Energy retrofitting of existing residential buildings: developing a decision process for energy saving and cost effectiveness

Navid Asadzadeh Aghdaei

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ENERGY RETROFITTING OF EXISTING RESIDENTIAL BUILDINGS:
DEVELOPING A DECISION PROCESS FOR ENERGY SAVING AND COST EFFECTIVENESS

A thesis submitted in partial fulfilment of the requirements for the award of the degree:

DOCTOR OF PHILOSOPHY
From
UNIVERSITY OF WOLLONGONG

By
NAVID ASADZADEH AGHDAEI

SUSTAINABLE BUILDINGS RESEARCH CENTRE
FACULTY OF ENGINEERING AND INFORMATION SCIENCE

May 2018
Declaration

I, Navid Asadzadeh Aghdaei, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the Sustainable Buildings Research Centre, Faculty of Engineering and Information Sciences, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Navid Asadzadeh Aghdaei
May 2018
Abstract

The present research project is designed to assist in decision-making of householders to determine beneficial strategies that improve energy performance of existing dwellings and reduce the cost of energy.

The focus of the thesis is on existing residential buildings and envelope improvements. A hybrid approach, combining the output of quantitative analysis and the qualitative assessment, was used to produce a set of ‘representative’ dwelling designs for the current residential stock. Quantitative analysis of accessible The Australian Bureau of Statistics (ABS) databases was undertaken on the Australian residential sector, focused on the investigation of building envelope characteristics. A qualitative investigation was carried out with focus on defining a set of New South Wales (NSW) housing typologies from experts and practitioners working in NSW residential energy-efficiency and building sector.

The outcome of the hybrid approach was used for the development of representative dwelling simulation models to aid the quantification of the potential for energy efficiency upgrades at the stock level, as well as aiding the related policy evaluation and development. The initial ‘representative’ dwelling designs matrix undertaken for this study produced a large number of representative dwelling simulation models, many of which were not substantially distinct from each other in terms of energy performance. For this reason, Taguchi and ANOVA methods were used to produce a reduced number of representative dwelling simulation models that incorporated significant attributes for the determination of the energy performance. The development of twelve representative dwelling simulation models was the main outcome of this analysis. Differential Sensitivity Analysis (DSA) was then undertaken for assessing the significance and influence of input design parameters on the amount of energy needed to maintain the indoor conditions of representative dwelling simulation models within an acceptable temperature range. Six key building design parameters were identified as having high influence coefficients through differential sensitivity analysis such as airtightness level, window-to-wall ratio (WWR), window types and the level of insulation for the ceiling, the wall and the floor.
Regression analysis was used from the simulation results of the representative dwelling simulation models to develop simple energy prediction models based on the building parameters most strongly influence the annual thermal energy requirements. The predictions from the regression analysis show differences from EnergyPlus-simulated annual thermal energy requirements were in the order of 10%-15% in dwelling models. The coefficient of determination ($R^2$) was over 0.85, indicating a rational relationship between simulations and the energy prediction models, and suggesting that the annual heating and cooling energy requirements can be forecasted within an acceptable range using the energy prediction models.

The energy prediction models were then used to develop a simple retrofitting decision-making tool that offers a cost-benefit assessment of different dwelling types within a range of retrofitting strategies. This tool takes into account the current thermal condition of the building, the impact of specific envelope improvement measures on the energy consumption and associated costs of strategies. The developed tool was used in order to assess the economic feasibility of representative dwelling types in terms of initial investment cost and associated energy/cost saving of retrofitting scenarios through considering the risk of fuel price changes in the future. The outcome of analysis was evident that the energy efficiency is the clear economic way forward for the existing representative dwellings. The analysis also showed that the high cost savings would be achievable by applying the thermally efficient designs in dwellings over a 20-year period. Thermally efficient building designs with high capital cost are more economical options compared to dwelling retrofitting options with lower capital cost with increasing fuel price trend in future.

Decisions for energy retrofits and associated cost of it involve a certain degree of complexity and it is difficult for homeowners to have an informed opinion about the effectiveness of these retrofits without seeking expert advice. The advice from experts is often financially prohibitive for homeowners and for that, this study developed a simple retrofitting decision-making tool that suits a specific climate and building stock and enables decisions to be made for envelope retrofits.

Recommendations for research to further characterise residential building sector, reduce the uncertainties identified in this study, and improve the decision-making process are also provided.
Acknowledgements

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<td>Australian Building Codes Board</td>
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<td>ABS</td>
<td>Australian Bureau of Statistics</td>
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<tr>
<td>ACH</td>
<td>Air Changes Per Hour</td>
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<tr>
<td>AIRAH</td>
<td>The Australian Institute of Refrigeration, Air Conditioning and Heating</td>
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<tr>
<td>ANOVA</td>
<td>Analysis of Variance</td>
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<tr>
<td>ASBEC</td>
<td>Australian Sustainable Built Environment Council</td>
</tr>
<tr>
<td>ASHRAE</td>
<td>American Society of Heating, Refrigeration and Air Conditioning Engineering</td>
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<tr>
<td>BCA</td>
<td>Building Code of Australia</td>
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<td>BCP</td>
<td>Basic Community Profile</td>
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<td>BEER</td>
<td>Building Energy Efficiency Register</td>
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<td>Brick Veneer</td>
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<td>CDA</td>
<td>Conditional Demand Analysis</td>
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<td>CIBSE</td>
<td>Chartered Institute of Building Services Engineers</td>
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<td>CIE</td>
<td>Centre For International Economics</td>
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<td>CO₂</td>
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<td>COP</td>
<td>Coefficient of Performance</td>
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<tr>
<td>DPP</td>
<td>Depreciated Payback Period</td>
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<td>DSA</td>
<td>Differential Sensitivity Analysis</td>
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<td>ECM</td>
<td>Energy Conservation Measures</td>
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<td>English Housing Survey</td>
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<td>International Energy Agency</td>
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<td>HVAC</td>
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<td>IC</td>
<td>Influence Coefficient</td>
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<td>IFH</td>
<td>Illawarra Flame House,</td>
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<td>IEQ</td>
<td>Internal Environment Quality</td>
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<td>IP</td>
<td>(Indigenous) Profile</td>
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<td>IPCC</td>
<td>Intergovernmental Panel On Climate Change</td>
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<td>IRR</td>
<td>Internal Rate of Return</td>
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<td>IWEC</td>
<td>International Weather For Energy Calculations</td>
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<td>LW</td>
<td>Lightweight</td>
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<td>MBE</td>
<td>Mean Bias Error</td>
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<td>NATHERS</td>
<td>Nationwide House Energy Rating Scheme</td>
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<td>National Institute of Water and Atmospheric Research</td>
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<td>NN</td>
<td>Neural Networks</td>
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<td>NPV</td>
<td>Net Present Value</td>
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<td>Abbreviation</td>
<td>Full Form</td>
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<td>NSW</td>
<td>New South Wales</td>
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<td>OA</td>
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<td>PP</td>
<td>Payback Period</td>
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<td>Reference Meteorological Year</td>
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<td>S/N ratio</td>
<td>Signal to Noise Ratio</td>
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<td>Sustainable Buildings Research Centre</td>
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<td>SD</td>
<td>Solar Decathlon House</td>
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<td>SHGC</td>
<td>Solar Heat Gain Coefficient</td>
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<td>Slab on Ground</td>
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<td>Typical Meteorological Year</td>
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<td>TRY</td>
<td>Test Reference Year</td>
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<td>University of Wollongong</td>
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<td>VBA</td>
<td>Visual Basic for Application</td>
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<td>VIF</td>
<td>Variance Inflation Factor</td>
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<td>WPP</td>
<td>Working Population Profile</td>
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<td>WWR</td>
<td>Window to Wall Ratio</td>
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<td>WYEC</td>
<td>Weather Year For Energy Calculations</td>
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<td>XCP</td>
<td>Expanded Community Profile</td>
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<td>ZCA</td>
<td>Zero Carbon Australia</td>
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</table>
List of publications associated with this thesis

Chapter 4

Chapter 5

Chapter 6
Chapter 1: Introduction

1.1 Background and motivation

A substantial reduction in the greenhouse gas (GHG) emissions of developed nations is required in the near future to mitigate the projected impacts of climate change. There is broad public debate regarding the most effective methods to achieve GHG emission reductions. It has been widely recognised that improving the efficiency of energy use must play a key role in any solution. Many studies (Climateworks Australia, 2010, IPCC, 2014) have suggested that up to 30% of current energy use can be avoided with a net economic benefit through energy efficiency improvements across many industries.

The building sector has a major role in the worldwide energy consumption (ASBEC, 2008). The existing buildings account for 30% of the world's (Swan and Brown, 2013), 40% of the US (EIA, 2013), 37% of the EU (Pérez-Lombard et al., 2008) and 19% of Australia's (The Centre for International Economics (CIE), 2007) current energy consumption. Also, 21% of the world's greenhouse gas emission is due to current building stock (Swan and Brown, 2013). Greenhouse gas (GHG) emissions result in air pollution, climate change and eventually global warming. These contributions are expected to increase due to the world’s population growth (United Nations, 2013). Fig 1.1 shows the International Energy Outlook report (EIA, 2016) for the worldwide energy demand prediction.

![Fig 1.1: World energy consumption, 1990-2040 (EIA, 2016).](image-url)
The International Energy Agency (IEA, 2015) reported that the current state of energy consumption and CO₂ emissions are crucially unacceptable and over the standards. The 2014 Intergovernmental Panel on Climate Change Fifth Assessment Report entitled as ‘Urban areas’ also emphasised the importance of transforming and adapting urban areas to a changing climate (IPCC, 2014). Therefore, sustainable building design and construction practices have recently been receiving increasing attention in order to help construct green/zero energy buildings with reduced/controlled chemical emissions and a minimum impact on the climate.

Based on IPCC (2007b) report, buildings have the highest energy saving and toxic waste reduction potential. Hence, governments and international organisations have put significant effort towards addressing existing building energy efficiency problems since the last two decades. Innovation of new technologies and development of energy efficiency programs and policies related to building retrofitting and refurbishing projects are aiding to reduce energy demand and improve indoor environmental quality. Proper retrofitting and refurbishment strategies greatly assist to minimise the energy consumption and maximise the thermal comfort of existing buildings. A number of studies (Bell and Lowe, 2000, English Heritage, 2007) indicated that retrofitting of existing buildings is an efficient approach to improve operational performance at a lower cost than a new construction by determining appropriate refurbishment strategies.

In Australia, the building sector contributes to producing 140 Million Metric tons (Mt) (ASBEC, 2012) of greenhouse gas emissions (GHG) which is about 23% (ZCA, 2013) of Australia’s total GHG emissions. Residential dwellings are also responsible for approximately 60% of these emissions (ASBEC, 2008) from construction and operation of 8 million existing dwellings (ABS, 2011c).

New buildings in Australia are required to meet minimum energy requirements as defined by the Nationwide House Energy Rating Scheme (NatHERS). The NatHERS requires new buildings to meet certain heating and cooling efficiency levels based on the climate zone they are located in. Whilst the introduction of energy efficiency targets in building code of Australia (BCA) in 2003 have vastly improved the thermal performance of newer buildings, a large portion of Australian residential stock was built before 2000. These dwellings were constructed before the
advent of building regulations with regards to energy performance, sustainability and comfort of the occupants. Therefore, they are likely to have poor energy performance and indoor environmental quality (GBCA, 2009).

To improve the energy performance of residential buildings in Australia, there is a need for additional actions other than upgrading the building standards for new buildings because the replacement rate of the housing stock is just 1-3% per annum (Ma et al., 2012). Research from UK (Davies and Osmani, 2011) shows that the energy performance of new British buildings which have implemented the new building regulations is up to 40% and 70% higher than the buildings built in 2002 and 1990, respectively. Langston et al. (2008) also opined that refurbishment of buildings has become an integral strategy to ameliorate the financial, environmental, and social performance. It is therefore essential to develop sustainable retrofitting or refurbishment strategies for the Australian existing housing stock to achieve high performance dwellings in terms of energy consumption and occupant thermal comfort. According to the U.S Department of Energy (2016), the operational cost of buildings can be reduced by energy efficiency retrofits, as well as its benefits for attracting tenants, minimising carbon cost and gaining a market edge. Retrofitting provides a great opportunity to enhance energy efficiency, thermal comfort and occupant health as well as adding value to properties (Langston et al., 2008), reducing operational cost (U.S Department of Energy, 2016) and providing stability when changes in energy prices and regulatory aspects occur (ASBEC, 2012, Akande et al., 2016, Riley and Cotgrave, 2011).

Retrofitting is a vast and complex subject. There are many challenges in the process of retrofitting existing buildings. Constraints and uncertainties such as climate change, different physical condition of properties, regulation updates, human behaviour, market transformation and different financial limitations affect the retrofitting process. No single solution or intervention is capable of delivering the substantial reductions necessary on a national scale or even within an individual property. Dealing with these constraints and uncertainties is so vital for the success of a retrofitting project.

Nowadays, sustainability has to be included in the briefing, conceptual and design development phases of each project, regardless of project procurement types.
and project sizes (Castillo and Chi Chung, 2004). There are a large number of retrofit measures and technologies that are available in the market for saving energy in buildings. Determination of appropriate retrofit measures to achieve a meaningful improvement is a complex process that needs deep knowledge of thermodynamics and consumption practices of occupants. In addition, there are so many constraints and limitations which have an influence on selecting the appropriate retrofitting approach like “specific building characteristics, total budget available, project target, building fabric, etc” (Ma et al., 2012). The optimal solution can be made by a trade-off among a range of energy related and non-energy related (economic, technical, environmental, regulative, social, etc.) factors.

1.2 Aim and objectives

The motivation of this research is to assist homeowners, architects and builders to determine beneficial retrofitting strategies in order to improve the energy performance of existing dwellings and to mitigate their operational cost.

The aim of the research presented in this thesis is to develop a framework to assess the cost-benefit of retrofit strategies for improving the energy performance of existing dwellings. A set of representative dwellings for residential buildings constructed from 1970 to 2000 in the Australian stock is developed to be used in building performance simulation. Focus has also been given to identifying significant parameters that impact heating and cooling energy requirements to aid in energy retrofitting decision-making. Simplified energy estimation models are also developed based on the building parameters that most strongly influence the annual thermal energy consumption in residential buildings. Energy estimation model can remove the burden of performing a detailed dynamic simulation of the building that requires a significant amount of experience, time, and efforts from the shoulders of building designers and experts in retrofitting of dwellings. This study offers a simplified decision-making tool with cost-benefit assessment capabilities to provide an easy way for identification of energy and cost effective envelope upgrades in houses.

The specific objectives of the study are to:
1. Conduct a review of existing literature to identify the methods of energy performance improvement, and available retrofitting strategies in dwellings.

2. Develop representative simulation models of existing dwellings by identifying key building envelope attributes that influence energy consumption for heating and cooling purposes of different climate conditions.

3. Investigate influential retrofitting parameters that reduce heating and cooling loads by using a range of representative dwelling simulation models.

4. Develop linear regression models to predict the thermodynamic performance of building envelope upgrades of different residential housing types from the existing building stock.

5. Develop a decision-making tool to assist users to estimate current energy performance of dwellings in terms of heating and cooling loads and suggest retrofitting improvement strategies by taking into account investment budget cost and energy saving analysis. Analyse the cost-benefit of retrofitting to rapidly quantify the impact of retrofit parameters on energy performance and the associated cost with different fuel pricing scenarios in existing dwellings.

1.3 Summary of methodology

The above objectives will be addressed with the methods described in detail in Chapter 3 and a summary which is given in this section.

A statistical review along with qualitative investigations was undertaken on accessible data of the Australian residential sector, focusing on residential buildings constructed between 1970 to 2000. This was conducted with the purpose of developing stock typologies and representative dwelling simulation models to aid the quantification of potential retrofitting upgrades in reducing heating and cooling loads. Taguchi and ANOVA methods were combined with a Building Performance Simulation (BPS) tool and used to produce a reduced number of representative
dwelling simulation models that incorporated by significant parameters. Developed representative dwelling simulation models used for determination of thermal energy requirements of existing residential building stock. Differential Sensitivity Analysis (DSA) was then undertaken for the developed representative dwelling simulation models to quantify the effect of design parameters on the amount of energy needed to maintain indoor thermal conditions within a comfortable range. Parametric energy analysis was also undertaken on design parameters which were found to be influential in representative dwelling simulation models. In parametric analysis process, Taguchi order layouts were developed for the purpose of creating a database of annual energy usages in dwellings by performing simulations for a series of important design parameters. The results of parametric analysis were then used to develop simple regression energy estimation models to estimate annual building energy consumption for the three major climate zones in NSW. The capability of the used thesis methodology was also examined by employing a method in calibrated dwelling simulation model. Finally, a simple decision-making spreadsheet tool was developed to improve the utilisation of research results. This tool can also be used to generalise the findings in a way that could be used for other building envelope upgrades. Cost estimations were then made to evaluate the cost-benefit of retrofitting parameters in the representative dwelling simulation models based on capital cost, payback period, and net present value by accounting for different future fuel pricing scenarios.

1.4 Research questions

The research questions associated with the above objectives are:

1. How can Australian and NSW dwellings typologies be defined to support building envelope energy retrofitting decisions in an easy way?

2. What are the predominant archetypes of dwellings built from 1970 to 2000 in NSW, according to the construction characteristics influencing the heating and cooling requirements?

3. What is the cost-benefit of different dwelling envelope retrofits and risks associated with electricity price changing?
1.5 Structure of the thesis

An overview of each chapter is presented below and in Figure 1.2.

Chapter 1 introduces the background and the issues associated with decisions for retrofitting existing residential buildings. It covers aims and objectives, a summary of the methodology and a summary of the thesis structure.

