enhance the precision, depth and inclusion of BIM models in the framework, *LoD 300* was found to be target for the framework development and verification goals as the topmost LoD for the design stage.

8.3.2. Objective 2: Identifying variables that play key roles in energy consumption of residential buildings

Performing Objective 2 was commenced with a review on the design and construction classifications of parameters affecting buildings energy consumption including physical properties and building envelop, building layout, occupant behaviour and HVAC and appliances (Section 5.2). It was inferred that physical properties and building envelop are the key drivers in the thermal losses and are then vital in the optimisation in the early design stage. This category

includes the building configuration, shell and material related elements including walls, insulation, floors, roofs and windows representing thermo-physical properties and the mechanisms of heat transfers or heat stores into the geometries (Section 5.2.1). It was also identified that building layout category of variables mostly covers the design brief of the building such as the number of rooms or the number of spaces requiring heating and cooling, size of the building, architectural shape and building orientation. It was found out that it is a bit difficult to generalise or quantify the complex interrelationship of the planning and layout of spaces on the energy consumption requirements (Section 5.2.2).

Occupant behaviour was further recognised as one of the most important but challenging categories in influencing building energy consumption. It was found difficult in investigation, especially in the design stage, due to the complicated characteristics and unpredictable personal behaviour (Section 5.2.4). It was also revealed that a clear understanding of the schedule of building operation is important to the overall accuracy of the energy estimation (Section 5.2.4). The last but not least, HVAC and appliances contain the parameters relevant to heating, ventilation, air conditioning and electrical appliances within buildings. It was resulted that this category is very significant in the optimisation since electricity has the highest percentage in HVAC among all building services installations and electric appliances. It was also confirmed that modelling, simulating and optimising these variables are complicated because each appliance and device has its different production configuration with different energy efficiency index (Section 5.2.5).

A three-round Delphi study was designated for complimenting the literature and brainstorming of experts for building energy variables and their implications toward the design stage, BIM and optimisation, prioritisation and confirmation of the variables (Section 5.3). Twenty-three responses were collected in the first round and 35 variables were extracted from the qualitative answers through a quick textual analysis method (see Table 5.2). Furthermore, with respect to the open-ended question in the first round on the respondents' implications for the applicability of variables for BIM, optimisation and design stage, very insightful achievements were obtained (Section 5.3.2.1). In terms of BIM compatibility, it was stated by the experts that very generic variables cannot be considered in this study since the semantic values of very generic variables are not associated with the topological relationship within the BIM model. Therefore, the result of literature and Delphi was synthesised in which a generic parameter of 'material' was divided into 'internal wall material', 'external wall material' and 'roofing material' falling to the predefined ranges of BIM families.

Besides, some of the experts mentioned that the variables with twofold effects need to be also omitted because BIM has not been yet equipped with intelligent fuzzy rules to identify the root causes of two-fold parameters and so, these variables cannot be optimised. Therefore, the variables of 'building size' and HVAC system were broken down into the variables of 'meter square of rooms heated' and 'meter square of rooms cooled' and, the 'type of main space heating equipment used' and 'type of main space cooling equipment used', respectively. Checking the subjectivity and objectivity of the variables was also another recommendation by respondents and as a result, a too subjective variable; 'morphology' was omitted due to not being still parameterised and measured in BIM. The respondents put also forward their implication regarding the design stage as the scope of this PhD study and stated that the variables relevant to the occupancy profile of buildings cannot be involved in the design-stage focused study as these variables are within the operation phase of a building project lifecycle.

Thus, applying the technical recommendations by the respondents and running normative assessment method via considering the 50% cut-off criterion rule resulted in 19 variables (See Figure 5.2). Wide range of variables which cover different aspects of buildings energy parameters were achieved in the end of Round 1. For instance, external wall materials, internal wall materials, wall thickness, insulation type, roofing materials, Ground floor system, window glazing types and doors glazing types covered the physical properties and building envelop parameters. There were also parameters including ceiling height, meter square of rooms heated, meter square of rooms cooled, window to wall ratio and building orientation which belong to the architectural design and building layout aspects of the influential parameters. Variables such as lighting, daylighting, external and internal shading addressed the required considerations in designing for energy efficient lighting and solar exposure. Finally, the parameters of cooling space equipment used and heating space equipment used applied the HVAC system design significance (Section 5.3.2.1).

The prioritisation round (Round2) was conducted with the experts to prioritise the 19 variables derived from the first round with using 18 responses and the five point Likert scale method (Section 5.3.2.2). The cut of rule of receiving the Likert point equal to 3 or above was resulted in having 13 variables with the Kendal Coefficient Concordance of 0.149 (see Table 5.5). The findings of this round indicated the emphasise of the respondents on the role of physical properties and building envelop in the energy consumption of residential buildings. Since the top three parameters of the ranking; insulation, roofing material and external wall material belong to this category of variables. Moreover, the other parameters of windows glazing type, ground floor system and lighting were also fixed in this round. With respect to the architectural design and

shape, building layout pertinent variables including ceiling height, meter square of rooms heated and cooled, window to wall ratio and building orientation were found significant in this round. Types of main space heating and cooling equipment affiliated with HVAC category were also maintained. Finally, as a result of prioritisation round, 6 variables of internal wall material, internal and external shadings, wall thickness, doors glazing and daylighting were removed.

In the confirmation round (third round), 15 completed responses were obtained and the list of Round 2 was reconsidered in light of the consensus opinion of the respondents (Section 5.3.2.3). Accordingly, the final matrix of 13 parameters (see Table 5.7) and their relevant weightings along with the enhanced concordance score of 0.267 was attained. It was revealed that the consistency was remarkably enhanced in the third round where it attained a 80% improvement in the reliability and consistency of the results as compared to the second round. These variables fixed the key asset for energy optimisation of buildings in the design stage through running AI (in the next objective) to exploit the parametric definition inherited in the BIM technology. These variables were then parametrised via AI approaches including machine learning and data prediction, classification and optimisation algorithms in order to be approachable in the BIM environment via securing the geometrical, topological and semantic associations.

8.3.3. Objective 3: Investigating the AI-based algorithms in energy optimisation

The third objective was intended to develop the package of AI algorithms for energy optimisation (Chapter 6). Driven by the achievement of Objective 2, full scale parametric energy simulation was conducted on a hypothetical residential building as case study and in four climates of temperate, tropical, cold and arid to generate a dataset (Section 6.2). The dataset size reduction techniques of metaheuristic-parametric approaches including holistic cross reference and evolutionary solver function were resulted in generating 4435 of datasets including 13 inputs (the variables of Delphi) leading to the output (annual energy consumption) (Section 6.4). Trends and nature of the dataset for categorical and continuous variables were identified through descriptive statistics (Section 6.4). It was indicated that considering both continuous and categorical data, the generated output covered a wide range of distribution which is of advantage for the optimisation purposes as to enabling more precise optimisation.

Comprising both quantitative and qualitative parameters in one dataset led to developing both prediction and classification algorithms using ANN and DT, separately and integrally in order to find the best type of inclusion of these algorithms (Section 6.5). First, ANN algorithm was established for the whole dataset with the conceptual architecture of 13 neurons of variables

in the input layer, 7 neurons in the hidden layer and one neuron of annual energy load in the output layer (Section 6.5.2). Different types of ANN training algorithms and percentage of training, testing and validating of data were tested and the batch with 70%, 15% and 15% of the cases for the training, testing and validating of data under the Trainlm class were trained (Section 6.5.1). It was realised that ANN worked well on the data with the mean square error of 0.557228 and at the 26th iteration and the overall R value of 0.81186 which presented a strong performance as an objective function in the optimisation problem (Section 6.5.2.2).

Second, the dataset including categorical and continuous parameters were again developed through DT algorithm (Section 6.5.3). DT model was configured with containing the categorical data, integer classification of continuous parameters and the annual energy load as the output with four levels of low, medium, high and excessive energy consumption (Section 6.5.3.2). C4.5 training and the information-gain were calculated based on the entropy concept to apply learning the data and attribute selection. As a result, four types of Tree; simple, medium, complex and bagged structures were tested using the energy dataset. Confusion matrix plots and the comparative performance of actual vs. predicted were then employed as the accuracy indicators. It was deduced that the Bagged Tree consisting of 90 complex trees outperformed significantly the other classifiers with the average accuracy of 87.30% (Section 6.5.3.3).

Hybrid algorithm development was the third step in fulfilling this objective. The reason behind this matter was the attempt to develop a unified approach in handling both continuous and discrete parameters in their original format and needless of transformation. Thus, the dataset was split into the continuous and categorical groups, ANN and DT were run respectively on each dataset and the weighted average of the output was calculated (Section 6.5.4). From the classification side, Bagged Tree DT algorithm was trained on the data containing 15 complex trees in the structure and producing the acceptable error; 0.8 cross-validated error. From the prediction side, ANN algorithm was established with 6, 7 and 1 neurons in the input, hidden and output layers and the best validation performance was recorded at the 109th iteration with MSE of 0.40974 which was satisfactory.

Therefore, the hybrid algorithm of prediction and classification was composed from coupling ANN and DT that covered both quantitative and qualitative parameters with the hybrid error rate of 0.6. This rate of error was found to be satisfactory vis-à-vis that of similar studies. Moreover, the normalised predictive performance of single ANN, single DT and hybrid model were plotted against the normalised actual energy data and the superior performance of hybrid

model was confirmed (see Figure 6.23). This objective revealed that hybrid algorithm of ANN-DT is capable of making a powerfully integrated engine for building energy optimisation in BIM.