Chapter 2 presents a review of the existing literature relevant to the understanding of the generic building energy retrofitting methods. It covers common methods and solutions to achieve building energy efficiency improvements. The chapter includes a review of retrofit improvement processes, including the use of Building Performance simulation (BPS), Design Of Experiment (DOE), Sensitivity analysis (SA) and Regression model analysis methods that were used in this thesis in order to develop representative simulation models and to predict savings from retrofit strategies.

Chapter 3 outlines the techniques used to achieve the specific objectives of this research. Details are provided on qualitative research methods and available database investigation, Building Performance Simulation tool, Design of Experiment (Taguchi) with ANOVA methods, Differential Sensitivity Analysis (DSA), linear regression analysis, and cost evaluation methods that were undertaken for achieving the objectives of this research.

In Chapter 4, the Australian and NSW key building characteristics are investigated and analysed. Results from a statistical analysis of Australian Bureau Statistics (ABS) data resources and a qualitative analysis of expert opinions were used to identify common typologies with a range of construction attributes.

Chapter 5 describes the process of investigating the influence of dwelling envelope attributes on the heating and cooling energy requirements of dwellings. Building Performance Simulation tool and Taguchi method were used to develop representative dwelling energy simulation models of defined common typologies in the current stock. In this chapter, current thermal energy performance of the developed representative dwelling simulation models was investigated and compared with the model of a highly efficient house. Influence of floor area on total heating and cooling of the dwelling was also analysed.
Chapter 6 has two parts. The first part presents results from the Differential Sensitivity Analysis (DSA) that used to study the effect of building envelope parameters on the yearly cooling and heating loads of representative dwelling simulation models. The second part develops simple energy estimation models that aim to predict the thermal performance of different types of dwellings. The thermal performance of developed representative dwelling simulation models is based on the resulted high influential improvement parameters. The capability of offered methodology in this study is investigated by applying the proposed regression method in an existing dwelling with calibrated energy simulation model.

Chapter 7 presents an envelope decision-support tool that is developed to assist the identification of effective envelope energy efficiency upgrades for houses and associated cost-benefits. Analyse the cost-benefit of retrofitting strategies in representative dwelling models is undertaken by employing decision-support tool.

Chapter 8 outlines the conclusions of this research project, and relevant limitations, and recommendations for future research.

Fig 1.2 aligns the outline of the thesis with expected outcomes that satisfy the research objectives.
<table>
<thead>
<tr>
<th>Chapters</th>
<th>Specific chapter’s target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chapter 1</td>
<td>Introduce the background of the research, aim and objectives, summarise the methodology and the thesis structure.</td>
</tr>
<tr>
<td>Chapter 2</td>
<td>Review of literature that is relevant to the project objectives.</td>
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<tr>
<td>Chapter 3</td>
<td>Describe in detail the research methodology.</td>
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<tr>
<td>Chapter 4</td>
<td>Characterise the Australian residential building stock in terms of building envelope attributes. Define the Australian and New South Wales residential common typologies.</td>
</tr>
<tr>
<td>Chapter 5</td>
<td>Develop simulation models of representative dwelling types and investigate their current energy performance. Analyse influence of floor area on dwelling thermal performance.</td>
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<tr>
<td>Chapter 6</td>
<td>Evaluate retrofitting design parameters and select the most effective parameters on representative dwelling simulation models thermal performance in different climates. Develop simple thermal energy estimation models of representative dwelling types based on the influential building parameters that were extracted. Examine the applicability of the developed method on calibrated simulation model of a real building.</td>
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<tr>
<td>Chapter 7</td>
<td>Develop a decision-making tool spreadsheet to evaluate the energy and economic effectiveness of potential envelope retrofitting decisions with regards to capital costs and fuel prices. Estimate the cost-benefit of different retrofitting scenarios on representative dwelling simulation models.</td>
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<tr>
<td>Chapter 8</td>
<td>List the research conclusions and recommendations for future work.</td>
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Fig 1.2: Chapter structure of this thesis.
Chapter 2: Literature review

2.1 Introduction

Developing building retrofitting strategies based on different typologies by using Building Performance Simulation (BPS) is a complex process and demands knowledge in several areas. This literature review chapter intends to lay out an overall review of the existing literature to identify the gaps and propose solutions relevant to the target of this study.

This review includes:

- The generic energy performance of Australian residential dwelling, retrofitting problems and available improvement strategies for existing buildings.
- Available retrofitting decision methods.
- Tools used for simulation of building energy and thermal performance.
- Statistical methods for predicting and improving the energy performance of residential dwelling models.
- Available cost-benefit techniques for decision making around retrofitting.

2.2 Global environmental perspective

Nowadays, many concerns of environmental impacts and global climate change have taken place due to extensive use of non-renewable energy resources. Level of global greenhouse gas (GHG) emissions and energy consumption have grown by 70 percent during last decades (IPCC, 2007a) and it is expected to increase due to more human activities.

International Energy Agency (EIA, 2008) probed into the impact of different sectors upon the world energy consumption and GHG emission, as shown in Fig 2.1. The result shows that households have a 29% contribution in global energy consumption and 21% in global GHG emissions, primarily by usage of fossil fuels in an operational phase in every country. Building sector accounts for 40% of the
energy consumption in the US (EIA, 2013), 37% of the energy consumption in EU (Pérez-Lombard et al., 2008) and 19% of energy consumption in Australia (CIE, 2007) which projected to increase.

![Pie charts showing energy consumption and CO₂ emissions by sectors.](image)

Fig 2.1: Shares of global final energy consumption and CO₂ emissions by sectors, 2005. Adopted from (EIA, 2008).

However, the building sector can greatly decrease CO₂ emission and energy consumption up to 30% to 40% by implementing energy efficiency measures in buildings, respectively (IPCC, 2007a, CIE, 2007).

To decrease the world GHG emission and the energy consumption and improve economic condition and living standard, make developments within building sector is vital in every country. It is clear that buildings energy efficiency has to be a primary purpose of energy policymakers at regional, national, and international levels.

### 2.3 Australian environmental perspective

One of the economically viable ways to reduce the consumption of energy and GHG emissions is improving the energy efficiency of the existing building stock in Australia. The proportion of energy consumption and GHG emission varies with different Australian sectors, as it is demonstrated in Fig 2.2. This figure shows that
the Australian building sector is responsible for about 19% and 23% of total energy consumption and GHG emission per year, respectively (ASBEC, 2008).

In Australian building sector, residential sub-sector has a great potential to influence on GHG emission production and energy consumption. This is due to Australian households come among the top consumers of energy and emitters of GHG in the world, as shown in Fig 2.3 and Fig 2.4. The result of Fig 2.3 shows that production rate of CO₂ emission in Australian households has had a low decline while the world CO₂ emission level has decreased greatly from 1.5 tonnes to less than 1 tonne per household from 1990 to 2010. Fig 2.4 also shows that Australian houses are consuming energy at twice than the world average.
Fig 2.4: Average household electricity consumption (kWh/hh) in 2010 (World energy council, 2011).

However, Australian Sustainable Built Environment Council (ASBEC, 2008) also published that the potential abatement of the residential and commercial sector is up to 61% and 39% into building sector, respectively.

Addressing energy consumption and GHG emission is an essential action that requires all Australian sectors to cooperate through innovative energy-efficient solutions (Ardente et al., 2008). In this regard, this research will put its primary focus on Australian building sector specifically residential dwellings, to help in improving the energy efficiency of Australian dwelling stock.

2.4 Energy performance of Australian dwellings

Improving the efficiency of Australia’s existing building stock is an important way to reduce emissions in the near future.

Australia relies on fossil fuels (coal, gas, oil etc.) for generating electricity that mainly consumes by households. Coal and gas emit much higher greenhouse gas (GHG) emissions than renewable energy sources while they are the cheapest fuel sources for generating electricity in Australia (Australian Energy Regulator, 2008). Greenhouse gas (GHG) emissions and energy consumption for Australian residential sector (except for transport) have increased by 28% (DCC, 2008) and 30% (ABS, 2009-2010) between 1990-200, respectively. A number of factors play a role in this growth including a rise in the population, an increase in the house sizes, and the fact that residents use more appliances and IT equipment. Therefore, floor area, quality of
dwellings and the behaviour of the occupants that can significantly influence household energy consumption and GHG emissions (GHG) production have been analysed.

The annual Australian residential energy consumption during the last decades has been shown Fig 2.5a. This figure shows that the rate of residential energy consumption has an almost constant increase from 1976 to 2011. This might be due to the growth of the Australian population or change occupant energy consumption pattern (or even both reasons). Therefore, the average energy consumption of the Australian residential dwellings is also investigated and presented in Fig 2.5b. As can be seen, the average energy consumption per dwelling has gradually decreased during the last decades. This result concludes that the reason for an increase in the rate of annual Australian residential energy consumption can be the population growth. However, Fig 2.5b also shows that while the average energy consumption of the new dwellings built in each decade is still lower than the total dwellings of that decade, it has increased compared to the new dwellings built in the previous decade. An investigation on the variation of the dwelling floor area, population, dwelling type in last decades might assist to find the reason.

![Graph of Australian total residential energy consumption](image1)

![Graph of Average dwelling energy consumption](image2)

**Fig 2.5:** a. Australian total residential energy consumption (adopted from (Bree, 2014)) and b. Average dwelling energy consumption (GJ/yr).

Australian population and total residential dwelling floor area are also shown in Fig 2.6a and Fig 2.6b. The result of Fig 2.6a shows that Australian population has only increased by about 34% from 1986 to 2011 while the total residential dwelling floor area has increased over 125% (Fig 2.6 b). This shows that the rate of increase
in the total residential dwelling floor area is significantly (almost 4 times) higher than the rate of population growth. This proves that the average Australian residential dwelling floor area (area/dwelling) has been increased during the last decades. As a reason, a deeper investigation has been provided into the Australian residential dwelling types for similar decades.


Fig 2.7a shows the total number of rooms exists in Australian dwellings from 1976 to 2011 and the total number of new rooms, which have been added in each decade. Fig 2.7a supports that the total number of rooms in Australian dwellings has increased above 100% since 1976. The average energy consumption of the Australian residential dwellings has also been calculated based on the total number of rooms in each decade and presented in Fig 2.7b. This figure displays that although the average energy consumption of the new dwellings built in each decade has increased compared to the new dwellings built in the previous decade, the average room consumption has decreased. This is reasonably expected due to build the higher quality buildings.
Fig 2.7: a. Total number of dwelling rooms and b. Average energy consumption per dwelling room in each decade.

Moreover, Australian Bureau of Statistics data (ABS, 2006) in Fig 2.8 shows an 18% increase (from 17.7 to 20.9 GJ) in energy consumption per person from 1993 to 2003. This can also have a major impact on the total energy consumption of new and existing dwellings.

Fig 2.8: Energy consumption per person (ABS, 2006).

The analysis of statistics shows that the total energy consumption in the residential sector has been increased during last decades. Nevertheless, the newly built dwellings consume less energy in comparison with dwellings built before while floor areas, number of rooms, and average energy consumption per person in new buildings have significantly increased. It can be concluded that a large proportion of current energy consumption in the residential sector belongs to the existing dwellings which have been built before the introduction of Australian uniform building code and energy efficiency policy consideration in 2000. Therefore, appropriate solutions are required to be applied in Australian existing dwellings stock to decrease the energy consumption and GHG emissions from this sector.
2.5 Building improvement or replacement solutions

The building sector highly influences the total natural resource consumption and emissions production. The energy demand in the life cycle of buildings can be put into two groups: direct and indirect. The first group, direct energy, is the one used in construction, operation, renovation, and demolition of buildings. The indirect energy is energy used in the production of material for constructing buildings (Sartori and Hestnes, 2007).

In recent years, a wide range of innovative approaches to uptake for the efficiency of building sector has emerged; however, “building improvement” and “building replacement” approaches are just limited solutions for the existing dwellings.

Building improvement can be defined as “all initiatives, which extend the lifespan of buildings or increase the value of properties, or both” (University of Georgia, 2012). Building replacement is demolishing an old building and developing a new one to achieve value. The value may be measured in high energy security, economic, climate, environment and social terms (IEA, 2004).

Building replacement was one of the popular approaches, prior to the emergence of energy consumption and GHG emission issues, to address the existing buildings challenges. However, building improvement for energy efficiency is currently identified as the appropriate and cost-effective solution for existing buildings issues (Commonwealth of Australia, 2004).

The trade-off between building improvement and building replacement solutions should be carried out by three levels analysis. According to Nippala and Heljo (2010), building solution trade off levels are i) The energy assessment: it consists the amount of energy requires for demolishing properties and the energy needs for renovating buildings. ii) The cost assessment: it includes analysis of the property’s value, cost of demolishing, cost of a new property construction and cost of maintenance (including heating costs). iii) The feasibility assessment: it involves the evaluation of assumed costs and rental yields for both existing and new properties.

The building solution method was examined in residential apartments in Finland by Nippala and Heljo (2010). The result of this study shows that the building
Improvement is the best alternative in terms of energy, cost and profit in comparison with replacement. Demolishing and rebuilding new building have significant impacts on the environment, society and economy (Power, 2009). Replacing the building is an expensive and high emission-producing process due to the amount of non-renewable energy resources required for demolition and waste disposal procedure. A study from Baker (2009) also confirmed that building improvement is the favoured option in terms of environmental impacts during building’s lifetime. The newly built building might have less environmental impacts while the refurbished building is the lowest emitter over a long period until it reaches a breakpoint. The CO₂ emissions for a new building and the refurbishment of an existing building over time are illustrated in Fig 2.9. Building replacement method produces large energy debts for the environment in the short run, and if that period is beyond the time of climate crisis, the life-cycle emissions are irrelevant.

![CO₂ emissions over time for demolishing, rebuilding, and refurbishing](image)

Fig 2.9: CO₂ emissions over time for demolishing, rebuilding, and refurbishing (Baker, 2009).

Bin and Parker (2012) also compared the pre and post retrofit ecological footprint of a century home. The environmental performance of the house during the three phases (i.e. pre-use phase, use phase and post-use phase) of its full service life was examined. The results showed that enhancing energy performance through renovation is an environmental friendly action which also helps the building service life works for longer decades. In 2008, a German programme was concluded with results from 342,000 apartment retrofits (United Nations Environment Program,
The retrofits of this program included: improved wall and ceiling insulation; upgraded windows; heating system upgrades; photovoltaic systems; and solar thermal systems (United Nations Environment Program, 2008). This specific German retrofit programme was able to reduce the CO₂ emissions associated with the operation of German buildings by 2%.

The rate of replacing the existing building stock with new constructions is in the order of 1-3% per year (Ma et al., 2012). This rate shows that in the short term, building new low energy constructions in Australia will not have a significant impact on the current level of GHG emissions production and energy consumption from the building sector. Improvements for existing buildings are therefore considered as an effective way for mitigating the energy and environmental impacts of the Australian building stock.

There is a range of options available for improving the energy efficiency of existing buildings, and the range is ever increasing as new technologies become commercially available. The Existing Building Survival Strategies handbook (Arup et al., 2009) lists 200 different strategies to minimise building electricity consumption. Hens (2010) reported on the results due to the retrofit of a two-storey house built in 1957. It was shown that the benefits of using solar boiler and PV panels are minimal compared to using better insulation, energy efficient windows, better air-tightness, upgraded ventilation, and central heating.

The energy savings and cost effectiveness of individual retrofit options in single family buildings were studied by Cohen et al. (1991) based on analysing metered energy consumption and actual installation costs. The results showed that the ceiling insulation and wall insulation are cost effective while the windows replacement was not a good retrofit option for the specific climate since it had a very small normalised annual energy saving (2–5%).

Stovall et al. (2007) performed a series of experiments to examine the effectiveness of wall retrofit options. The results from the experimental tests were applied to an energy model to estimate whole house energy impacts. It was found that, for the specific climate of the study, external insulative sheathing is especially effective in reducing the heat transfer through walls with greater framing heat transfer paths.
Nabinger and Persily (2011) performed a retrofit study in an unoccupied manufactured house to investigate the impacts of air-tightening on ventilation rates and energy consumption. The results showed that the reduction in the house infiltration rates depend on weather conditions and the manner in which the heating and cooling system is controlled, but in general these rates were reduced by one third due to the retrofits.

In following sections, relevant methods for enhancing the thermal performance while reducing the energy consumption of existing dwellings will be reviewed.
2.6 Existing residential stock modelling

One of the most cost-effective methods to reduce GHG emissions is refurbishing existing buildings (IPCC, 2014, McKinsey & Company, 2008) especially residential sector. However, performance assessment of single dwelling with regards to energy use, sustainability is a complex task that involves significant cost, time, knowledge, and expertise. Improvement of an existing building stock, in a given location or jurisdiction, is more challenging than a single building retrofitting. This is due to the variety of building types and households that lead to quite different technical, social and economic situations.

Stock modelling is a method by which the total primary energy usage and primary energy-related environmental influences of housing stock at local, regional, national, and global levels can be evaluated. Furthermore, stock modelling can be applied in establishing energy supply prerequisites such as the corresponding environmental impacts, and overall requirements of the housing stock of dwellings due to changes in their geometric details or thermal characteristics or operating parameters. The section offers a review of various modelling techniques used for modelling residential sector energy use.

A variety of approaches can be implemented to improve the thermal performance of the existing residential sector. There are two broad categories of the techniques in modelling residential energy consumption: “Top-down” and “Bottom-up”. The terms refer to the hierarchal position of data inputs in comparison with the housing sector as a whole. Top-down models round up an estimate of the total energy consumed by the residential sector and other related variables to attribute the energy consumption to characteristics of the entire housing sector. In contrast, bottom-up models calculate the energy consumption of individual or groups of houses and then extrapolate these results to represent the region or nation (Swan and Ugursal, 2009).