8.3.4. Objective 4: Developing a framework of AI application in BIM in terms of energy optimisation purposes and processes

The core contribution of this research was to achieve AI-enabled BIM-inherited EED; an integrated framework of AI application in active BIM to optimise the EED of residential buildings. Hence, this objective was designed to include the achievements of Objectives 1, 2 and 3 and conducted through, first, driving the optimisation engine and, second, performing the key stages toward framework establishment (Chapter 7). For this reason, the developed hybrid algorithm and its included datasets (results from Objective 3) based on the identified variables in Objective 2 were identified as the fitness function and target parameters of optimisation. GA algorithm was switched on and run on the objective function and data (Section 7.2). Consequently, the algorithm reached the superior convergence by 80 generations (see Figure 7.2). Simultaneously, the methods of crossing over and mutation were applied to minimise the risk of early termination and the optimum diversity of the solutions was achieved via the average distance plot (see Figure 7.3).

Framework development was composed from five main phases of database development, exchange, optimisation, switchback and updating (see Figure 7.4 & Section 7.3). The primary purpose of performing these steps was to integrate AI algorithms of prediction, classification and optimisation with BIM and keep the homogeneity of the optimised data. Database development was mostly concerned with modelling and information standard strategies in the workflow (Section 7.3.1). Representing model elements and the associated technical components such as shape, size, location and orientation in the most accurate and realistic way was the prerequisite of the model federation of all disciplines involved in BIM platform. However, beyond geometrical information, it was intended to include the non-geometric and functional properties through adhering to *LoD 300*. It was found that this LoD headed further to maintain the semantic association with the geometrical and topological configurations of data enrichment of BIM models (results from Objective 1).

The database exchange was set to facilitate the exchange and interoperability of the developed database resulting from the database development (Section 7.3.2). Two consecutive functions of IFC information export and its interoperability interface with Revit DBlink came to the fore to export and explore the data (results from Objective 1). More specifically, first, building

layout, HVAC and physical properties and building envelop parameters were obtained as the project information (results from Objective 2). Entity class definitions were attached onto the project information and sent to standardising and structuring according to IFC schema. The database was then synthesised with ODBC and made accessible for Matlab and hence, the reciprocal relation between Matlab and BIM was achieved (see Figure 7.5). Database optimisation gestated the optimisation procedure (results from Objective 3) of the exchanged database by exerting query-able ontologies on the semantic, topological and geometric entities (Section 7.3.3). Using parameters placeholders, the available values were specified in Matlab Integrated Simulator by calling AI package. ANN-DT hybrid objective function was activated and the initial prediction and classification results were delivered to GA in order for being optimised. Hence, the optimum combination of parameters was found and stored in a new database (see Figure 7.6).

To ensure the dynamic integration of the optimised data with the existing RevitDB, the database switchback phase was executed (Section 7.3.4). The key was to incorporate the control with the query command on the optimised database. As a result, this stage provided a system for BIM to link the modifications of the model database with the updated one. The last phase of the objective 4 was done for updating the database by overwriting the optimised parameters with their initial version (Section 7.3.5). Object oriented modelling concept allowed to generate the comparative report of the BIM variations once model updated. Furthermore, the automatic propagation of the optimisation and relevant changes were expedited throughout the model. The performed phases were ultimately directed toward AI-enabled BIM-inherited EED framework which created the interdisciplinary data interoperability of EED in the seamless integration of BIM with AI algorithm packages.

8.3.5. Objective 5: Assessing and validating the functionality of the framework using case studies

The last objective of this PhD study was to deliver a proof of concept for the developed framework and validate its performance toward an integrated optimisation of building EED (Section 7.4). Henceforth, a real-life project of a multiunit residential building located on Sydney was used and modelled in Revit to validate the functionality of the framework (Section 7.4.1). The parameters and constraints required for occupant behaviour and an energy simulation were determined and the baseline case was simulated in GBS in order to reveal the current energy consumption level of the building (Section 7.4.2). As a result, monthly electricity and the total energy consumption including electricity, hot water and gas for heat pump were calculated (Section 7.4.3) and the relevant graphs were plotted (see Figure 7.9). By aggregating these

monthly consumptions, three crucial figures of the annual electricity consumption, annual fuel consumption (gas) and annual peak demand were obtained with the records of 58,001 kWh, 164,195 MJ and 15.3 kW, respectively. These quantities fall to the average household energy consumption in Australia, according to the authorities (GBCA 2013).

Upon implementing the AI-enabled BIM-inherited EED framework, significant changes were made in the model elements and the optimised construction specifications were recorded (Section 7.4.4). The baseline model was updated with the optimised parameters and the energy simulation was again run for reflecting the status of post-framework implementation (Section 7.4.5). The outcomes of annual electricity consumption, annual energy consumption and annual peak demand were computed at 29,531 kWh, 109,076 MJ and 14.0 kW, respectively. These figures indicated a remarkable decline in the annual electricity consumption, fuel consumption and peak demand from the baseline to the optimised case especially for electricity energy in which, it was cut by half in the usage (see Figure 7.13). The new quantities represented the sixth star class of energy consumption for the case study based on the Australian Green Building Council (GBCA 2013) standard and confirmed the practical function of the framework.

The validation objective continued with two more verification procedures to demonstrate the result-oriented reliability of the optimisation and framework operation (Section 7.4.6). First, the concept of reliability threshold was applied to position the energy optimisation results within the circled ratio of the minimum and maximum values for the optimisation problem. Therefore, 4 to 6 Green Star rating of energy category of GBCA (2013) guideline, corresponded to 42% to 72% of energy consumption reduction, was set as the benchmark of the reliability (see Figure 7.15). It was approved that 50% of decline in the energy consumption, resulted from applying the framework, perfectly matched with the benchmarking threshold. Furthermore, paired sample t-Test was utilised to show the statistical significance between the baseline and optimised results. It was then specified that two pairs of data were significantly different from zero by 0.168 at 95% of confidence interval (see Table 7.4) which further verified the statistical significance of the optimisation performance and validated the applicability of the framework.

Finally, sensitivity analysis test was run to identify the reliability of the framework in case of being exposed to the uncertainty and noise interferences (Section 7.5). Therefore, 4 sensitivity analysis scenarios of 10%, 20%, 30% and 50% of random data missing and noise interference were conducted to assist with comparative evaluation of regression values and reveal any significant discrepancy arisen from enforcing uncertainties. It was inferred that the framework works well and keeps the homogeneity and reliability up to 30% of data missing and noise

interferences with the R values of 0.76, 0.75 and 0.75 for 10%, 20% and 30% scenarios, respectively. However, the sensitivity of the framework was a bit increased in the 50% scenario which is applicable for very large datasets with few number of parameters. Hence, the validity and security of the framework against four case studies of uncertainty scenarios including random data missing and noises up to 50% of the database asset were further justified.

Summarising the key processes and findings of research objectives showed that the objectives from 1 to 5, presented in Chapter 1, were fulfilled successfully and satisfactorily. Achieving these objectives has accomplished the aim of this study and contributed to the body of knowledge in different ways, as discussed below.

8.4. Contribution to Knowledge

The contribution to the body of knowledge is the most significant aspect of any PhD study (Chileshe 2005). Bourke (2007) itemised the contribution of a PhD study to the knowledge based on two criteria of originality and Implications For Practice. He decomposed originality into three sub-criteria of conducting novel empirical works, carrying out research in an uncharted area and genuine synthesisation.

8.4.1. Originality

Thus, the originality of the contribution to knowledge was structured in terms of its subsets as the following.

• Conducting novel empirical works. The knowledge creation is usually processed through developing a new theory, improving an available theory and/or rebutting a theory, wholly or partially, in light of empirical data (Handfield & Melnyk 1998). In this study, a novel empirical work was conducted on the basis of three broad theories of sustainability, information and optimisation and their practical aspects in the construction context; sustainable construction drivers, BIM and AI toward the unified approach of AI-enabled active BIM-inherited EED (Objectives 1 and 2). A novel CDE approach was founded based on BS1192 to further generalise the applicability of this study for higher levels of BIM diffusion and implementation. The developed framework was established and validated via collecting empirical data (Objectives 3, 4 and 5). Evidencing of originality for built environment research (Chileshe 2005), this fact approved the transferability and applicability of existing theories from other disciplines to the built environment area.

- Carrying out research in an uncharted area. Driven by collecting the empirical data, the research tried to authenticate AI-enabled active BIM-inherited EED in the built environment context. It was performed via the linkage of the outcomes of Objectives 1 and 2 with the results from running Objectives 3 and 4. To the best of the researcher's knowledge, not much research has been found in applying BIM and AI integrally in the EED of built environment field. In addition, the study attempted to apply previously developed theories of sustainability, information and optimisation from other disciplines of science, engineering and mathematics to a new area in the built environment context. This fact shows the efforts in confirming the validity of those theories in this field (Chileshe 2005).
- Genuine synthesisation. Objective 1 was primarily executed to identify the typologies of research and the available categories of approaches. Objective 2 was a synthesise of the literature review and experts' viewpoints on the building energy parameters and their significance in such studies. Objective 3 was also a synthesisation of previously separated methods of AI in prediction and classification algorithms. Ultimately, Objective 4 was specifically conducted to synthesise the outcomes of prior objectives into a unique framework development (AI-enabled BIM-inherited EED). Therefore, the rule of a genuine synthesisation; "making a new interpretation of existing material" was followed for evidencing the originality in PhD studies (Walker 1997, p. 150).

8.4.2. Implications for Practice

Implications for Practice (IFP) are the second category of expectation for PhD studies in contributing toward the practical knowledge. Such contributions are specifically significant for construction and built environment due to the urgent need for enhancing the construction process efficiency (Yi & Chan 2013). The IFPs of the present study's findings are presented below, drawing from the taxonomy proposed by Bartunek and Rynes (2010) who mentioned three items of potential audience, enhanced awareness and new learning areas identification for IFP areas which are used in the discussion below.

• Potential audience. Drawing upon the practical application of AI-enabled BIM-inherited EED framework in the design stage, architects, designers, engineers, sustainability auditors and research community can be benefitted as the first tier of audiences. In the second tier, BIM managers, design managers and project managers can take advantage of the BIM diffusion levels in the EED and set the appropriate strategies in organisational implementation of those adoption stages.