Fig 2.10 shows the top-down and bottom-up techniques groupings in modelling residential energy consumption which will be discussed in the following sections.
2.6.1 Top-down approach

As statistical models, top-down models deal with energy supply needs and costs in broad samples of dwellings in terms of the impacts of socio-economic and technological features on a local, regional, national or global energy use. Top-down models are econometric or techno-econometric. It categorised with input information on household technological components. Top-down models explore energy use of residential sector and other relevant characteristics in relation to the variables of the entire residential sector (Swan and Ugursal, 2009). Depending on the type of technique, a top-down model requires aggregated data. This approach is based mainly on input information on demography, employment, trade, growth, investment, tax rates, units of dwellings in the housing stock, house production, export/import, appliance sales, ownership and ratings, goods production, climatic conditions, income and price of variables, within the supply needs. Sources of residential energy data for top-down models include the preliminary estimate of the total residential sector (aggregated values) as published by governments which compile gross energy values submitted by energy providers and the billing records of energy suppliers.

Top-down models have strengths in the need for only aggregated data and in particular their reliance on historical residential records. However, two main
drawbacks are identified for top-down models: reliance on historic residential records which renders top-down models incapable of being used to model discontinuous advances in technology; and a lack of detail regarding energy consumption of individual end-uses which removes the ability of top-down models to establish major areas for upgrades for energy/emissions abatement. Therefore, in a situation where deep national emissions reductions are sought, the suitability of a top-down approach for policy knowledge is limited.

2.6.2 Bottom-up approach

Bottom-up models are statistical and engineering models which assess energy supply needs and costs of individual dwellings towards the combined energy use value of the stock. Bottom-up models can be used to compare buildings and the energy supply systems to gain a detailed perception of production and operation energy alternatives. It also assists comparisons between various building and supply systems. A bottom-up approach allows the evaluation of the effects of new technologies and potential upgrades, for which top-down methods are less suitable as they rely on statistical data based on historical or current practice (Gustavsson and Joelsson, 2010). Depending on the exact technique used, the method can be used to measure the effects of the geometric details, thermal characteristics, and operating parameters on the residential energy use of the individual households. Unlike top-down models, these effects can then be weighted by the prevalence of the representative dwellings to represent the locality, region or nation. Sources of the input data required in bottom-up models include information on geometric details, thermal characteristics, and operating parameters of the dwellings.

Sources of residential energy data include billing data, housing surveys which provides detailed information rather than aggregated values; and “sub-metering” (i.e. consignment of energy metering devices on the large energy consuming appliances within the household to determine both the components of the house energy consumption and their usage profile as a function of time (Swan and Ugursal, 2009).

There are three main types of bottom-up models: Conditional Demand Analysis (CDA) technique; Neural Networks (NN) technique; and Engineering Methods (EM) models.
1. Conditional Demand Analysis (CDA): CDA refers to regression analysis based on the presence of household appliances. It is the appliance-specific approach. In comparison to EM models, CDA models are easier to develop and use, and do not require as detailed data (Aydinalp et al., 2002). By regressing total dwelling energy consumption onto the list of owned appliances which are indicated as a binary or count variable, the determined coefficients represent the use level and rating. Unlike EM models which depend upon assumptions on the time of the first person getting up in the morning, and the period of the house unoccupied during the day, the Conditional Demand Model utilises observed data on consumer behaviour. For the CDA the input information is a simple appliance survey from the occupant and energy billing data from the energy supplier; and a dataset with a variety of appliance ownership throughout the sample (Swan and Ugursal, 2009). The reliability of a CDA technique is dependent on a large number of variables. The use of CDA technique has been performed by few studies such as (Aydinalp-Koksal and Ugursal, 2008, Larsen and Nesbakken, 2004).

2. Neural Network (NN): NN is characterised by computing systems, which attempt to model the structure and function of biological neurons (Mihalakakou et al., 2002). While neurons represent interconnected processing elements, the arrangement of the inter-neuron bonds, including the character of the bonds plays a significant role in establishing the structure of a network. The structures of NN models are characterised by a grouping of neurons into layers whilst signals then flow to or from the input and output layers, depending on the structures of the network.

3. Engineering Models (EM): EM techniques are used to assess energy supply needs and costs of individual dwellings towards the combined energy use value of the stock. It assesses the cost-benefit and marginal cost of carbon abatement for different energy efficiency and renewable energy options. This method characterised by developing a representative database of the housing stock. Sources of the input data required in
bottom-up models include information on geometric details, thermal characteristics and operating parameters of the dwellings. Unlike top-down models, engineering techniques incorporate a high level of detail and flexibility, and they can fully develop the energy consumption of the residential sector without any historical energy use information. The study identified three main EM techniques:

i. Distributions: This is an engineering technique based on the distribution of appliance penetration (i.e. the number of households using a particular appliance), number of households, appliance ratings and hours of appliance usage to calculate the end-use energy of each household. The end-use energy is evaluated based on the product of the above variables and the inverse of the appliance efficiency. The residential energy use at a local, regional or national level is evaluated based on the combined appliance energy uses. (Kadian et al., 2007, Jaccard and Baille, 1996) applied the distributions technique in their studies.

ii. Samples: This technique is characterised by the collection of detailed information of real house samples using on-site surveys. These real house samples then become the representative sample of the housing stock. However, it is necessary for the sample to be large enough for it to fulfill that role. A number of authors have performed the use of samples techniques (Larsen and Nesbakken, 2004, Farahbakhsh et al., 1998).

iii. Typologies or Archetypes: EM can also be applied to a limited set of dwellings that represent classes of houses found in the residential sector, commonly referred to as “Archetypes” (Swan and Ugursal, 2009). This is an engineering technique which uses the taxonomy of a housing stock based on its geometric details, thermal characteristics and operating parameters. The descriptions of each major class of house represent part of the input information required to assess energy supply needs and costs of individual dwellings towards the combined energy use value of the stock and to assess the cost-benefit and marginal cost of carbon abatement for different energy efficiency and renewable energy options. The assessed energy use of the individual typologies or archetypes is then
mapped onto the prevalence of the number of houses best described by each type to be representative of the local or regional or national housing stock (Swan and Ugursal, 2009). The use of typology technique has been performed by several studies (Ballarini et al., 2014, Wan and Yik, 2004, Yao and Steemers, 2005, Shimoda et al., 2004) and proved as an efficient method for areas that information is limited.

2.6.3 Choice of stock modelling methods

In the previous sections, top-down and bottom-up approaches were reviewed to employ in housing stock modelling. The detailed review of the literature discussed previously shows that a number of drawbacks in top-down models, which makes them unsuitable for this study, are more than bottom-up models. The top-down models require input information which heavily depends on the historical energy consumption (Swan and Ugursal, 2009). On the other hand, bottom-up models particularly Engineering Model (EM) explicitly calculates the energy consumption based on detailed housing information which is a more suitable model for this study.

In Section 2.6.2, it was shown that Conditional Demand Analysis (CDA) models are regression-based which depends on a large number of appliances in the database (Aydinalp-Koksal and Ugursal, 2008). The CDA models rely on observed data on consumer behaviour. It should be reminded that the survey data available in Australia contains information only on the average occupancy.

Moreover, the number of appliance ownership through the house sample is limited as the study considers only the house heating and cooling systems, especially as other appliances such brown and white goods are be separated from the building. Therefore, this technique can be removed for the purposes of this study.

Distributions technique depends on the number of households using a particular appliance, a number of households, appliance ratings and hours of appliance usage to evaluate end-use energy of each household. Such level of input data is inadequate to assess the full impact of energy conservation measures. This technique, therefore, can also be discarded for the purposes of this study.

Sample models also relied on detailed information of historic records of energy usage and other household variables obtained on-site from the individual dwellings.
This method can cover the broad range of houses within the housing stock to analyse the ability for use in establishing regions with high energy-energy consumption (Swan and Ugursal, 2009). However, this method required individual dwelling assessment that is costly and sometimes not accessible in many studies, so this method has been removed for applies in this study.

Typology or archetype model is a technique used to distinct classes of houses. Archetypes are representative types of actual dwellings according to vintage, size, house type, etc. In stock aggregation, it is possible to develop several typologies or archetypes definitions for each major class of house and utilise these descriptions as the input data into energy modelling software tools. Archetypes can help to assess the impacts of different dwellings in housing stock. It has the potential to support existing housing stock analysis by making assumptions regarding changes in the housing stock and energy retrofit measures. It also can be used to make future energy projections. Stock aggregation can be used to highlight areas where potential improvement in resource use and economic efficiency existed through quick analysis. It allows policy makers to analyse how policies in one area (such as energy security or housing affordability) can affect other impacts from buildings. This approach also helps to optimise regulations and market incentives to achieve specific targets as well as the development of priorities in research and development section.

Kavgic et al. (2010) reviewed “nine energy end-use models based on building typologies with five related to the UK building stock. In the UK, development of typologies is typically based upon the English Housing Survey (EHS). The results from this survey, combined with other available data sources, have been used to develop housing typologies at different levels of disaggregation like building form, occupancy, and climatic location”.

Typology method is also useful for building users who are keen to improve dwelling performance through retrofitting scenarios. According to previous studies, the bottom-up method by employing the typology development technique has been selected to achieve defined objectives of this study.
2.7 Building performance simulation

To analyse the building thermal comfort and energy performance in retrofitting process, building performance software (BPS) is required for analysis. BPS is widely employed in the retrofit improvement process to predict energy savings from possible upgrades (Ma et al., 2012). BPS programs provide beneficial information about the influence of energy retrofits on the thermal and energy performance of buildings. However, BPS programs indeed need accurate inputs from construction material properties, building geometry, building occupancy, electrical loads, HVAC equipment, and local climatic conditions. The schematic diagram of a whole-building BPS is provided in Fig 2.11.

![Schematic diagram of whole-building BPS](image)

Fig 2.11: Calculation process of generic whole-building simulation (Daly, 2015).

Various BPS programs have been developed for evaluating energy efficiency, renewable energy, and sustainability in buildings. Crawley et al. (2008) reviewed twenty main simulation programs and compared their characteristics and capabilities. DOE-2, BLAST and EnergyPlus were nominated as the best-known example of available BPS programs for analysing the energy behaviour of buildings and associated heating, ventilating and air-conditioning (HVAC) systems (Zhao and Magoulès, 2012).

DOE-2 is a public domain program that produced by the US Department of Energy. DOE-2.1E predicts the hourly energy use and energy cost of a building given hourly weather information, a building geometric HVAC description and utility rate structure.

BLAST is a Building Load Analysis and System Thermodynamics (BLAST) simulation program which helps in predicting energy consumption, systems
performance, costs of new or retrofit building designs in different types and sizes. Hourly building energy analysis for designing the mechanical equipment as well as checks for compliance with design energy budgets can also be obtained in this engine.

EnergyPlus is a modular and structured code program that developed based on the most popular features and capabilities of BLAST and DOE-2 whole-building energy simulation engines. It is a simulation engine with input and output of text files. Loads calculated (by a heat balance engine) at a user-specified time step (15-minute default) are passed to the building systems simulation module at the same time step. The EnergyPlus building systems simulation module, with a variable time step, calculates heating and cooling system and plant and electrical system response. Several user-friendly interfaces have been developed for this engine as well (Al-Homoud, 2001).

In this study, DesignBuilder, a third party graphical user interface for the EnergyPlus thermodynamic simulation engine, has been used for energy simulation and prediction, which will be discussed in Chapter 3.

2.7.1 Building performance simulation with representative buildings

The unique characteristics of each building is a big obstacle in the investigation of building energy retrofitting in any studies. Every building is unique with distinctive characteristics that impact the consumption of energy and success of potential retrofitting strategies. Significant effort is required to delicately simulate an individual building hinders and produced an adequate detailed energy model to support successful retrofit strategy. Thus, simplification is deemed necessary for this matter. One of the common technique in developing a simplified model is to use ‘Representative or ‘archetypal’ buildings (Ballarini et al., 2014, Wan and Yik, 2004, Yao and Steemers, 2005, Shimoda et al., 2004). The representative building actually represents an average building in the segment of the building stock under consideration. One hypothesis about this approach is that even if a representative building does not precisely represent a specific building, it will answer an
intervention in a similar way as other building with similar use or form. This will also explain how actual buildings might be affected by interventions.

Previous studies (Famuyibo et al., 2012, Kavgic et al., 2010) used statistical data to explore the building stock under consideration. The statistical data was used to investigate representative models and characterise the building stock. This method provides information in effective degree and sufficient level of uncertainty. A representative building can be made in BPS after the selection of the basics such as construction, building geometry, mechanic services and internal loads. Evans et al. (2014) was proposed a method for the attachment of information database to 3D mapping sources. In this model, a 3D stock model with real details about geometry and construction can be simulated through the appropriate reference services and activities. Representative building model in BPS helps to predict the energy consumption in various building types in several climate zones.

The estimated energy consumption in BPS also leads to creating a bottom-up stock model of the energy consumption in a specific zone by multiplying the building numbers in that zone. In addition, representative buildings are the measures of consistency in modelling approaches and inputs for those who use simulation to examine various subjects.

2.7.2 Local weather conditions

As identified in Judkoff et al. (2008), accurate BPS relies on precise input data. One key input is the information about weather conditions with data related to humidity, wind speed, dry bulb temperature etc. Whilst it is possible to simulate a building with actual weather data from a particular period, this is desirable for many applications (for instance during calibration), simulation for optimisation of building energy retrofits generally requires average weather data (Daly, 2015).

Daly (2015) “was reviewed two methods that commonly used to extract a ‘typical’ year from a dataset of hourly weather observations. These methods result in the Test Reference Year (TRY) and the Typical Meteorological Year (TMY) formats. A TRY is an actual year of observed data, selected from a database by progressively removing the years with particularly high or low monthly average conditions until only one year remains”. A TMY creates a year of representative weather data by
assembling the ‘most average month’ from the database for each calendar month. A weighted average of important parameters is created for each month, and the month which most closely matches the average is selected for the TMY. For example, a TMY might consist of the weather observations from Jan 1995, Feb 1989, March 2000, There is a range of typical weather years available from different sources developed with the TMY procedure, including TMY, TMY2, TMY3, Weather Year for Energy Calculations (WYEC), WYEC2, International Weather for Energy Calculations (IWEC) and Reference Meteorological Year (RMY). The differences between the various files are in the source of the base data, and the weighting given to parameters when determining the most average months. IWEC (ASHRAE, 2001) and RMY weather files are available for Australian locations and both rely on data from the Australian Bureau of Meteorology. Historically, Australian simulations users have used TRY files obtained from ACADS- BSG. Since 2001 IWEC files have been available for Australian capital cities, and since 2006 RMY files have also been available. “Meteorological Year (RMY)” climate files from NatHERS are also available for a typical year for every Australian climate zone (NIWA, 2012) and will be used for simulations in this study. In the following sections, a range of methods that are applied to develop the representative buildings and improve the energy efficiency combined with building performance software in this research are reviewed.

2.8 Design of experiment

To develop stock modelling for the current residential stock, a unique set of potential building configurations that represent the full range of construction types is required. However, this process would result in a large number of building simulation models. In this study, to cut down the total number of simulation models for the current stock and reduce the required number of simulation runs for development of energy prediction model, principles from the Design of Experiment (Taguchi method) has been used.

Design of Experiment (DOE) is a branch of applied statistics to evaluate the factors that control the value of a parameter or a group of parameters. The DOE is a statistical approach to the investigation of system or process in which it allows a
judgment on the significance of input variables to the output (Lin; et al., 2013). DOE provides a predictive knowledge of complex and multi-variable process with few trials that minimises the project cost and cycle time. In many of these experiments, certain factors are held constant while the levels of another variable are altered in order to study the effects of such factors. DOE experiment order layout can be used in studies that practically are impossible due to a large number of input variables and a high cost of conducting experiments. Different types of DOE designs are available and the choice depends on the objectives of the study.

DOE is commonly classified into two experiment order layouts (Park and Ahn, 2004) as full factorial and fractional factorial. A full factorial order design is an experimental design consists of two or more factors; each with a discrete possible level. This design identifies all possible combinations of levels across all factors. This experiment allows studying the effect of each factor on the response variable, as well as on the effects of interactions between factors on the response variable. Full factorial is recommended to use two levels, called “high” and “low for involved factors if the process output is linear between the two levels. When the number of factors is equal to six or greater, a full factorial design will require a large number of runs that is not very efficient. For example, if there are k factors each at 2 levels; a full factorial design requires about $2^k$ runs. The full factorial design requires performing a large number of experiments to be carried out which causes high laboriously, complexity and cost in work. In this case, the use of a fractional factorial design is recommended (Chlela, Riederer et al. 2009).

Fractional factorial designs defined as a factorial experiment in which only an adequately chosen fraction of the combinations selected from all the possibilities (Mohan et al., 2005) that generate the most information.

The fractional method uses a special set of arrays called orthogonal arrays (OA). In an orthogonal array experiment, the independent variables’ columns are “orthogonal” to each another. The orthogonal table can systematically form combinations of variables without redundant experiments through the variable-level array with rules (Yu-Ri and Hae Jin, 2016). However, Design of Experiments requires a good knowledge of the phenomenon studied in order to consider the most significant factors (Plessis et al., 2011).
DOE can be used by several methods such as Response surface designs, Taguchi design and Mixture designs for different purposes (Minitab Statistical Software Support, 2016a).

Response Surface Design is a method that “uses to analyse the model curvature in the range of data and identify factor settings that optimise the response. This method is usually used after identifying the most important factors in the process by conducting the factorial or fractional factorial experiment”.

Mixture experiment is “a special class of response surface experiments that use for investigation a product made up of several components or ingredients. Designs for this experiment are useful for product designs and development activities in industrial situations that involve formulations or mixtures”.

Taguchi design is a method that “helps to choose a product or process that functions more consistently in the operating environment. Taguchi designs use orthogonal arrays, which estimate the effects of each factor independently of all the other factors. This can heavily reduce the time and cost associated with the experiment when fractionated designs are used”.

In this study to reduce the number of the required experiments, fractional factorial order layout by using Taguchi method will be designed for different analysis.

2.8.1 Taguchi method

Taguchi method is a statistical method that involves reducing the variation in a process through the robust design of experiments. The overall objective of the method is to produce a high-quality product at a low cost (Fraley et al., 2007). The Taguchi method offers ready to use design tables for fractional factorial. The experimental order layout proposed by Taguchi involves using orthogonal arrays (OA) to organise the parameters affecting the process. Taguchi method tests pairs of combinations instead of examining all of the possible combinations like the full factorial design. This allows for the collection of the data necessary to determine the factors that most affect product quality with a minimum amount of experimentation, thus saving time and resources.
Taguchi method is adopting the Taguchi’s elements single-handedly from the experimental designing stage to the final optimisation process. The parameter design of the Taguchi method utilises OA, signal-to-noise (S/N) ratios, main effects, and analysis of variance (ANOVA). OA provides a set of well-balanced (minimum experimental runs) experiments and Taguchi’s S/N, which are logarithmic functions of desired output; serve as objective functions for optimisation (Datta et al., 2008).

Previous studies (Athreya and Venkatesh, 2012, Daneshvar et al., 2007, Du Plessis and Du Villiers, 2007) show that Taguchi approach has become a widely accepted methodology in many fields.

DOE (Taguchi method) has recently been used in studies that focus on the optimisation of energy efficient buildings. Zahraee et al. (2014) “combined the energy simulation with Taguchi method to optimise main elements in the green residential buildings in Malaysia based on energy consumption response. In this study, three main factors were selected with two levels to optimise in buildings. This paper showed that the potential of using Taguchi method in optimising the effect of the main elements on energy saving by considering the effect of uncontrollable factors such as humidity, temperature, and airflow”.

Yi et al. (2015) “used Taguchi and ANOVA methods in developing a metamodel for building form optimisation. The results showed effective energy optimisation of building is possible by utilising Taguchi method. This method led to the establishment of a metamodel for further employment of emergy analysis in decision-making for advanced design studies”.

Dillon (2014) “utilised the DOE to investigate the sensitivity of parameters on the building’s energy usage. A range of parameters was found that significantly influence the building’s energy performance. In this study, the influential parameters were further investigated with a GA. The reason for using the two-step process in the methodology was that the DOE is computationally faster than the GA. The GA is an evolutionary optimisation technique that uses the results of previous simulations to determine the future simulations. This study summarised that DOE is a non-evolutionary technique that determines simulations before running the optimisation. Since the simulations are predetermined for the DOE, it can run multiple and simultaneous simulations to reduce computational time.”
Taguchi’s contribution to the optimisation processing has been far ranging as it provides a considerable reduction of time and effort needed to determine the important factors affecting product quality as well as to obtain the optimal process conditions. Previous studies show that using a DOE (Taguchi method) with a building energy model can help to analyse the effect of parameters on the design by using a small number of simulations. In this study, DOE (Taguchi method) has been utilised in the development of representative dwelling simulation models and prediction of energy performance. The detail of this method will describe in Chapter 5 and Chapter 6. As mentioned in Section 2.7, in order to employ a DOE design for this thesis the DesignBuilder program is used.

2.9 Sensitivity analysis

There is a large number of strategies that can be used in retrofitting of building energy simulation models whilst typically only a much smaller subset of these strategies will influence the output significantly (Daly, 2015). Sensitivity is a generic concept (Nguyen and Reiter, 2015) to understand the impact of simulation assumptions on simulation outputs. Sensitivity analysis can be useful in determining the relative influence of different input parameters (Daly et al., 2014). The aim of sensitivity analysis is to observe the model response following the variation of a given design parameter. It is a way to get great insight into the design process and optimisation strategies (Fabriek, 2013).

Sensitivity analysis is used in building energy research which works as a powerful tool for designers to quantify the effect of various design parameters and to identify sources of uncertainty (Daly et al., 2014). However, it is an area without a well-defined or generally accepted procedure/process (Lam and Hui, 1996).

Sensitivity analysis is useful for investigating the variation in a model output from perturbing input parameters by an arbitrary amount, i.e. ±1%. Hamby (1994) is reviewed three different categories for parameter sensitivity analysis:

- Local sensitivity analysis method is assessing the influence of individual parameters. This includes Differential Sensitivity Analysis, One-at-a time sensitivity measures, Factorial Design, Sensitivity Index, Importance Factors, and Subjective Sensitivity Analysis.
- Global sensitivity analysis is utilising random sampling methods (simple random sampling, Monte Carlo, Latin Hypercube). In this group are listed the methods: Scatter plots, Importance Index, ‘Relative Deviation’, ‘Relative Deviation Ratio’, Pearson's r, Rank Transformation, Spearman's ρ, Partial Correlation Coefficient, Regression, and Standardised Regression techniques.

- Sensitivity tests involving segmented input distributions: the Smirnov test, the Cramer Von-Mises test, the Mann–Whitney test, and the squared-ranked test.

Lomas and Eppel (1992) examined “the performance of three sensitivity analysis methods (Differential Sensitivity Analysis, Monte Carlo Analysis, and Stochastic sensitivity analysis) on three building energy programs. The study indicated that both Differential Sensitivity Analysis (DSA) and Monte Carlo Analysis yielded similar results and could be applied to the widest range of thermal programs. This study highlighted Differential Sensitivity Analysis (DSA) as the preferred technique for research into building energy use. It gives insight into the individual sensitivity meaning the influence on predictions of variations in each individual input parameter. The remaining parameters stay identical at their “base-case” values (Lomas and Eppel, 1992)”.

Differential Sensitivity Analysis (DSA) has been used extensively in the field of building energy analysis (Lomas and Eppel, 1992, Lam and Hui, 1996, Petersen and Svendsen, 2010, Lam et al., 2008, Tian, 2013).

Samarakoon and Soebarto (2011) presented “the findings of local sensitivity analysis of the building with a particular focus on inputs arising from the characteristics and behaviour of building users. The study investigated the percentage change in total energy consumption across the tested input range of RMY weather data for Kent Town, Adelaide. The result of the Samarakoon and Soebarto (2011) study showed that the most significant influence on energy consumption belongs to the window-to-wall ratio, followed by occupancy profile, equipment usage schedules, thermostat set point, illuminating set point, and occupancy load density”.
Mottillo (2001) was modelled and analysed “10 different types of buildings in multiple Canadian locations with a range of parameters by using the DSA. The analysis showed that the thermal resistance of walls, roof, and fenestration, lighting power density, minimum outdoor air rates, pump type, efficiency of the heating equipment, and temperature setpoint schedules have the largest impact on the predicted energy savings”.

Rasouli et al. (2013) applied “sensitivity analysis to explore the thermal performance for a two-story office building in Chicago, Illinois, USA. The results indicated that the most important factor for HVAC system energy is the ventilation rate”. Demanuele et al. (2010) used “sensitivity analysis to determine the key factors affecting the total energy use in a UK school. It is found that the important variables are related to occupants, such as office and class equipment load and hours of use, heating schedule and set-point temperatures”.

Tian (2013) recommended “the local sensitivity analysis as the simplest method and still very useful in building performance analysis”.

The previous studies concluded that DSA is the preferred method in building performance analysis if the system is linear since both individual and total sensitivities are calculated. In most cases, the assumption of linearity is valid, but it may not hold for some variables (Simm et al., 2011). DSA provides information about the sensitivity of parameters at a single point in the parametric space (Bertagnolio, 2012). DSA does not allow the interaction between parameters to be assessed. However, the differential sensitivity analysis is still very useful even with its shortcomings. This is due to its low computational cost, simple implementation, and easy interpretation (Tian, 2013).

2.10 Regression model analysis

There are a number of approaches that can be applied in a broad range of projects to predict the energy consumption of buildings (Zhao and Magoulès, 2012). Statistical regression modelling is a technique to model and analyse several variables to develop a functional relationship between one or more dependent variable(s) and independent variables. When dealing only with one response variable, the regression analysis is called univariate regression; while when dealing with two or more
response variables, the regression is called multivariate regression (Fumo and Rafe Biswas, 2015). The univariate linear regression analysis attempts to model the relationship among variables by fitting a linear equation to the data. When there is more than one predictor variable (multiple linear regression), the linear fitting is attempted by keeping constant all factors except one of the predictor variables. It should be noted that a relationship between a response variable and a predictor variable does not necessarily imply that the predictor variable causes the response variable. However, there is some significant association between the two variables.

Multiple linear regressions along with ANOVA are most commonly used methods for modelling responses in terms of different independent variables in hard turning applications (Dureja et al., 2014). This technique has shown promising results because of the reasonable accuracy and relatively simple implementation when compared to other methods (Fumo and Rafe Biswas, 2015).

Mottahedi et al. (2015) developed “a multi-linear regression model to predict the effect of building shape on total energy consumption in cold-dry and warm-marine climate regions in the USA. In this study, simplified model combined with building simulation software programs to conduct a parametric study in order to investigate the effect of building parameters on total heating and cooling load. The analysis of energy models showed that there was a strong interaction between building shapes, their locations and level of energy consumptions. It also showed that in cold-dry climate zone the main source of energy consumption was related to space heating while there was not a significant difference between heating and cooling in warm-marine climate zone. It was also envisioned that the developed regression models can be used to estimate the total energy consumption in the early stages of the design when different building schemes and design concepts are being considered.

In another study (Asadi et al., 2014) multiple linear regressions were used to predict energy consumption of commercial building in the relationship between the 17 explanatory variables. Building materials, wall thickness, building shape, and occupant schedule were identified as sensitive design parameters in building energy analysis. Asadi et al. (2014) used a building simulation software to build and simulate individual building configuration by employing the Monte Carlo simulation techniques. The results of the energy simulations from a combination of 17 key
building design variables and 7 building shapes were implemented into a set of regression equations to predict the energy consumption in a different design scenario. The result of the analysis showed a good agreement was seen between the predicted data based on the developed regression model and DOE simulations with a maximum error of 5%.

Catalina et al. (2008) were also developed “multiple regression models to predict heating energy demand based on the main factors that effect on the building's heating energy consumption. This study (Catalina et al., 2008) found that the developed regression model performs well in prediction of future heating energy consumption. The results of this study also indicated that the building global heat loss coefficient, the south equivalent surface, the difference between the indoor setpoint temperature and the solar air temperature have a significant effect on building heating load”. Hygh et al. (2012) was also “developed an energy assessment tool by using a multivariate regression model to quantify energy performance of office buildings in four different cities of USA. This study considered 27 building parameters including size, geometry, and location. The results suggested that a linear regression model can serve as the basis for an effective decision support tool in place of energy simulation models during early design stages”.

Fan et al. (2015) was “established and tested a statistical linear regression model for household energy demand in individual and regional households in Australia. The result of this study showed the reasonable accuracy has happened in forecasting the energy consumption of individual households by using the regression method. This study also summarised models that would be highly useful to understand the potential implications of different choices, forecast the impact of different residential trends and assist households in improving their energy efficiency through targeted policies and programs”.

A review of previous studies proves that the regression analysis is a appropriate statistical method used for development of energy prediction models in buildings. In this research, the linear regression analysis will be applied to the residential sector with a focus on whole-building energy consumption in representative dwelling simulation models. Discussion of this method will be presented in chapter 6.
2.11 Economic analysis

A refurbishment is often designed based on generic indications of retrofit actions without considering the economic feasibility. There have been several publications on energy conservation measures in various types of buildings in the past 30 years. A few of these publications studied the economic dimension of energy saving measures between different refurbishment scenarios (Kellow, 1989, Blok, 2004, Ouyang et al., 2009).

An important role in the economic evaluation of retrofitting project is the balance between costs and benefits of each measure. There are various economic evaluation methods available for economic assessment in building retrofitting. The main indicators to evaluate the economic feasibility of energy efficiency projects are Net Present Value (NPV), the Internal Rate of Return (IRR) and the Payback Period (PP) (Tommerup and Svendsen, 2006, Bernhard, 1992, Marco et al., 2015, Leal et al., 2015).

Nikolaidis et al. (2009) proposed “a variety of energy saving measures in an existing building with specific construction and energy characteristics. This study was also conducted an in-depth economic analysis by using the Net Present Value (NPV), the Internal Rate of Return (IRR), the Savings to Investment Ratio (SIR) and the Depreciated Payback Period (DPP) for the economic evaluation of energy-saving measures. The result of IRR evaluation criterion showed that the upgrading of artificial lighting is the most effective investment which follows by insulation as well as the installation of an automatic temperature control system at the burner – boiler system. The use of solar heaters was economic enough and profitable, contrary to the replacement of windows and door frames and the partial upgrading of heating systems that constituted very low return investments. Results of NPV as an evaluation criterion and a uniform evaluation period showed that the insulation of the roof or the pilotis of the building constitute the most effective interventions. The replacement of windows and door frames are once again very low return investments”.

In another study, Ćuković Ignjatović et al. (2016) presented “a case study of refurbishment and energy efficiency upgrade of a family house in Belgrade. In this
study, three retrofit scenarios were compared in terms of economic evaluation of the refurbishment action based on the relation between investment, energy savings (NPV) and payback period. The result showed that the payback period for the high-efficient retrofit scenario is the longest since it includes more complex improvement measures. However, the immediate payback for the high-efficient retrofit scenario is promising if the increment in value of the property takes into account”.

Doukas et al. (2009) presented “a decision-support model for the identification of the intervention and further evaluation of energy-saving measures in an existing building. This study used the systematic incorporation of energy management system data to analyse the everyday operation of buildings (lighting, heating, cooling, etc.) and evaluate the financial feasibility of energy saving measures lists based on net present value (NPV), internal rate of return and payback period. Results of financial evaluation showed that the installation of lighting's intensity control systems, replacement of existing low-efficiency lamps (e.g. incandescence) with more efficient ones with ballasts, insulation of heat leakage openings and installation of monitoring systems for the measuring and registering of air quality help to improve the performance of buildings”.

Based on a review of the studies, NPV and payback period combined with energy price forecast are selected as appropriate methods for economic analysis and these methods will be employed in Chapter 7 of this study.
2.12 Retrofitting barriers

The implementation of energy retrofit strategies for increasing the energy efficiency of the existing buildings has a significant effect on reducing the total energy demand (Huang et al., 2012, Saidur, 2009, Flourentzou et al., 2002, Ardente et al., 2011, Golić et al., 2011, Alam et al., 2016). However, retrofitting existing buildings for energy efficiency posed a big challenge because it involves substantial funding and decision-making from a wide range of sources such as climate change, services change, human behaviour change, government policy change, etc (Ma et al., 2012).

The success of building retrofit scenarios depend on many issues. Potential barriers against uptake of energy efficient retrofitting have been identified as: Regulatory barrier, Economic barrier, Knowledge barrier or Social barrier (Alam et al., 2016) all of which directly affect retrofit strategies and hence the success of a retrofit project.

There are many building retrofit technologies readily available in the market. However, the decision about retrofit technologies (or measure) for a particular project is a multi-objective optimisation problem subject. Making retrofitting decisions involve constraints and limitations, such as specific building characteristics, total budget available, project target, building services types and efficiency, building fabric, etc. Other challenges may include financial limitations and barriers, perceived long payback periods and interruptions to operations. The willingness of building owners to pay for retrofits is another challenge if there is no financial support from the government. “split incentives” is often a key issue in retrofitting projects. The cost of the retrofit generally falls to building owners while the benefit often flows primarily to the tenants. However, retrofitting of building offers great opportunities for improvement of energy efficiency, occupant satisfaction, reduction of maintenance costs and enhancement of thermal comfort. It also helps to improve a nation's energy security and corporate social responsibility, reduce exposure to energy price volatility and make buildings more liveable (Ma et al., 2012).
Ma et al. (2012) categorised “the key elements that have significant impacts on building retrofits as policies and regulations, client resources and expectations, retrofit technologies, building-specific information, human factors and other uncertainty factors”.

Policies and regulations are energy efficiency standards, which set minimum energy efficiency requirements for retrofitting of existing buildings. Governments may provide financial support and subsidies to assist building owners and developers in achieving the required energy performance targets through implementing energy retrofit measures. Often the range of government programmes available is complex, even within a single jurisdiction.

Client resources and expectations determination are required to achieve project targets and goals. This knowledge of expectation helps to identify which kind of retrofit technologies should be used. Since investment decisions for energy efficiency are quite complex, it is always difficult for clients to decide whether investment in retrofits is worthwhile or no. Based on a survey of one hundred firms, Harris et al. (2000) identified “the factors that influence a firm's decision on investment in energy efficiency. It was found that there are a large number of factors involved and the most widely used decision-making rule is the payback period”.

Retrofit technologies are energy conservation measures (ECMs) used to promote building energy efficiency and sustainability. Retrofit technologies have a range from the use of energy-efficient equipment, advanced controls and renewable energy systems to the changes of energy consumption patterns, and the application of advanced heating and cooling technologies. Retrofit measures should be considered in terms of economic payback, complexity, and ease of implementation (CIBSE, 2004).

The effectiveness of a building retrofit is also dependent on building-specific information, such as geographic location, building type, size, age, occupancy schedule, operation and maintenance, energy sources, utility rate structure, building fabric, services systems, etc. For a particular project, the optimal retrofit solutions should be determined by taking into account building specific information.
Human factors are other important elements that affect the success of building retrofits. Human factors may include comfort requirements, occupancy regimes, management and maintenance, activity, and access to controls (CIBSE, 2004). Several studies (Yohanis, 2012, Owens and Wilhite, 1988) showed that the changes in occupant behaviour, occupant controls, and comfort range can lead to significant energy savings. The energy savings are often achieved with no or low capital investment.