- Enhanced awareness. As a result of the growing importance of sustainable design in the construction industry, this research will raise the awareness of involved parties and potential audiences in the field. Identification of the significant building energy variables and quantification of their level of significance, along with development of the framework which was verified based on the relevant industrial standard can significantly enhance the knowledge and information of practitioners in putting them into practice. They can be informed from the modern methods of EED, the challenges of prediction and optimisation of energy performance and BIM and AI effects on this procedure.
- New learning areas identification. Highlighting the practical challenges and issues arising from findings of a study is a source of learning and obtaining further knowledge for its potential audiences. The findings of this research revealed that it is of crucial importance for designers and practitioners in streamlining the EED in BIM environment. It is done via obtaining an in-depth view toward BIM process, enhancing the LoD of design models and setting model elements appropriately with the topological, geometrical and semantic associations of BIM models. These challenges alongside the others like the most effective methods of BIM and AI integration shed a light on the areas necessitating further reading and education for the target groups of practitioners.

8.5. Limitations

This section is to acknowledge the limitations of the current research in spite of its significant contributions that made to the body of knowledge. Thus, the limitations can be mentioned as the below:

- First and foremost, the research was solely scoped to the design stage, in terms of the
 project lifecycle. Therefore, the construction and operation stages were excluded
 from the investigation whereas, these project phases have considerable impacts on
 the energy consumption of buildings. This limitation imposed the restriction on the
 parameters identification initiative and lifted the occupant behaviour category from
 the pool of variables which were brainstormed by the Delphi respondents.
- The technical sophistication of the research led to apply purposive sampling strategy
 and invite only the experienced and informed experts on BIM and EED for the Delphi
 study. Henceforth, pre-screening techniques were conducted due to limitations

stemming from the necessity of recruiting experienced and/or informed practitioners in the field. This, in turn, increased the risk of sampling error and selection bias from specific area. Generally, it is difficult to completely avoid from selection bias in the research however, it should be acknowledged and declared by the researchers (Ritchie et al. 2013).

- Parametric dataset development indicates the third item of limitation in which the
 data were collected from parametric energy simulation of a hypothetical low-rise
 residential building and in four climates. For this reason, the dataset ranges could not
 cover the mid and high rise residential models and further restricted to four generic
 climates of cold, temperate, tropical and hot-arid.
- From AI side of the study, prediction and classification algorithms were limited to ANN and DT. The optimisation algorithm was also focused on GA. Although these types of algorithms were selected based on the particular and justified reasons and their different combinations were further investigated, the AI-BIM integration typology of research was yet to be generalisable to the other types of AI.
- Revit was the BIM suit deployed in the study and fixed to the framework. This decision was substantiated in view of its powerful parametric engine and popularity within the industry and academic environment. Nevertheless, this choice dictated some degrees of restraints on the BIM inclusion of the framework. BIM as a process is driven by an extensive range of the software packages including modelling, analysis, simulation and estimation. Such a wide range of the application may require to be tested exclusively and fitted to the framework.

8.6. Recommendations for Future Studies

The limitations of research pave the way for further studies in the field. Research has a cyclical characteristic and does not end up with an obvious point (Zou & Sunindijo 2015). Therefore, the agenda for future studies could be explained as follows.

In addition to the design stage, construction and operation phases have undeniable impacts on the sustainability and energy efficiency of built environment. In order to understand the overall situation of the project lifecycle with respect to the AI-enabled BIM-inherited framework, these phases and their Life Cycle Assessment (LCA) could be conducted. Studying the design, construction and operation phases on a LCA perspective can provide valuable insights towards their integration with BIM and the data sources required. This notion will significantly

affect the number and nature of the variables of building energy and their inclusion in AI and the framework development.

The Delphi study was run through three rounds, purposive sampling method and mostly from energy and BIM viewpoints. Such empirical study could be more robust where the number of rounds are increased to cover the different aspects of research problems, challenges and solutions. Moreover, some intrinsic biases toward the respondents in the non-random sampling can be alleviated by employing random and snowball sampling techniques. To perceive the problem from broader perspective and in addition to BIM and energy experts, the data can be collected from larger sample with more mixed specialties such as AI people.

The energy dataset was generated based on the metaheuristic-parametric setting of a hypothetical low-rise residential building, one generic layout design and four climates. The simulation can be more extended to the mid and high-rise residential with various design layouts and even to the other types of buildings such as institutional, office, commercial, industrial and healthcare facilities. Besides, more climatic regions should be evaluated to improve the generalisability of the data ranges. Additionally, real life buildings datasets can be utilised via infield collection or applying instrumental devices to get data from operation. Such considerations in data collection and generation further raise the reliability and validity of the research and its findings.

Applying different types of AI algorithms and testing their performance enhance the precision of heuristic and metaheuristic machine learning. This want entails an in-depth investigation of a wide range of prediction, classification and optimisation algorithms and their second generation; deep learning classics. Deep learning algorithms have introduced the new type of supervised machine learning in which feature selection is executed according to the multiple levels of representation. Corresponded to this research arena, using deep learning algorithms can circumvent the empirical Delphi study in the initial parameters identification task as it automatically picks up the parameters from a pool. Furthermore, Deep learning unnecessitates the researcher from using data size reduction techniques. Considering that the implementation of deep learning method needs strong computational hardware and software support.