Building retrofits are also affected by many uncertainty factors. A good estimation of uncertainty factors is essential to help select the best retrofit options to maximise building energy efficiency during its whole lifespan.

In order to overcome some of the identified barriers above, there is a range of policies and guidelines with the requirement of reducing emission and energy consumption through existing building retrofiting. However, there is still a lack of a comprehensive guideline outlining to achieve these targets in reality. Therefore, this thesis will offer a decision-making tool for retrofitting the existing residential buildings based on energy and cost efficiency in New South Wales of Australia to overcome the associated retrofitting barriers.

2.13 Chapter summary

This chapter provided a review of the key literature and knowledge relevant to the present project. First, the rationale for building upgrades from an environmental perspective in world and Australia were explored with the capability of existing building improvement solutions. It also included a review of current residential dwelling energy performance in Australia. This literature informed the research questions and the methodology employed to answer these research questions. The necessity of energy retrofit in Australian dwellings was highlighted in the current literature.

An extensive review of previous studies relating to stock modelling was undertaken. The studies highlighted stock modelling methods and effective approaches to select appropriate building retrofitting strategies in terms of cost and energy saving. A Bottom-up stock modelling approach was reviewed and selected as the method for the development of representative dwelling simulation models of
current housing stock in this thesis. Building performance simulation programs reviewed and EnergyPlus engine was selected as an appropriate program. Design of Experiment was introduced with reviewing the similar researches. Taguchi method was utilised for the development of representative dwelling simulation models and creation of energy databases in this research. Differential sensitivity analysis combined with building simulation modelling was explained as the method for identifying the influential retrofitting parameters for this thesis. The chapter also reviewed techniques for development of energy prediction models and economic assessments of retrofitting strategies.

The objective of this research is to create a decision support tool that can be used in designing an energy efficient and economically feasible retrofitting plan for existing dwellings. The proposed decision support tool uses proven retrofit methods to assess the effect of influential envelope parameters on the total energy and cost performance of dwellings.

Most of the previous studies focused on new buildings, and this thesis focuses on designing a cost-benefit decision-making tool for existing dwellings in Australia that are representative of residential building stock.

Chapter 3 presents the research methodology designed to address the research objectives, which have been designed to fill these knowledge gaps.
Chapter 3: Research design

3.1 Introduction

This chapter described the overall design of this research project and the methods used to address the aims and objectives. The detailed information regarding the specific methods employed to meet an individual objective is included in the relevant chapters. In this chapter, the research methodology is explained and the limitations to the scope of this study are defined. The statistical and quantitative data sources that were collected and analysed for insights into the existing building stock in this study are introduced. This study employed a mixed-methods approach (i.e. statistical and qualitative analysis) to facilitate the characterisation of the current building stock.

An outline of the simulation approach that is used to investigate the impact of building variable inputs or envelope attributes/characteristics on the thermal performance of dwellings is presented. In addition, justifications for the selection of the method are provided. This includes a description of the simulation tool, the reference building that was utilised, and the locations studied. A brief description of the method that was used to evaluate the applicability of the energy prediction model in a real building case is also included in this chapter. Fig 3.1 depicts the overall method followed in this research project, showing major methods employed to meet the objectives listed in Chapter 1.
Fig 3.1: Overall research design flowchart, illustrating the mixed-methods approach to the research problem.
3.2 Research scope

Typical construction attributes of the Australian dwelling stock are provided in the first part of the thesis and a set of dwelling designs are developed. A hybrid method that merges statistical and qualitative data sources was used in order to determine the most common typologies and range of construction attributes of existing residential stock. Evaluation of energy conservation options and the associated cost on “representative” building designs have also been utilised to develop a cost-benefit envelope retrofitting strategy framework for a significant part of the Australian residential building stock.

Research in building energy retrofitting involves a wide range of data sources and requires expert knowledge in numerous areas. This research focuses on quantifying the influence of passive building upgrades on the thermal performance of representative dwelling types by using a Building Performance Simulation (BPS) tool. To achieve the aims and the objectives outlined in Chapter 1, the scope of this study is limited in the following ways:

- The study covered the Australian residential buildings built between 1970 to 2000, in accordance with the BCA Class 1 definition and based on ABS data sources. A Class 1A is a single residence that may be a detached house or one or more attached dwellings (ABCB, 2013). The reason for selecting dwellings constructed between 1970 to 2000 was that the major growth happened in the construction of houses in this period while the first introduction of energy efficiency regulations in Australia was in 2003 (HIA, 2003).

- The main data resource of this study is the Australian Bureau of Statistics (ABS), which contained useful building construction attributes information. The ABS data is also not available at address level, but it does cover Statistical Areas Level 1 (SA1s) that are built from whole Mesh Blocks (ABS, 2016).

- The research in this study is focused on the three main climates of New South Wales in Australia.
All retrofit strategies considered were proven as commercially available measures. Consideration was only given to energy efficiency measures. On-site generation, demand response, and power quality strategies were not considered in this study.

This study is limited to consideration of end-use energy efficiency in terms of energy load requirements for heating and cooling purposes that meet pre-specified set-points.

This study just considered required heating and cooling loads to continuously maintain indoor comfort conditions within an acceptable range. Occupant presence patterns for using the heating and cooling at different periods of the day were neglected.

### 3.3 Research methodology

Knowledge of building degradation and obsolescence commonly leads to successful and efficient retrofit scenarios. A successful retrofit or refurbishment scenario for an aged building is a necessary action that elaborates building performance. In this research, feasible retrofit strategies for energy efficiency in the existing dwellings will be assessed by developing a simplified cost-benefit decision-making tool. This study includes several steps and follows a continuous course of procedures for dwellings built in the last decades (1970s, 1980s, 1990s, 2000) in New South Wales (NSW) and whole Australia.

The phases of the followed methodology are summarised in Fig 3.2.

![Research methodology phases](image)

Fig 3.2: Research methodology phases.
Phase one: Definition of the Australian residential building stock typologies (as per Fig 3.2) consists of:

i) Hybrid approach: statistical analysis of building data resources and qualitative analysis of expert opinions that identified the common typologies in the stock with a range of representative construction attributes, as discussed in Section 3.5.

ii) Building performance simulation (BPS) combined with Design of Experiment (Taguchi Method) were used to develop representative dwelling simulation models by identifying the construction attributes that have a significant contribution on the heating and cooling energy demand. The thermal performance of developed models was also investigated. It is described in Section 3.6 and Section 3.7.

Phase two: Investigation of retrofitting solution in developed representative dwelling simulation models involves:

i) Building performance simulation (BPS) was combined with Differential Sensitivity Analysis (DSA), as discussed in Section 3.8, for identifying the most influential building improvement parameters that reduce heating and cooling loads in models.

ii) Design of Experiment (Taguchi method) was used to reduce the total number of required simulations, in order to create the energy database of highly influential parameters. This is to develop simple energy prediction models of representative dwelling types, as explained in Section 3.9.

iii) Building performance simulation (BPS) results were calibrated with experimental data for a specific case study, as explained in Section 3.10, to verify the capability of the methodology designed in this study.

Phase three: Economical analysis includes cost-benefit assessment of retrofitting upgrades, as described in Section 3.11, with providing prediction in capital cost, Net Present Value, and a payback period of selected strategies.

Phase four: An envelope improvement decision-making tool, as shown in Section 3.12, was developed to provide a framework for users to analyse the cost-benefit of a range of retrofitting upgrades through different future fuel price scenarios in a range of dwelling types.
3.4  Analysis of accessible data

Research into the existing building stock is heavily influenced by the data which is readily available to researchers. Thuvander (2002) has shown in Fig 3.3 that building stock data have a number of layers. Data that could be known if there were no constraints (time, money, personnel, etc.) is ‘Achievable’ data. The other type, ‘Existing’ data, is data that has previously been captured. ‘Available’ data is existing data that is in a format that could be used but may not be accessible due to privacy concerns or similar issues. ‘Accessible’ data is available data without restrictions to access and is available in a format compatible with the study.

Fig 3.3: Accessible data is a subset of available, existing and achievable datasets. Various restrictions between each layer hinder research into the existing building stock (Thuvander, 2002).

The key driver of this research project is the poor availability and accessibility of data related to residential buildings and their energy usage in Australia. This study performed analyses of several data sources that are related to the Australian residential industry. Significant effort was made for identification and assessment of all useful existing and available data sources relevant to discussed research questions in Chapter 1. Available data from the ABS housing datasets, in conjunction with other relevant resources, were collected and analysed to determine the common construction attributes/characteristics of the Australian building stock.
3.5 Hybrid assessment of stock dwelling characterisation

One of the main objectives of this research was to provide a better knowledge about the range construction attributes of existing residential stock in Australia. This assessment focused on the development of a number of housing typologies and representative dwelling types that are most prevalent particularly in New South Wales and also in Australia.

To achieve this objective, a hybrid approach has been used, combining the input from the analysis of the data that were extracted from accessible ABS datasets and qualitative assessment from the perspective of experts. This approach was recommended by (Edge Environment, 2012) in a scoping study of current practice to establish dwelling design archetypes. The approach is also consistent with IEA Annex 31 (CMHC, 2001) and the TABULA (IWU, 2014) project approach.

The available data on Australian Bureau of Statistics (ABS) database for Australia and NSW’s housing stock were collected and analysed to determine the common construction attributes of the Australian residential stock from 1970 to 2000. The results are supposed to be used in the potential typologies and representative dwelling simulation model development. The building construction attributes that were extracted from the statistical analysis were used to produce an initial typology outline. This outline adapted as an input in the qualitative assessment work for a housing typology development project (Daly et al., 2016) in NSW. This will be explained in chapter 4. For qualitative assessment purposes, typology development workshops were also run at the SBRC in Wollongong with a range of key stakeholders. The first workshop focused on defining a set of housing typologies based on initial typology outline, and the second was aimed at defining attributes specific to each typology.

Once the typology workshop was completed, the ABS common construction attributes of dwellings were reassessed with the outcome of housing typology definition draft. This was provided for identification of the most common existing typologies and preparation of the detailed matrix of construction attributes to finally develop representative dwelling simulation models in current stock.
NSW housing typology development (Daly et al., 2016) was a project that undertook a program of work in 2015 to determine the main housing typologies existing in NSW. This was part of a broader suite of work supported by the NSW Office of Environment and Heritage (OEH) and UOW. The author was involved in all parts of this project. The outcome of the statistical analysis and initial typology outline from this study was used as an input in typology workshop.

3.5.1 Australian Bureau of Statistics housing database

Australian Bureau of Statistics (ABS) housing database is a comprehensive and accurate available data resource in Australia that was available for this research. There are a number of useful records collected by ABS related to dwellings, many of which have been used in previous studies.

The ABS has collected information on the Australian housing stock through infrequent surveys and census questions. There is little consistency in the characteristics for which information was gathered at each instance, as there are many gaps. The last major Australian survey which was concerned with the energy performance of the housing stock was the 1986 National Energy Survey Household Appliances, Facilities and Insulation (ABS, 1987). The EES study (EES, 2008) provided a comprehensive review of the information collected in the 1986 National Energy Survey, broken down to a state level. Since 1986, there have been a number of surveys that have collected partial information on the existing housing stock. Basic information is generally collected in each census survey, and the ABS has undertaken three sample surveys which collected some information about dwellings. The datasets used in this research are namely:

- Environmental Issues, Energy Use and Conservation (ABS, 2011a) (also conducted in 2008) had a sample of approximately 33,000 dwellings and provided information on the dwelling structure, presence of insulation, source of energy and types of system for heating and cooling.

- The Australian Housing Survey (ABS, 1999) (also conducted in 1994) had a sample of 13,714 households and provided information on the age of building, the main material of outside walls, number of bedrooms, the main material of roof, etc.
- Census of Population and Housing 2011 (ABS, 2011b) (conducts every 5 years) had a survey on 21,727,158 people in Australia on Census night. It contains six separate profiles, Basic Community Profile (BCP), Place of Enumeration Profile (PEP), Aboriginal and Torres Strait Islander Peoples (Indigenous) Profile (IP), Time Series Profile (TSP), Expanded Community Profile (XCP) and the Working Population Profile (WPP), providing information on key Census characteristics relating to persons, families and dwellings.

3.6 Building performance simulation program

The performance assessment software compares the actual or anticipated performance of buildings to explicitly documented criteria for expected performance (Kordjamshidi, 2011). Nowadays Building Performance Simulation (BPS) has been massively improved by advancements in computerised technology. It is possible to design and analyse how efficient building designs are. BPS helps to accurately predict the thermal behaviour of buildings with the use of numerous simulation models by users. A cursory look at the reviews of such simulation models reveals how advantageous they are (Littler, 1982, Clarke, 2001, Al-Homoud, 2001, Kordjamshidi, 2011). One key advantage of using an appropriate computer simulation in providing information about thermal performance is that it requires less time and cost as the accuracy level is the same as a physical experiment.

This research relied heavily on Building Performance Simulation (BPS) in order to develop representative dwelling simulation models, investigate the sensitivity of building energy consumption, develop energy estimation, and assess the cost-benefit of retrofitting strategies. This study utilised a DesignBuilder that is a widely used and accepted tool by the building design and the retrofitting industry. It is a third party graphical user interface for the EnergyPlus thermodynamic simulation engine.

EnergyPlus is a proven BPS tool which is commonly used in the Australian context (Ryan and Sanquist, 2012, Yalcintas, 2008, Asadi et al., 2012). Energy Plus has been used as the energy simulation software in several Australian research projects (Copper and Sproul, 2013, Castleton et al., 2010, Rahman et al., 2010). EnergyPlus was developed by numerous famous developers and has been tested and

DesignBuilder has been also used in many studies in Australia (Chowdhury et al., 2008, Rahman et al., 2010, Rahman et al., 2011), and has been verified with ASHRAE 140-2001 (ASHRAE, 2001b). The use of DesignBuilder simplifies the input of geometric building data into the EnergyPlus engine. There are comprehensive details about DesignBuilder in the program documentation (DesignBuilder Software 2011).

3.6.1 Australian climate zones

Australia is a large continent with a wide range of latitudes from 9° S to 43° S and various climatic conditions that lead to different heating and cooling requirements for different locations. According to ABCB (2016a), there are eight main climate types across the country which are represented by 69 different climate data files from Nathers rating system (NatHERS, 2017). Fig 3.4 exhibits the distribution of eight regions based on temperature and humidity and shows that six of these eight climate types are found in New South Wales. Fig 3.5 shows New South Wales’s climate zones. In the current study, New South Wales, especially the coastal region was considered as the location of the residential buildings. In New South Wales, the majority of existing dwellings are located in the coastal region. The existing building stock is likely to vary across different study locations, due to climate, history and local building practices. Considered locations for this study were geographically diverse, and represented three of the eight climate zones, namely:

- Mascot-BCA zone 5 (warm temperate)
- Nowra-BCA zone 6 (mild temperate)
- Goulburn-BCA zone 7 (cold temperate)
The main general climatic characteristic of zone 5, zone 6 and zone 7 is low diurnal (day/night) temperature range near the coast to high diurnal range inland with distinct seasons. Summer and winter temperature can exceed human comfort range. Hot to very hot summers with moderate humidity in zone 5 and zone 6 and dry in zone 7 are likely to be found. Spring and autumn are ideal for human comfort in zones 5 and 6 while it is variable in zone 7. In winter, zone 5 experiences mild
temperature with low humidity while zone 6 experiences mild to cool and zone 7
cold to very cold temperature with massive rainfalls (DOIIS, 2013).

This study employed “Climate Consultant” software to do some preliminary
analysis of the comfort temperature in climate zone 5, zone 6 and zone 7 by
producing a psychometric chart through the 8760 hours of a year.

Mascot- Zone 5 as warm temperate, Nowra- Zone 6 as moderate and Goulburn-
Zone 7 as a cold area are considered. While Goulburn weather file was not available,
the closest climate zone to this region was Canberra which was selected for analysis
and simulation in this study.

3.6.2 Climate analysis

Hourly weather data in the EnergyPlus (.epw) file format is required for
DesignBuilder. Section 2.7.2 provided a full description of typical weather files. In
the present study, a 12-month weather profile, based on “Meteorological Year
(RMY)” climate files for 2012 from NatHERS, has been used to simulate a typical
year for every climate zone (NIWA, 2012).

In this section, weather files of Mascot-Zone 5, Nowra-Zone 6 and Goulburn-
Zone 7 will be analysed and compared with each other based on ASHRAE standard
55 and the current handbook of fundamental model for thermal comfort. This
analysis has been done to make a better preliminary judgment on NSW climate
zones for both the duration of every season (autumn, winter, spring and summer) and
annually. The ‘Climate Consultant’ software is a graphic-based computer program
that helps to understand local climate. It uses annual 8760-hour EPW format climate
data for the analysis (UCLA, 2016).

The analysis of climatic parameters includes dry-bulb temperature, relative
humidity, and wind. These are shown in Fig 3.6, Fig 3.7, and Fig 3.8 for Mascot,
Nowra and Goulburn, respectively.

According to Fig 3.6a, the analysis of typical weather files shows that the dry-
bulb temperature in Mascot-Zone 5 is rarely below 0 or above 27 centigrade, and it
generally experiences comfort temperature (between 21-27 centigrade) in 35% of the
year. Relative humidity and wind speed are often high in this climate zone. Relative
humidity is over 60% for 80% of the annual hours and wind speed is between 5-9
m/s for around 75% of the time. An analysis of climatic parameters of Nowra-Zone 6 from Fig 3.7 indicates that dry-bulb temperature in this area is between 21 to 27 centigrade just 20% of the time while the rest of the time it is below 21 to zero centigrade. Relative humidity is below 60% for 22% of the annual hours. Despite Mascot-Zone 5, wind speed in Nowra is between 3-5 m/s for 64% of the year. An analysis of dry-bulb temperature for Goulburn-Zone 7 shows that this area experiences temperature between 0-21 centigrade during 83% of the year and a relative humidity of over 60% in 65% of that time. This area has an average wind speed between 3-5 m/s for about 50% of the year.