BIM-inherited EED is recommended for further research and development because of its appreciation in higher dimensions of BIM diffusion into the EED. The higher level of BIM adopts into the EED and sustainable construction in general, the more opportunities emerge in testing and investigating new areas and approaches toward the sustainable built environment. The BIM

suits which are capable of this level of adoption (discussed in Chapter 3) should be in the spotlight for the verification and comparative studies amongst in order to warrant this new field of research.

Appendices

Appendix A. Research Themes, Outcomes and Gap Spotting of BIM-EED

		esear 'hemo			esear			G	ap Spo	tting	
									Negle	ct	
Reference	Conceptual	Case Study	Survey	Study Analysis	Framework	Tool/System Prototype	Confusion	Overlooked	Under- researched	Lack of Empirical Research	Application
(Chaisuparasmikul 2006)		√		✓							√
(Zeng & Zhao 2006)		√		√							✓
(van Treeck & Rank 2007)	√			<u> </u>		√				√	,
(Hedges, Denzer & Asme 2008)		√		√			√			<u> </u>	
(Poerschke & Kalisperis 2008)		√		✓							√
(Attia, Beltrán, De Herde, et al.			√	√							
2009)											
(Charalambides 2009)		√				√		√			
(Loh, Dawood & Dean 2009)	√					✓				✓	
(Sanguinetti, Eastman &		√			✓						√
Augenbroe 2009)											
(Stumpf, Kim & Jenicek 2009)		√		✓							√
(Verstraeten et al. 2009)		√		✓					✓		√
(Yoon, Park & Choi 2009)		√		✓							✓
(Bank et al. 2010)		√				✓		✓	✓		
(Douglass 2010)		√		✓							√
(Ferrari, Silva & Lima 2010)		√		✓							√
(Kim, Jin & Choi 2010b)		✓		✓			✓				
(Knight, Roth & Rosen 2010)		✓		✓							√
(Majid, Marsono, Golzarpoor &		√		✓							√
Hamidi 2010)											
(Majid, Marsono, Golzarpoor &	✓				✓					✓	
Sadi 2010)											
(Chen & Gao 2011)		✓				✓			✓		
(Cho, Chen & Woo 2011)		✓		✓			✓				
(Cormier et al. 2011)	✓					✓				✓	
(Douglass & Leake 2011)		✓		✓							√
(Hitchcock & Wong 2011b)	✓			✓						✓	
(Kim & Anderson 2011)		✓				✓		✓			
(Kim, Kim & Choi 2011)	✓					✓				✓	
(Kim & Woo 2011)		✓		✓				✓			
(Kim et al. 2011)	✓				✓					✓	
(Oh et al. 2011b)		✓				✓			✓		
(Raheem, Issa & Olbina 2011)		✓		✓							√
(Ryu et al. 2011)		✓		✓							√
(See et al. 2011)		✓				✓	✓				
(Somboonwit 2011)		√		✓							√
(Tahmasebi, Banihashemi &		√		√							✓
Hassanabadi 2011)											
(Welle, Haymaker & Rogers	✓					✓				\checkmark	
2011b)											

(Im, Bhandari & Ashrae 2012)		√			√		√				
(Kim, Lee & Kim 2012)		· ✓			√				√		
(Kim, Kim & Seo 2012)		√				√		√	,		
(Kim & Han 2012)		√		√				,			✓
(Kurnitski et al. 2012)		· /		<u>,</u>			√				· /
(No, Hong & Kim 2012)		· /		<u>,</u>			·	√	√	✓	· /
(Park et al. 2012a)		✓		•		✓		•	√	Y	•
(Reeves, Olbina & Issa 2012)		V		√		•			•		√
(Smith 2012)		✓		→							✓
(Shakouri & Banihashemi 2012)		√		√							√
(Somboonwit & Sahachaisaeree		✓		✓							✓
2012)		•		•							•
(Spiegelhalter 2012)	✓				✓					✓	
(Thomas & Schlueter 2012)	✓				✓					✓	
(Andrey, Artem & Pavel 2013)	✓				V ✓					✓	
	•		✓	√	•					✓	
(Bahar et al. 2013)		✓	•	∨						V	✓
(Balaras et al. 2013)		∨		∨ ✓							∨
(Bolotin et al. 2013)		∨		v		√		√	√		· ·
(Cemesova, Hopfe & Rezgui 2013)	√	v			✓	V		V	V		
(Grinberg & Rendek 2013)	✓				✓					√	
(Hu 2013)	V				✓					✓	
(Jansson, Schade & Olofsson 2013)		√				√		✓			
(Jeong et al. 2013)		√				✓			✓		
(Jung et al. 2013a)		√		✓							√
(Kim & Anderson 2013)		V				√					√
(Kim et al. 2013)		√				√					✓
(Kovacic et al. 2013)		√				✓		✓			
(Maile et al. 2013)		✓		✓							✓
(Motawa & Carter 2013b)	✓				✓					√	
(Sinha et al. 2013)		√				✓			✓	✓	
(Wong & Fan 2013a)		√		✓							✓
(Yan et al. 2013b)		✓				✓		✓			
(Yu et al. 2013)	✓				✓					✓	
(Zhang, Liu & Xu 2013)		√		✓							√
(Abdalla & Law 2014)		✓		✓							✓
(Alam & Ham 2014)		✓		✓							✓
(Calquin, Wandersleben & Castillo		✓		\checkmark							✓
2014)											
(Cheng & Das 2014)		✓				✓	√				
(Eguaras-Martínez, Vidaurre-		✓				\checkmark					✓
Arbizu & Martín-Gómez 2014)											
(Gokce & Gokce 2014)		✓				✓			✓		
(Gudnason et al. 2014)	✓				✓					✓	
(Gupta et al. 2014)		✓				✓		✓	✓		
(Ham & Golparvar-Fard 2014)	✓				√					✓	
(He et al. 2014)		✓		✓							✓
(Jabi 2014)	✓				✓					✓	
(Jašek et al. 2014)	√				√		√			✓	
(Jeong et al. 2014)		✓				✓		✓			
(Jiang & Lei 2014)		✓		✓							✓
(Kadolsky, Baumgartel & Scherer	✓				✓					✓	
2014)											
(Katranuschkov et al. 2014)	✓				✓					✓	
(Li & Zheng 2014)		✓		✓							✓
(Li et al. 2014)		✓		✓							✓