Fig 3.6: Climatic parameters graphs of Zone 5-Mascot through a year.

Fig 3.7: Climatic parameters graphs of Zone 6-Nowra through a year.
Fig 3.8: Climatic parameters graphs of Zone 7-Goulburn through a year.

The analysis of Psychometric charts for thermal comfort based on climatic design parameters also confirms that the low level of comfort condition in the mentioned three climate zones. Fig 3.9a shows that Mascot-Zone 5 by 1551 hours, Nowra-Zone 6 by 1101 hours and Goulburn-Zone 7 by 1195 hours out of 8760 hours just experience 17.7%, 12.6% and 13.6% indoor comfort temperature throughout the year, respectively. The results of weather file analysis revealed that during a large percentage of a year these climate zones experience discomfort temperature. Hence, improving thermal comfort by employing a range of retrofitting design strategies is necessary for the dwellings in these areas which will discuss in Chapter 6.
Fig 3.9: Psychometric chart of a. Zone 5-Mascot b. Zone6-.Nowra and c. Zone 7-Goulburn climates.

3.7 Representative dwelling simulation models

This study employed Building Performance Simulation (BPS) to investigate a retrofit solution for typical dwellings in current residential stock. One method used to simplify modelling effort and allow generalisation to be made regarding attributes of the building stock under consideration is the use of typologies or representative building models (discussed in Literature Review Section 2.6.2). In the context of this research, a ‘representative dwelling simulation model’ is a theoretical building, which is generally developed to be representative of most common building types in a particular setting. For this research project, representative dwelling simulation models have been developed based on defined common typologies from the conjunction of statistical and qualitative analysis and then retrofitted for three different climate zones in NSW. The use of representative buildings suggests that results were not influenced by the idiosyncrasies of existing buildings and the findings were more likely to be broadly applicable. It does, however, introduce the need to use numerous assumptions and ‘typical’ inputs and remove the possibility of building specific attributes informing the retrofit improvement process. This study primarily utilised a variety of assumption in the process of converting commonly-defined typologies with detailed ABS construction attributes to develop representative dwelling simulation models, as followed and discussed in details in Chapter 5.
- A basic three bedrooms, timber frame detached house plan from NSW government housing provider, was assumed for building configurations (Thomas, 2011). This floor plan can be considered a widely common type of building especially in New South Wales (NSW).

- The floor plan was adjusted to give a window-to-wall ratio (WWR) of 15% and then perturbed to create three floor areas (78 m², 122 m² and 156m²), Original plan geometry has been shown in Figure 3.10.

- The generic plan was modified to reflect the full range of attributes and modelled in three climates of New South Wales in Australia (Climate zone 5, 6 and 7).

- The NatHERS indoor comfort conditions, which vary according to climate zone, time of day, and indoor space type were utilised for this study (NatHERS, 2012). The total heating and cooling demand to keep the internal spaces within the comfortable range for all hours was the output measure considered for this work.

Fig 3.10: a. A basic three bedroom, timber frame detached house plan and b. The 3D view from NSW government housing provider (Thomas, 2011).

Residential building attributes and associated material thermal properties assumptions used for baseline representative dwelling simulation models have been gathered from AIRAH technical handbook (AIRAH, 2013) and presented in Table 3.1.
Table 3.1: A detailed matrix of construction attributes used for development of representative dwelling simulation models. Material thermal properties are sourced from (AIRAH, 2013).

<table>
<thead>
<tr>
<th>Model input factor</th>
<th>Model variable input levels</th>
<th>R-Value (m²K/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>Detached</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Brick veneer</td>
<td>0.534</td>
</tr>
<tr>
<td></td>
<td>Double brick</td>
<td>0.679</td>
</tr>
<tr>
<td></td>
<td>Fibro</td>
<td>0.437</td>
</tr>
<tr>
<td>External wall</td>
<td>Gypsum board</td>
<td>0.319</td>
</tr>
<tr>
<td>Floor</td>
<td>Slab on Ground</td>
<td>0.287</td>
</tr>
<tr>
<td></td>
<td>Suspended Timber</td>
<td>0.439</td>
</tr>
<tr>
<td>Roof</td>
<td>Steel sheet</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>Clay Tile</td>
<td>0.370</td>
</tr>
<tr>
<td>Ceiling</td>
<td>Gypsum board no insulation</td>
<td>0.347</td>
</tr>
<tr>
<td></td>
<td>Gypsum board With poor</td>
<td>1.34</td>
</tr>
<tr>
<td></td>
<td>insulation</td>
<td></td>
</tr>
<tr>
<td>Floor area</td>
<td>78 m²-122 m²-156m²</td>
<td></td>
</tr>
<tr>
<td>Bedrooms</td>
<td>Two-Three</td>
<td></td>
</tr>
<tr>
<td>Airtightness</td>
<td>Poor-Medium</td>
<td></td>
</tr>
<tr>
<td>Orientation</td>
<td>North-East-South West</td>
<td></td>
</tr>
<tr>
<td>Window to Wall ratio</td>
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<td></td>
</tr>
<tr>
<td>Glazing</td>
<td>Single glazed</td>
<td>-</td>
</tr>
<tr>
<td>NatHERS Climates</td>
<td>5/6/7</td>
<td></td>
</tr>
<tr>
<td>Thermostat setting</td>
<td>Winter 20°C- Summer 24.5°C</td>
<td></td>
</tr>
<tr>
<td>COP</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Occupants</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Energy supply</td>
<td>Electricity</td>
<td></td>
</tr>
</tbody>
</table>

3.7.1 Taguchi method

In this study, a major barrier to the use of ABS data in typologies is the inability to access data at the property address level, due to privacy concerns. This prevents the consideration of cross-correlation and clusters of multiple attributes for particular buildings. Therefore, for the purposes of stock level energy performance modelling based on ABS data, a model which represents each unique set of potential building configurations should be created to represent the full range of construction types (attribute matrix) as discussed in Section 3.7. However, this process would result in a large number of building simulation models. By recognising that certain construction attributes will have less significant effects on performance, the total number of representative dwelling simulation models can be reduced. To cut down the total number of simulation models and to prioritise the attributes for representative simulation models, principles from the Design of Experiment (Taguchi method) has been used.

The Taguchi mix-mode design method was used to reduce the required model runs. This method uses a fractional factorial order layout, termed Orthogonal Arrays (OA) (Yang and Tarng, 1998) to reduce the number of simulations required for
exploring the influence of building model attributes in the representative models. The selection of an appropriate OA depends on the number of attributes and their levels, i.e. the number of building parameters and their possible values. To ensure accurate analysis (Sadeghifam et al., 2015), important variables such as size, orientation, and climatic data had been considered in design attributes.

Applying the Taguchi method allowed factors to be weighted equally and assessed independently of all other factors (Minitab Statistical Software Support, 2016c). The Taguchi method applies the signal-to-noise ratio (S/N); i.e. a measure of robustness, to minimise the effect of noise and to optimise the performance process (Zahraee et al., 2015). In this study, the delta S/N ratio; that is the difference between the maximum and minimum average signal-to-noise ratios of the attributes level, was used to determine the relative similarity of the building attribute levels. ANOVA was also performed in order to determine the contribution of each attribute to the total model energy demand.

Signal to noise (SNR) ratio has been calculated by using Equation 3.1 and Equation 3.2.

\[ \text{SNR} = \frac{P_{\text{signal}}}{P_{\text{noise}}} = \frac{\mu}{\sigma} \quad (3.1) \]

Where \( \mu \) is the signal mean or expected value and \( \sigma \) is the standard deviation calculation of the noise.

Or

\[ z = -10 \log \left( \frac{\sum_{i=0}^{n}Y_i^2}{n} \right) \quad (3.2) \]

In the above formula, \( n \) is a number of values in each experimental conditions and \( Y_i \) is each observed value.

By this method, significant construction attributes can be prioritised and the representative dwelling simulation models can be developed. Minitab statistical software has been used for running the analysis in this research. Minitab is well-known for its ease of use in statistical analysis (Minitab Statistical Software Support, 2016d).


3.8 Differential sensitivity analysis method

Sensitivity Analysis is a commonly used tool in building energy research to determine the key factors. However, it does not have a well-defined or generally accepted procedure/process (Lam et al., 1997). Individual studies employing sensitivity analysis methods have highlighted Differential Sensitivity Analysis as the preferred technique for research into building energy use. By the same token, Differential Sensitivity Analysis (DSA) was a key analysis tool employed in this research. Previous studies (Thomas, 2011, Bertagnolio, 2012, Daly et al., 2014) identified non-dimensional influence coefficients as a useful index for building sensitivity studies and preferred technique for research into building energy use. A detailed description of the applied DSA method is included in Chapter 6.

The generic DSA method followed for this study was consistent with previous work in this field (Molinari, 2012, Simm et al., 2011) and is summarised as below:

- Define a building configuration with parameters set at the most likely base case values;
- Assign minimum and maximum values for each parameter of interest;
- Simulate the building in the base case configuration;
- Simulate the building and vary each parameter of interest from its minimum to maximum value, while it keeps all other parameters constant at their base case values;
- Analyse the results, and obtain sensitivity indices for each parameter of interest;

This study calculated the non-dimensional influence coefficient for use as a comparison index in sensitivity analyses. The general equation for this influence coefficient is shown in Equation 3.3.

\[
\text{Influence Coefficient} = \frac{\Delta OP}{\Delta IP} = \frac{\% \text{ Change in output}}{\% \text{ Change in input}} \quad (3.3)
\]

Where \( \Delta IP \) and \( \Delta OP \) are the changes in input and output parameters, respectively; \( IP_{bc} \), \( OP_{bc} \) are the base case values for output and input, respectively.
The base-case design parameters and the range of variation were determined with reference to: Section J of the Building Code of Australia (ABCB, 2015); the default values included in AIRAH guides (AIRAH, 2013); market products; and previously published input values from Australian studies (Branz Ltd, 2014, Tony isaacs consulting, 2009, Belusko and Timothy, 2011, DOIIS, 2013). The developed ABS representative dwelling simulation models were first simulated using the base-case inputs, and then the parameters of interest were changed one at a time while holding all the other parameters constant, for three climate zones in NSW. The total building energy requirement load for each case and the average influence coefficient across each parameter range were then calculated and presented in Section 6.3.1.

3.9 Energy prediction model development

“Regression analysis is a statistical technique used to relate variables” (Bowerman and O'Connell's, 1990). The chief goal of conducting a regression analysis is to “build a mathematical model that relates a dependent variable to independent variable(s). Regression analysis was found to be an efficient and beneficial method for developing energy prediction equations from the results of building energy simulation” (Catalina et al., 2008, Sam 2013, Selkowitz, 1985, Misuriello and Fireovid, 1989, Chou et al., 1993, Wilcox, 1991). This technique helps to predict one variable based on the knowledge of the other variable. Regression analysis, or more precisely multiple ‘linear’ regression analysis “is a way to relate the building energy performance to many design variables in the simulation input using a linear form of the equation.

The present study is concerned with the development of linear regression models to predict the yearly energy demand (heating and cooling) for representative dwelling simulation models in three climates in NSW.

In this study, a parametric study was employed by using the Designbuilder building energy simulation program. The goal was to obtain simplified energy equations that relate six major design parameters in representative dwelling simulation models. However, if the number of design parameters is high, a high number of simulations would be required to generate the data for the regression model (Sam 2013). To tackle this problem, Taguchi fractional factorial order layout
was again proposed for each dwelling type in every climate to reduce the required number of simulation for creating the database of the simplified regression model development in this study.

The general form of energy equation that has been used in this study is shown in Equation 3.4:

\[
E = K + (a \text{ Parameter } 1) + (\beta \text{ Parameter } 2) + (Y \text{ Parameter } n) \quad (3.4)
\]

Where \( E \) = total annual heating and cooling and \( K \) = regression constant

Multicollinearity between variables has been also considered with using the variance inflation factor (VIF). The VIF evaluates the degree to which the variance of an estimated regression coefficient raises the given correlating parameters (Martz, 2013). Moreover, the main parameters were selected from a Differential Sensitivity Analysis, as described in Section 6.3.1 and their wide ranges were taken from different available resources (Branz Ltd, 2014, Tony isaacs consulting, 2009, Belusko and Timothy, 2011, DOIIS, 2013).

3.9.1 Regression model evaluation

In this study, to evaluate the accuracy of developed regression models, an independent group of simulation results was considered. Thirty-five simulation runs have been undertaken for each model in three climates and results were compared with regression model prediction. In a random numerical experiment, the random number generator in Microsoft Excel helped to produce six sets of input design parameters to be used for simulations. Those randomly generated input variables which aided to develop a number of different simulation models were not dependent upon any of the variables that were used to develop regression models databases. They have been set against the results of the regression models.

3.10 Method validation

Method validation process was designed to evaluate the reliability of estimation model in the real world. To achieve this target, Solar Decathlon House (IFH, 2014) simulation model was used as a case study to evaluate the accuracy of energy prediction model in the existing house. In this process, a methodology that was used for developing the energy regression models in representative dwelling types has
been re-applied in the existing highly efficient house. It was prepared to examine the validity of applied energy retrofitting method in this study. To evaluate the reliability of the method, firstly, energy model of Solar Decathlon House (SD) (IFH, 2014) has been created in DesignBuilder and simple energy prediction model of it obtained. Energy simulation model of Solar Decathlon House (SD) has been calibrated with recorded temperature data for a short period. A calibrated simulation model was implemented as a case study to calculate the annual heating and cooling energy requirement demand of a house in Mascot climate. Series of independent simulations outcomes (annual heating and cooling demand outcome) were compared with the outcomes of similar regression model prediction to investigate the method reliability.

In this work, the annual energy demand of a calibrated model from simulation aided to estimate the reliability of the developed regression models.

### 3.10.1 Energy prediction model development

In this study, Solar Decathlon House (SD) case study was selected because it was available to the author to validate the method of this study. This house was the winner of Solar Decathlon House competition in China in 2013 and is located in Innovation campus of University of Wollongong (IFH, 2014).

The simulation model of the house was developed in DesignBuilder program based on real construction characteristics provided by the documentation of the Solar Decathlon House (IFH, 2014). The goal was to obtain a simplified energy equation that predicts the energy demand of the case study by varying five different parameters, as would be explained in Chapter 6. This regression model development follows the same procedure as one of the developing regression models for the representative dwelling simulation models in this study (Section 3.9 and Chapter 6).

To reduce the number of simulation models in creating the Solar Decathlon House simulation database, the Taguchi fractional factorial order layout was again proposed in Mascot climate. The simplified regression model for predicting the energy requirements for heating and cooling of the Solar Decathlon House (SD) was developed.

The general form of energy equation that has been used in this study is shown in Equation 3.4.
3.10.2 Calibration of energy simulation model

In order to verify the developed regression model method and evaluate the building energy simulation skill of the researcher (author) in producing accurate simulation energy models, a calibrated simulation model was required.

Graphical comparison between computational results and experimental data is a common validation method in a simulation work and “If the computational results ‘generally agree’ with the experimental data, the computational results are declared ‘validated’ (Baharvand and Hamdan Bin Ahmad, 2013).

In this study, a free running air temperature of the Solar Decathlon House (SD) simulation model was created and the results were compared with the recorded experimental data for a similar period.

To investigate the match between the simulated and measured temperatures, the Mean Bias Error (MBE) and the Cumulative Variation of Root Mean Squared Error (CVRMSE\textsubscript{hourly}) were used (Raftery et al., 2011).

3.10.3 Method verification

To determine the reliability of the developed regression model in predicting the energy performance of the Solar Decathlon House, an independent set of simulation results from the calibrated model was used to verify the predictions of its regression model. Several simulation runs have been undertaken for the Solar Decathlon House model in Mascot climate. The random number generator in Microsoft Excel was used to generate sets of input design parameters for simulations. The randomly generated input variables were used to develop a new set of simulation models. The results of simulation models were compared with the outcomes of the regression model predictions to assess the reliability of designed methodology.

3.11 Cost evaluation

Quality and cost estimation could be necessary for any project to successfully obtain defined scopes (Cleopatra Enterprise, 2016). Accumulating benefits is a long-term occurrence; however, evaluating the required capital cost in the initial years and rendering the effects of an investment in financial terms are also essential.
In this work, a cost-benefit analysis has been used which is a systematic approach to evaluate economic weaknesses (costs) and strengths (benefits) of investment alternatives in order to enable a cost-effective retrofitting for a range of dwelling types. Typically, a “Base Case” is developed and its performance is compared and contrasted against one or more improvement alternatives that show a high degree of improvement over the base case. The cost-benefit analysis assesses the incremental variations that happen before retrofitting and after retrofitting made to dwelling models in terms of:

a) Initial investment cost
b) Energy and cost saving
c) Payback period
d) Net Present Value (NPV)

Due to the sensitivity of cost data in the building industry, the access to such data in the public sphere is cumbersome (Morrissey and Horne, 2011). However, uncertainty in cost data leads to coordination and communication issues that cause varying accounts of costs and values (Elhag et al., 2005, Akinsola et al., 1997).

In this research, individual retrofitting option prices were reviewed, extracted and recorded from a variety of resources in Australia such as Rawlinsons Construction Handbook (Rawlinsons, 2015), Cordell Housing Cost Guide (Corelogic, 2016), and other available market suppliers (knauf insulation, 2016).

Cordell Housing Building Cost Guide is a real-time data and business tools for a building and construction industry which delivers sales leads, market intelligence as well as fast and accurate estimation. Cordell remains a connoisseur when it comes to construction costs since 1969. With over 250 pages in length, Cordell’s construction cost guideline includes 41 trade categories with supply and fix prices for more than 6,000 items. Rawlinsons Construction Handbook is yet another essential reference book that provides an elaborate building cost source that embraces all sections of the building industry.

In addition, due to lack of resources with regard to costs for airtightness improvements during building retrofitting, the relative impact of different draught sealing measures from Draught Sealing Retrofit Trial report (Sustainability Victoria,
2015) has been used to calculate the cost of airtightness improvement in this research.

The retrofitting options were compared together in every model in terms of required capital cost, the payback period and Net present value (NPV) with different future fuel price scenarios.

Optimistic, neutral and pessimistic electricity price scenarios were developed to provide better prediction in the cost-benefit calculation of retrofitting options. Future energy price trends have been defined based on published studies that did extensive modelling on future energy price outlooks for Australia (Jacobs Australia Pty Limited, 2016, Economics, 2015).

The Payback Period and Net Present Value (NPV) methods are utilised to evaluate and assess the cost evaluation of energy saving measures (Nikolaidis et al., 2009). The NPV sums the discounted cash flows; it simultaneously merges and converts money (e.g. incomes, expenses, etc.) from different periods. Equation 3.5 is the formula for the “determination of the NPV:

\[ NPV = -C_0 + \sum_{t=1}^{n} \frac{F_t}{(1+p)^t} = 0 \] (3.5)

where \( t \) is the time period, usually a year, \( F_t \) is the net cash flow for a year \( t \), i.e. \( F_t = B_t - C_t \), \( B_t \) the benefit (inflows) for a year \( t \), \( C_t \) the cost (outflows) for a year \( t \); the value \( C_0 \) reflects the initial investment, \( p \) the cost of capital, and \( n \) is the number of years for investment lifespan or, differently, the number of years for which the economic evaluation is requested”.

Payback period “constitutes a variant of the determination of the payback period of the initial investment \( C_0 \). This method determines the number of time periods (usually years) that are required until an investor recovers the initial outflow \( C_0 \) of an investment. This happens through net cash flows \( F_t \) that is expected as a result of this investment. However, this method is unable to measure directly the “value” of an investment; it simply aims at measuring the time that is required for the recovery of the initial outflow of a particular investment. According to DPP, the present value of the expected net cash flows \( F_t \) is calculated based on the cost of capital \( p \), and then
set equal to the initial investment $C_0$. The depreciated payback period is given by Equation (3.6):

$$DPP = \frac{-\ln\left(1-\frac{p_c a}{F_t}\right)}{\ln(1+p)}$$  \hspace{1cm} (3.6)

Where it is assumed that the net cash flows $F_t$ remain constant for every $t$.

Cost evaluation has been estimated as the cost-benefit of retrofitting options on the range dwelling types.

### 3.12 Decision-making tool

Modern simulation tools have powerful features that make quantifying the integrated performance of a building possible. However, these tools are not easy to use for everyone, in particular homeowners who seek to make informed decisions about house improvement. This issue increases the importance of having a housing retrofit evaluation framework that provides simple and easy assessment tool.

In the present study, a decision-making tool was made in MS-Excel (using VBA) by way of forming regression equations that describe the annual energy requirements and cost-benefit evaluation as a function of the tool, as described in Chapter 7.

The cost-benefit evaluation of a dwelling has a three-stage process:

a) Assessment of current performance

b) Selection of upgrading scenario

c) Cost-benefit assessment

Cost-benefit analysis of a range of dwelling attributes can be assessed by combining high influential parameters in the proposed tool. The parameters include window types, level of floor insulation, level of wall insulation, level of ceiling insulation, airtightness level and window to wall ratio. In total, the tool includes 15625 ($5^6$) potential design combination and associated cost of them. This means that whether or not a certain possible house design exists or is planned among representative dwelling types, it will conform to a unique combination of six parameters and is possible to be analysed for cost-benefit in this tool.
3.13 Methodology steps

I. Collect and investigate construction attributes of Australian dwelling stock and their changes from the 1970s, 1980s and 1990s through Australian Bureau of Statistics (ABS) Census of Population and Housing, City Profile and BCA resources (Section 3.5).

II. Statistically analyse the historical data in order to identify the main construction attributes of existing dwellings in the last decade’s 1970, 1980, 1990 and 2000. (i.e. types, structure, households composition, size, floor area, construction frame, building fabric, roof, floor, windows, external shadings, insulation, external walls) (Section 3.5).

III. Prepare the initial typology outline based on common attributes of statistical analysis (Section 3.5).

IV. Run the workshop to discuss the developed potential typologies and focus on defining a set of housing typologies that could be used to represent the housing stock (Section 3.5).

V. Augment the results of ABS analysis with the outcome of the workshop for identifying the most common typologies in the existing residential stock and developing a detailed matrix of construction attributes which represent the characteristics of each defined typology (Section 3.5).

VI. Develop representative energy simulation models of proposed common typologies and reduce the total number of models by employing Taguchi and ANOVA methods combined with BPS. Those methods help to identify the significant attributes for a given building geometry and aggregate the construction attributes based on their percentage of contribution (Section 3.6) and (Section 3.7).

VII. Identify the influential improvement design parameters by conducting Differential Sensitivity Analysis (one factor at a time) with minimum and maximum possible value in representative dwelling simulation models. The average Influence Coefficient (IC) across each parameter range on all
proposed representative dwelling simulation models was also calculated (Section 3.8).

VIII. Develop energy estimation models to predict the energy performance of various dwelling types, analyse the optional retrofitting improvement packages by running the analysis of high influential improvement designs with combining Taguchi, ANOVA and BPS methods (Section 3.9).

IX. Validate the designed methodology by applying the energy prediction development method in a case study and verify it with the results of a calibrated building performance simulation (BPS) model (Section 3.10).

X. Cost-benefit analysis of retrofitting upgrades is undertaken by quantifying the Net Present Value, and the payback period of retrofitting strategies by considering different future fuel price scenarios (Section 3.11).

XI. Develop a decision-making tool to assist homeowners to estimate the energy performance of their home and analyse improvement strategies which include prediction of future energy performance, investment budget and cost saving analysis (Section 3.12).

3.14 Chapter summary

This chapter has presented an overview of the tools used and the method followed in this research project to achieve the specific aims and objectives outlined in Section 1.2. The scope of the research has been defined, along with the locations considered in this study. The sources of accessible data for this research were outlined, and the general analysis techniques were defined. The BPS tool and general methods were introduced, to be further refined in the relevant chapters. Details of the quantitative and qualitative research methods used to investigate the current New South Wales (NSW) and Australia residential dwelling typologies and representative dwelling simulation models were also given. Chapter 4 presents the findings from the analysis of accessible data sources and the qualitative investigation for the development of common typologies in Australian building stock. Subsequent chapters present further details on the specific methods employed and the results and discussion of the original research findings.
Chapter 4: Quantitative and qualitative characterisation of Australian residential dwelling stock

4.1 Introduction

An objective of this study was to characterise the current state of the existing residential building stock in Australia, with the purpose of assessing the potential for energy savings through building retrofitting. Whilst this objective was addressed, to some degree, through the review of the existing literature, there remained significant gaps regarding the physical attributes of the existing building stock and the implications for building energy consumption and retrofitting potential.

This chapter presents the results of a series of activities that explored the physical attributes of Australian housing stock. Several accessible datasets were first analysed to provide an overview of the construction attributes existing in Australian housing and they were then summarised as a typology outline. As a part of a related project (Daly et al., 2016), a qualitative investigation into the common building types in NSW was undertaken. Daly et al. (2016) reviewed the developed initial typology outline from this study and then proposed a set of typologies definition for the NSW housing stock based on the feedback collected from a range of experts in NSW housing sector. The current author further extended the draft typologies defined as a part of the (Daly et al., 2016) project, on the basis of statistical analysis of existing datasets. This resulted in identifying the common existence typologies and development of a detailed matrix of construction attributes which will be presented in this chapter. The matrix of construction attributes was then used to inform the development of representative dwelling energy simulation models, described in Chapter 5 and Chapter 6.
4.2 Method

In this study, the range of common construction attributes in the Australian residential stock was explored. Also, a detailed matrix of common construction attributes and a set of common stock typologies were developed too. A hybrid approach was employed to define the typologies. This approach combined the output of data from statistical analysis of accessible databases and a qualitative assessment from experts and practitioners working in NSW residential energy-efficiency and building sector. The most common building attributes were combined with building typologies to produce a set of ‘representative’ dwelling designs. Part of the work presented in Section 4.4 of this chapter was undertaken as part of the Daly et al. (2016) project, in which the current author was a team member.

An extensive review of the information contained within accessible databases relating to Australian housing stock was undertaken. The key data from Australian Bureau of Statistics (ABS) database for the Australian housing stock were collected and analysed.

An initial typology outline was digested by using the results of the ABS database analysis. As part of the Daly et al. (2016), a formal process was then initiated to engage experts and practitioners to access their knowledge and opinions and to explore the validity and usefulness of the developed typology outline through a forum. The forum was held on the 13th of November 2015 at the Sustainable Buildings Research Centre (SBRC) in Wollongong. Once the workshop outcomes were processed, the results were augmented with the most common dwellings attributes, identified through an analysis of the ABS databases in this study. A matrix of construction attributes was then developed. This matrix represents the detailed attributes of defined common typologies and was used to determine the required number of representative dwelling types for the current market. The process followed in this chapter is shown in Fig 4.1.
4.3 Statistical analysis of housing databases

Substantial effort was made on the identification of possible data sources to improve knowledge of the energy performance of the Australian residential building stock, particularly the existing dwelling stock.

Previously, Safadi M (2016) identified a substantial number of Australian datasets from various agencies and determined which building attributes (if any) were held in each dataset. The result of Safadi M (2016) gap analysis identified significant shortcomings in the accessible datasets, with several key building attributes having minimal or no coverage within the datasets.
Several identified databases were potentially useful, but access to suggested data was not provided or has data quality and format issues to this thesis (Safadi M, 2016). The Building Sustainability Index (BASIX) database, contained a significant number of available attributes and records, was temporally limited to new buildings (post-2005). The Australian Building Sustainability Assessors (ABSA) database was also identified as potential source includes a survey and analysis of the house designs from high-volume builders. However, the database was limited temporally and the full database contained records from 2005 to 2012.

The Australian Bureau of Statistics (ABS) database contained main useful attribute information. It was an only available and one of the best accessible sources that provides insights into the current state of the Australian residential building attributes at the time of writing.

Australian Bureau of Statistics (ABS) database is a comprehensive and accurate available data resource in Australia. Several useful datasets or surveys which were related to dwellings and collected by Australian Bureau of Statistics (ABS), were used in this study. The major issue with ABS data is cross-correlation and that clusters of multiple attributes for particular buildings cannot be developed because it is extremely difficult to get access to data at the property address level. For example, the ABS does not aggregate wall construction type by floor type or insulation presence by wall construction type. Whilst the ABS database had significant limitations, it was appropriate for the scope of this research. The ABS grouped dwellings into a range of categories based on the dwelling construction attributes, and also provided high-level data into the Australian housing stock.

The ABS has collected information on the Australian housing stock through surveys and census questions. Details of ABS databases were provided in Section 3.5.1. In this study, data for dwelling structure, number of bedrooms, household composition, household tenure and wall materials were taken from 1976 and 1986 Census of Population and Housing (ABS, 1976,1986), the 1994 and 1999 Australian Housing Survey (ABS, 1999) and the 2011 Environmental Issues: Energy Use and Conservation survey (ABS, 2011a). Data for roof materials and frame system were gathered from 1994 and 1999 Australian Housing Survey (ABS, 1999); also data for Insulation and energy system details were taken from the 2008 and 2011

The following section presents the information and analysis of the Australian housing stock which was collected from ABS data sources. A summary of the information is provided in the conclusion of Section 4.3.1.4.

4.3.1 Australian Bureau of Statistics housing database

The ABS data does provide some high-level insights into the Australia and NSW housing stock. This section includes characteristics of existing dwellings in Australia and NSW, mainly built during the 70s, 80s, 90s and 2011s. The main housing characteristics analysed in this study are categorised as either:

- Construction Details
- Construction Materials
- Energy system details

Details of each category are presented in Table 4.1 and discussed in the following sections.

Table 4.1: Australian housing characteristic parameters.

<table>
<thead>
<tr>
<th>Construction details</th>
<th>Construction materials</th>
<th>Energy system details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dwelling Type &amp; Structure (e.g: Separate house, Medium density..)</td>
<td>Roof system (e.g: Metal and Tile).</td>
<td>Source of fuel (e.g: Electricity, Gas..)</td>
</tr>
<tr>
<td>Number of bedrooms (e.g: three, two..)</td>
<td>Floor system (e.g: Suspended Timber and Slab On Ground).</td>
<td>Heating and Cooling systems (e.g: Reverse cycle, Electric devices..).</td>
</tr>
<tr>
<td>Floor area (e.g: Occupied Residential Floor Areas)</td>
<td>Frame system (e.g: Steel, Timber ..).</td>
<td></td>
</tr>
<tr>
<td>Nature of occupancy (e.g: Rent, Mortgage and Fully owned)</td>
<td>Wall system (e.g: Brick Veneer, Double Brick, Timber..).</td>
<td></td>
</tr>
<tr>
<td>Household composition (e.g: Group, Single and Family)</td>
<td>Insulation (e.g: Insulation Place).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Window system (e.g: Double glazed, Tinted glazed...).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Window area</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Infiltration</td>
<td></td>
</tr>
</tbody>
</table>

4.3.1.1 Construction details

Dwelling type and structure

Dwelling Type is an important determinant of a residential building energy performance. The total number of residential buildings (occupied and unoccupied) has increased from 4,593,264 to 9,138,000 in Australia and from 1,651,961 to 2,871,000 in NSW between 1975 and 2011; however, approximately 10% of properties are vacant in both areas. The majority of the dwellings (over 78% and
92% in Australia and NSW) were constructed between 1976 and 1996. The total proportion of Medium and High-density dwellings have gradually increased during the survey years. However, the category of the separate house constitutes the vast majority of dwelling (roughly 70%) in all decades. The separate houses are the most common dwelling structures in Australia and New South Wales (NSW), with the proportion of 73% in Australia and 68% in NSW for 2011. This is shown in Fig 4.2.

![Figure 4.2: Australian and New South Wales dwelling types; adopted from (ABS, 1976, ABS, 1986, ABS, 2008, ABS, 2011a).](image)

The utilised definition of ABS predominant dwelling types (ABS, 2014) is summarised in Table 4.2.

<table>
<thead>
<tr>
<th>Separate house</th>
<th>All free-standing dwellings separated from neighboring dwellings by a gap of at least half a meter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium Density</td>
<td>All semi-detached, row, terrace, townhouses and villa units, plus flats and apartments in blocks of 1 or 2 storeys, and flats attached to houses.</td>
</tr>
<tr>
<td>High Density</td>
<td>All flats and apartments in 3 storey and larger blocks</td>
</tr>
<tr>
<td>Caravans, cabin, houseboat</td>
<td>All such mobile accommodation, both inside and outside caravan parks (including caravans in private backyards).</td>
</tr>
<tr>
<td>Others</td>
<td>Houses and flats attached to shops or offices, and improvised homes, tents and sleepers out on Census night.</td>
</tr>
</tbody>
</table>

**Number of bedrooms and floor area**

The ABS data (1976-2011) shows that dwellings with three bedrooms have the highest number and domination percentage in all decades. While the proportion of ‘four and more bedrooms dwelling’ has increased from 13% and 15% to 25% and 26% in NSW and Australia respectively, the proportion of ‘three bedroom dwellings’ has decreased from 41% to 38% in NSW and from 45% to 37% in Australia during the period of 1976 to 2011. This shows an increase in the average floor in recent
decades from 1976 to 2011. Three bedroom dwellings continue to be the most common dwellings in stock, making 38% of total dwellings in NSW and 37% in Australia in 2011. The details of dwellings bedrooms are shown in Fig 4.3.

The total area of residential buildings has significantly increased in both NSW (by 100%) and Australia (by 125%) between 1986 and 2011, as shown in Fig 4.4. ABS (2005) also reported that the average floor area of new residential buildings in Australia has increased by 37.4% (from 149.7 m² to 205.7 m²) between 1984-95 and 2002-03.

This reveals that an increase in the number of dwellings and a growth in average dwelling floor size (ABS, 2010b) have happened over the past decades in Australia.


Fig 4.4: Estimated total occupied residential floor areas (DEHWA, 2008).
Household composition and housing tenure

In Australia, there is a diverse range of household living arrangement. To simplify this analysis, households were classified into three main types: Family households, Group households, and Single occupant households. The proportion of single shared households had increased on the period from 1986 to 2011 and constituted 23% and 22% of all households in Australia and New South Wales, respectively. Whilst the proportion of family households decreased in the census year (76, 86, 96 and 2011), the total number increased over the same period, as shown in Fig 4.5. Family households in Australia increased by 35% and in New South Wales by 25% from 1976 to 2011. The main household type was consistently family household, making roughly 65% to 70% of all households from 1986 till 2011 in both NSW and Australia.

The results of housing tenure refer to the status of occupancy in houses is shown in Fig 4.6. The breakdown of tenure types shows that 42% of dwellings in NSW were fully owned, 30% were rented and 23% were with a mortgage from 1986 to 1996. This was similar to the proportion for the whole Australian stock (41%, 29% and 26%, respectively). However, the proportion of fully owned and renting tenure types decreased to 32% and 29% in NSW and 31% and 29% in Australia, while mortgage increased to 32% and 33%, respectively. It presents that approximately two-thirds of occupancy tenures in both NSW and Australia are owners and mortgage tenancies from 1986 to 2011.