(Lobos & Trebilcock 2014)		√				√		√			
(Mohanta & Jain 2014)		√		✓		·					✓
(Song 2014)		√		✓							✓
(Stojanovic et al. 2014)		✓				√		✓			
(Turkyilmaz 2014)		✓		√				-			✓
(Wen, Kuo & Hsieh 2014)	√				√					√	
(Wong & Kuan 2014)	✓				,	√				✓ ·	
(Xia & Ma 2014)		√		√						,	
(Zahraee et al. 2014)		· ✓		·							· /
(Zhang 2014)		-	√	· ✓					√		+
(Agdas & Srinivasan 2015)		√	ľ	•		√		√	-		
(Asl et al. 2015)		✓				<u> </u>	√	•	√		
(Asri et al. 2015)	√	•			✓		,		•	√	
	∨				✓					./	
(Banihashemi, Ding & Wang 2015)	V	✓		√	V					V	✓
(Batueva & Mahdavi 2015)	√	•		V	✓						· ·
(Cao et al. 2015)	v				V					✓	
(Cemesova, Hopfe & McLeod		✓				\checkmark		\checkmark	✓		
(Chair Wins & Wins 2015)	√				✓						
(Choi, Kim & Kim 2015)	∨									√	
(Christodoulou et al. 2015)	V				✓					V	
(Delghust et al. 2015)		✓				✓		✓			
(Deng, Das & Cheng 2015)	√				√					√	
(Eguaras-Martinez et al. 2015)	√				√					√	
(Giannakis et al. 2015)	✓				✓					✓	
(Ham & Golparvar-Fard 2015)		V				✓	✓		✓		
(Hamedani & Smith 2015)		✓		✓							√
(Inyim, Rivera & Zhu 2015)	√				✓			✓		✓	
(Jalaei, Jrade & Nassiri 2015)	✓					✓	✓				
(Jones et al. 2015)		√				√		✓			
(Katranuschkov et al. 2015)		√				✓			✓		
(Ke & Yan 2015)		√		√							√
(Kensek 2015)		√		✓							√
(Kim et al. 2015)		✓				✓		✓			
(Kim 2015)	✓				✓					✓	
(Lee, Kim & Choo 2015)		√		✓							√
(Lilis et al. 2015)		√		✓							✓
(Liu, Meng & Tam 2015)		✓				✓			✓		
(Reeves, Olbina & Issa 2015)		✓	✓	✓			√				
(Remmen et al. 2015)	✓				✓					✓	
(Rezaee et al. 2015)		✓		√							✓
(Robert et al. 2015)		✓		√							✓
(Shoubi et al. 2015)		√		√							√
(Strobbe et al. 2015)		✓		✓							✓
(Stundon et al. 2015)		✓		✓							✓
(Tan et al. 2015)		✓		✓							√
(Yang 2015)		✓		✓							✓
(Zhang & Zhong 2015)		✓		✓							✓
(Zhu & Tu 2015)	√				√					✓	
(Abanda & Byers 2016)		√		✓							√
(Banihashemi, Ding & Wang 2016)	√				√					✓	
(Chardon et al. 2016)		√				√		√			
(Choi et al. 2016)		√				√	√				
(Gourlis & Kovacic 2016)		√		√							√
(Guo & Wei 2016)		√		√							√
(Hu, Corry, et al. 2016)	√				√					✓	
J, ~~ ···· = v - v J											

(Hu, Zhang, et al. 2016)	✓					✓				✓	
(Jabi 2016)		√		✓							√
(Jeong et al. 2016)		✓		✓							√
(Jeong & Kim 2016)		✓		✓							✓
(Jeong & Son 2016)		✓		✓							√
(Jiang et al. 2016)	✓				√					✓	
(Kim et al. 2016)		✓				✓					✓
(Kim & Yu 2016b)		✓				✓					✓
(Kim & Yu 2016a)		√				✓					√
(Kota et al. 2016)	✓				✓					✓	
(Ladenhauf, Battisti, et al. 2016)		✓		✓							✓
(Ladenhauf, Berndt, et al. 2016)		√		✓							√
(Lee 2016)	✓				✓					✓	
(Migilinskas et al. 2016)		√		✓							√
(Niu & Pan 2016)			√	√				✓	√	✓	
(Pan, Qin & Zhao 2016)		✓		✓					✓		✓
(Ryu & Park 2016)		✓		✓							✓
(Sadeghifam et al. 2016)		√		✓							√
(Shin, Kim & Choi 2016)	✓				✓					✓	
(Wen & Hiyama 2016)			✓	✓				✓	✓	√	
(Yang, Ghahramani & Becerik-		✓		✓						_	✓
Gerber 2016)											
Total Number	43	11	6	79	37	45	13	23	23	47	75



UTS HUMAN RESEARCH ETHICS COMMITTEE ANNUAL REPORT / EXTENSION REQUEST

This report is to be completed every twelve months following the date of ethics approval, and at the completion of your research project. To cross the check boxes, double click on the check box and tick checked (under default value). Type your responses into the box which expand to accommodate your answers. If you have any queries on how to complete this report, please contact the Research Ethics Officer (Ph.: 02/9514 9772).

Project Title: Active BIM wi	ith Artificial Intelligence for Energy Optimisation in Buildings
UTS HREC Approval Num	ber: UTS HREC 2015000227
Current status of project:	(Double click on box and mark 'checked')
Not yet commenced (you have not commenced recruitment or data collection)	Estimated commencement date:
In Progress (You have commenced research or have put the research on hold)	Estimated completion date:
Completed (You have completed data collection and first stage analysis of data)	Approximate completion date: 1/4/2016
Discontinued (You have withdrawn or stopped the research due to insufficient or suspension of funding, or have stopped the research for another reason)	Approximate discontinued date:

Position	Name (include title)	Contact number	Email	Period of involvement
Chief Investigator/ Supervisor	Dr Grace Ding	02 9514 8659	grace.ding@uts.edu.au	1 year
Co- investigator	Dr Jack Wang	02 9514 2634	Jianguo.wang@uts.edu.au	1 year
(Student)	Seyed Saeed Banihashemi Namini	0406 639 380	Seyed.S.BanihashemiNamini@student. uts.edu.au	1 year

(Note: copy this section as required to accommodate the number of investigators)



PRINTED ON UTS (and/or joint) LETTERHEAD

CONSENT FORM
I agree to participate in the research project "Active BIM with Artificial Intelligence for Energy Optimisation in Buildings" being conducted by Saeed Banihashemi (561, School of Built Environment, Level 5, Faculty of Design, Architecture and Building, UTS, 15 Broadway, NSW 2007, 0406 639 380) with UTS HREC 2015000227, approved by the University of Technology Sydney, for his degree; PhD of Built Environment.
I understand that the purpose of this study is to develop an artificial intelligence-based (AI) active Building Information Modelling (BIM) in order to obtain an initial estimate of energy consumption of residential buildings and optimize the estimated value through recommending some changes in design elements and variables.
I understand that I have been asked to participate in this research because of my expertise in and that my participation in this research will involve with a three round Delphi queries in which may take up to 45 minutes/15 minutes for each session.
I am aware that I can contact Saeed Banihashemi or his supervisor(s); Dr Grace Ding and Dr Jack Wang if I have any concerns about the research. I also understand that I am free to withdraw my participation from this research project at any time I wish, without consequences, and without giving a reason.
I agree that Saeed Banihashemi has answered all my questions fully and clearly.
I agree that the research data gathered from this project may be published in a form that does not identify me in any way. I also agree that the information provided here may be used in the future for ongoing research and studies.
Signature (participant)
_Saeed Banihashemi



Participant Information Letter

Active BIM with Artificial Intelligence for Energy Optimization in Buildings

Dear Sir/Madam,

My name is Saeed Banihashemi and I am a PhD candidate of built environment at University of Technology, Sydney (UTS).

I am conducting research into developing an artificial intelligence-based (AI) active BIM in order to obtain an initial estimate of energy consumption of residential buildings and optimize the estimated value through recommending changes in design elements and variables.

The research would involve semi-structured interview and Delphi and should not take more than 60 minutes of your time. That is 30 minutes for interview and 30 minutes for the Delphi.

If you are interested in participating, I would be glad if you would contact me (and/or my supervisor).

You are under no obligation to participate in this research.

Yours sincerely,

Saeed Banihashemi Faculty of Design, Architecture & Building (DAB) Building 6, Level 5, Room 516 Tel: 0406 639 380

Email address: Seyed.S.BanihashemiNamini@student.uts.edu.au

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