### 4.3.1.2 Construction materials

Numerous materials have been used in dwelling constructions in Australia and New South Wales in recent decades. In the following sections, the data are provided and discussed with respect to dwelling construction materials used for the main elements of a dwelling from the Australian Census, Australian Bureau of Statics (ABS, 1976, 1986, ABS, 1999, ABS, 2011a):

#### Roof system

The most common roof materials used in Australian dwellings are “Tiles” and “Metal sheeting”. The ABS (1999) shows that Tiles and Metal sheeting were the primary roof materials by the proportion of 62% and 32% in Australia, and 71% and 22% in NSW, respectively. Typical recent detached houses (single and two-storey) have a ceiling height of 2.4 meters and older dwellings were typically 2.4 to 3 meters high (DEHWA, 2008). Fig 4.7 shows the percentage of different roof materials in Australia and NSW.
RMIT University report (Wong, 2013), while analysing dwelling designs to represent the most typical characteristics of recent residential buildings, found that the most common roof eave width for a detached dwelling is between 450 mm to 600 mm length in Australia. However, roof colour depends largely on the dwelling climate. For example, dwellings in colder climates use a darker roof colour compared to the ones in hotter climates.

**Frame and floor system**

The analysis of construction format of building frames, presented in Fig 4.8, indicates that a large percentage of Australian dwellings (60%) used timber/wood material (ABS, 1999) to build up their frame in 1999. Although there is limited data regarding floor materials of the dwellings in the ABS database, several resources have identified suspended timber and slab on ground as the main floor types in NSW and Australia (DEHWA, 2008, Wong, 2013).
Wall system

With regard to external wall material, ABS census data (2011) shows that the number of dwellings with brick veneer and double brick materials increased by 140% and 400% in Australia from 1976 to 2011. These numbers for dwellings with brick veneer and double brick materials in NSW are 135% and 215%, respectively for the similar period. The proportion of NSW houses with brick veneer reached 41% and with double brick reached 29% in the census of 2011. This was similar to the proportion of whole Australian stock (41% and 25% respectively).

The total proportion of dwellings constructed with brick veneer and double brick increased from 45% in the 70s to 65% and to 70% in Australia and NSW in 2011, respectively. The most common wall materials were subsequently fibro and timber at a similar time. Fig 4.9 shows the variety of Australian and NSW dwelling wall materials.


Insulation

Insulation of dwellings has changed substantially in Australia since 1987. Insulation installation has been encouraged by former state and federal governments. As a part of the Nation Building Economic Stimulus Plan starting in 2009, Australian federal government a Home Insulation Program under the Energy Efficient Homes Package, provided rebates to owners and renters to install insulation in dwellings up until February 2010 (ABS, 2009b).

Information about the insulation level in Australian dwellings, shown in Fig 4.10, indicates that the percentage of uninsulated dwellings has decreased from (55%) to
(30%) in Australia and from (45%) to (35%) in NSW between 94 to 2011, respectively. While the majority of Australia and NSW dwellings with insulation have ceiling insulation (95%), less than (25%) of them have installed wall insulation in 2011. Fig 4.11 shows the insulation places for Australia and NSW during different ‘Energy Use and Conservation survey’ years.

Approximately 15% and 10% of dwellings used Sisalation/reflective foil or Loose fill-Cellulose fibre materials for insulations, and less than ≈5% had a Loose fill-Rock wool in 1999 in Australia and NSW. Therefore, it is reasonable to assume Batts-fibreglass/wool/poly as dominant insulation materials and as the most common materials in dwelling insulation during the last decades in both areas, with a related proportion of greater than 60% and neglect of all other materials (ABS, 2011a).

Fig 4.10: Insulation in New South Wales and Australian dwellings; adopted from (ABS, 2008, ABS, 2011a).

Fig 4.11: Insulation place in New South Wales and Australian dwellings; adopted from (ABS, 2008, ABS, 2011a).
Window system

Energy Use and Conservation survey (2008) which was included the window treatment shows that 38% of dwellings in NSW had outside awnings and 27% had boxed pelmets. These were similar to the proportion of the whole Australian stock (47% and 31% respectively). These results suggest that more than one-third (35%) of all dwellings in Australia and (45%) in NSW did not have any type of window treatments (ABS, 2010a) to reduce heat loss or gain. The results have been shown in Fig 4.12. The ABS (1999) also found that over half of dwellings in years 1994 and 1999 in both areas only used a typical single glazing with timber frame without any treatment. According to the Australian Glass and Glazing Association (AGGA, 2012) report, windows in Australian households are the worst in the developed world. RMIT University report (Wong, 2013) found that single glaze with the window area between 10-35 m² per house is the most common type in Australian dwellings since last 10 years. These results have been achieved through the analysis of dwelling designs which showed the most typical characteristics of recent residential buildings.

![Fig 4.12: Window treatments in New South Wales and Australian dwellings; adopted from (ABS, 2008).](image)

**Infiltration**

Infiltration or uncontrolled air leakage into and out of a dwelling serves to transfer heat into and out of the dwelling and affects building energy performance largely. Australian homes are considered two to four times more leaking compared to dwellings in North America or Europe (Luther, 2007). This level of air leakage caused Australian homes to only receive two stars on the star rating scale (ZCA, 2013).
Moreland Energy Foundation Limited (2010) ran a project to measure the number of air changes per hour (ACH, a measure of air infiltration) in 15 typical Victorian homes. This study found that dwellings have an average of 29 ACH at 50 Pa. Comparing these findings to the Passivhaus standard of 0.6 ACH50 and the Australian best practice (7-10 ACH50), it is shown that there is a major problem with draught-proofing in Australian dwellings (Moreland Energy Foundation Limited, 2010). According to the Air Barrier Technologies Pty Ltd (2012), the problematic features of older buildings that should be considered are open fireplaces, wall vents, vented skylights, and cracks along skirting boards in houses with timber floors, doors, and windows with no weather stripping.

4.3.1.3 Energy system details

The following section provides a quick review of the energy systems of dwellings, such as household energy and ventilation system across Australia and NSW. This section provides an overview of the dwelling source of energy and heating and cooling systems. This has not been used in defining the typologies or representative dwelling attributes.

Heating system

The ABS analysis (ABS, 2011a) shows that electricity is the main source of energy for existing dwellings in the country, as shown in Fig 4.13. However, 48% and 39% of dwellings in Australia and NSW use main gas as the second source of energy. LPG/bottle gas and solar energy usage have been increasing in recent years. The primary source of space heating in Australia and NSW dwellings are shown in Fig 4.14. The usage of the wood source has decreased from 15% in 1999 to 10% in 2011, while consumption of electricity by 44% in NSW and 37% in Australia, and gas by 22% in NSW and 32% in Australia are accounted for the main sources of dwelling heating in 2011.
Fig 4.13: Source of energy in New South Wales and Australian dwellings; adopted from (ABS, 2011a).


Heating and cooling are significant end use in Australian household's annual energy consumption (more than 40%) (ABS, 2009a). Only about 20% of dwellings in cold weather are not using a heater in both Australia and NSW from 1999 to 2011 (Fig 4.15). Currently, the majority of dwellings have been using at least one heater (65%) for an average period of 1 to 6 months a year (ABS, 2011a). While the proportion of households using separate electric, gas and wood heaters has decreased in Australia and in NSW between 2005 to 2011, the proportion of dwellings that apply a reverse cycle unit as their main heater has increased about 10% and reached 32% and 34% for the same time in both areas, respectively, as shown in Fig 4.16.
Fig 4.15: Availability of heating and cooling systems in New South Wales and Australian dwellings; adopted from (ABS, 2008, ABS, 2011a).

Fig 4.16: Heating system in New South Wales and Australian dwellings; adopted from (ABS, 2011a).

**Cooling system**

A small portion of dwellings in Australia and NSW (35% and 28%, respectively) had a cooling system in 1999; however, this portion has grown to more than two thirds (73% and 64%, respectively) of the current dwelling stock in 2011, as shown in Fig 4.17. The proportion of Australian and NSW households with an evaporative system as their main cooler declined from 27% and 21% in 1999, to 18% and 10% in 2011. Conversely, reverse cycle or heat pump systems were the main coolers; 37% of Australian and 59% of NSW dwellings in 1999, up to 62% and 79% in 2011 for both areas, respectively. Cooling system statistics are shown in Fig 4.17.
4.3.1.4 Summary of statistical analysis

Data from a number of sources, primarily the Australian Bureau of Statistics (ABS), was used to identify the stock attributes of buildings constructed from 1976 to 2000. In order to leverage the limited data available, the results from numerous ABS surveys and census, collected from different sources, were collated and analysed. Fig 4.18 and Fig 4.19 present a summary of construction attributes breakdown data for the Australian and NSW housing stock as determined by the ABS data reviewed for this study.

These figures show the percentage of existing dwelling type, frame, wall and roof system with the average number of bedrooms in Australia and NSW residential stock until 1999.
Fig 4.18: Visual summary of ABS data for Australia housing stock collected from the surveys reviewed above; adopted from (ABS, 1999).

Fig 4.19: Visual summary of ABS data for NSW housing stock collected from the surveys reviewed above; adopted from (ABS, 1999).
According to the ABS data, on average, 70% of the housing stock in both Australia and NSW are occupied detached houses or bungalows, with two and three bedrooms, as shown in Fig 4.20.

In Australia, dwellings are made from a variety of materials; brick veneer (22%) and double brick (38%) are the most common wall materials. Tiles (62%) and steel (33%) are the most typical roofing materials. The vast majority of the insulated buildings have the insulation placed in the ceiling (98%) and the type of insulation is usually batts or fiberglass (62%). The minimum height of ceilings is 2.4m for habitable areas (ABCB, 1996) and single glazed windows are the most common window types (ABS, 2008). Whilst there are significant shortcomings in the available data, the airtightness of Australian homes has been shown to be below the expected standard (Biggs et al., 1986) and may be twice or four times more draughty when compared to those in North America or Europe (Luther, 2007). Whilst the ABS provided no survey data in relation to floor types, DEHWA (2008) stated that a significant number of Australian dwellings used concrete slabs and suspended timber for flooring. Fig 4.20 presents the highly common dwelling attributes available in the Australian and NSW stock. The figure shows the average value where data is taken from more than one survey and year.

4.3.1.5 Digest of initial typology outline

The range of dwelling attributes that exist in Australia and NSW have been identified. An initial typology outline for the current stock has been developed based on high-level ABS information. Typology outline included a set of typologies defined by the common dwelling types and external wall materials. This outline was then used to review and complete by experts for expanding of the current stock typologies, discussed in the following section. The reviewed typology outline was augmented with the most common attributes of dwellings from the ABS data reviews. This process resulted in a set of common typologies for existing Australian housing stock, and a detailed matrix of common construction attributes.

The defined initial typology outline based on ABS analysis is:

I. Detached, Brick Veneer;
II. Detached, Double-brick;
III. Detached, Lightweight Cladding;
IV. Semi-detached, Brick Veneer;
V. Semi-detached, Double-brick;
VI. Unit, Double-brick;
VII. Unit, Brick Veneer.

4.4 Qualitative analysis of initial typologies draft

The current section presents the process and understanding gained from NSW Housing Typologies forum (Daly et al., 2016) that reviewed developed typology outline.

The forum was organised as part of the NSW Housing Typologies Development project (Daly et al., 2016) in which the current author was involved. The NSW Housing Typologies project was a collaboration between the Sustainable Buildings Research Centre (SBRC) at the University of Wollongong (UOW) and New South Wales Office of Environment and Heritage (OEH). The project aimed to identify the major housing typologies existing in NSW and the potential to efficiently upgrade energy and sustainability in particular typologies (Daly et al., 2016).
The “Sustainable, Living Residential Building Forum” was held on the 13th of November, 2015 at the Sustainable Buildings Research Centre, in Wollongong. The forum had two separate workshops. The purpose of Workshop 1 was to reach consensus on a list of typologies for the NSW housing stock. The results from ABS analysis and digested typologies outline from the current author were used as an input in the workshop discussion. Workshop 2 defined features specific to each typology. The participants in the forum were separated into groups, and each was asked to focus on three of the proposed typologies. The results from the workshop were analysed and extended with data from several data sources catalogued through the database review, and the literature review. The author was involved in the process as a team member.

The forum discussion encompassed the central issues regarding the definition of dwelling typologies, the acceptability of the developed typology outline, and discussion of critical attributes for defining the typologies (Daly et al., 2016).

The NSW Housing Typologies Development project (Daly et al., 2016) resulted in eight draft typologies from analysing the initial typology outline input through workshops and information of previous studies.

The proposed NSW Housing Typology draft consists of eight typologies from Daly et al. (2016) and is listed in Table 4.3.

Table 4.3: Proposed NSW housing typologies draft (Daly et al., 2016).

<table>
<thead>
<tr>
<th>Stock Typologies Definition Draft</th>
</tr>
</thead>
<tbody>
<tr>
<td>Older, Detached, Brick Veneer</td>
</tr>
<tr>
<td>Newer, Detached, Brick Veneer</td>
</tr>
<tr>
<td>Detached, Double-brick</td>
</tr>
<tr>
<td>Detached, Lightweight Cladding</td>
</tr>
<tr>
<td>Semi-detached, Brick Veneer</td>
</tr>
<tr>
<td>Semi-detached, Double-brick Veneer</td>
</tr>
<tr>
<td>Unit, Solid Masonry</td>
</tr>
<tr>
<td>Unit, Brick Veneer</td>
</tr>
</tbody>
</table>

However, regarding the construction details of each typology, limited information was available (Daly et al., 2016). Therefore, the data sources discussed in the ABS section of the current chapter was reconsidered to determine the highly common typologies and expand the construction details of typologies that would allow building energy performance analysis to be undertaken.
4.5 Typology attributes matrix

The purpose of this section is to identify a set of detailed representative dwelling types in the Australian housing stock. The initial typology outline from ABS analysis was augmented with expert knowledge during the workshop in Daly et al. (2016) project, and it concluded eight typologies for NSW. The ABS analysis indicated there is not a substantial variation in dwelling trends through the states of Australia (ABS, 1995). Therefore, this typologies definition draft is applicable to all Australia in high level.

A comparison between the summary of most common dwelling attributes from ABS data analysis in Section 4.3.1.4, and the final stock typologies definition list from Section 4.4, demonstrates that detached typologies with external wall material of brick veneer, double brick and lightweight cladding are the most common dwelling types in both NSW and Australian housing stock. This study, therefore, used the following highly common typologies:

- Detached Brick Veneer
- Detached Double Brick
- Detached Lightweight Cladding

As investigated previously, a major barrier to the use of the ABS data is the inability to access data at the property address level, due to privacy concerns. This prevents the consideration of cross-correlation and clusters of multiple attributes for particular buildings. Therefore, assessing each common typology with the ABS detailed attributes leads to more than one type. For the purposes of developing the representative energy simulation models, based on a combination of common typologies and ABS characteristics, a detailed matrix which represents each unique set of potential building configurations was created. This matrix represents the full range of construction types in each defined typology.

Table 4.4 shows the matrix of common typologies mixed with the ABS’s most common attributes:
Table 4.4: A detailed matrix of construction attributes for highly common typologies.

<table>
<thead>
<tr>
<th>Type</th>
<th>Design Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>Detached</td>
</tr>
<tr>
<td>External wall</td>
<td>Brick veneer</td>
</tr>
<tr>
<td></td>
<td>Double brick</td>
</tr>
<tr>
<td></td>
<td>Fibro</td>
</tr>
<tr>
<td>Internal wall</td>
<td>Gypsum board</td>
</tr>
<tr>
<td>Floor</td>
<td>Slab on Ground</td>
</tr>
<tr>
<td></td>
<td>Suspended Timber</td>
</tr>
<tr>
<td>Roof</td>
<td>Steel sheet</td>
</tr>
<tr>
<td></td>
<td>Clay Tile</td>
</tr>
<tr>
<td>Ceiling</td>
<td>Gypsum board no insulation</td>
</tr>
<tr>
<td></td>
<td>Gypsum board With poor insulation</td>
</tr>
<tr>
<td>Bedrooms</td>
<td>Two</td>
</tr>
<tr>
<td></td>
<td>Three</td>
</tr>
<tr>
<td>Airtightness</td>
<td>Poor</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
</tr>
<tr>
<td>Window to Wall ratio</td>
<td>15%</td>
</tr>
<tr>
<td>Glazing</td>
<td>Single glazed</td>
</tr>
<tr>
<td>Orientation</td>
<td>North</td>
</tr>
<tr>
<td></td>
<td>East</td>
</tr>
<tr>
<td></td>
<td>South West</td>
</tr>
<tr>
<td>Floor area</td>
<td>78 m²</td>
</tr>
<tr>
<td></td>
<td>122 m²</td>
</tr>
<tr>
<td></td>
<td>156m²</td>
</tr>
</tbody>
</table>

The outcome of Table 4.4 would result in 864 of representative dwelling types that cover all the potential design configurations for common typologies in Australia. However, to ensure accurate analysis (Sadeghifam et al., 2015), important attributes such as size and orientation were also added. These typologies can also be used as the basic for energy modeling of common existing dwellings in the stock to apply retrofitting strategies on them.

4.6 Data limitation

The use of statistical analysis approach to defining the range of typologies is a relatively fast and simple way that can exhibit a major proportion of buildings in a stock. The development of typologies through statistical method has been used by a number of authors from a study at a regional level by Lechtenböhmer and Schüring (2011) to more recent studies at urban scales by Firth et al. (2009) and Shimoda et al. (2004). However, this approach may not offer precise results or insights into the specific challenges and possibilities for individual buildings. The accuracy of the method relies mainly on the availability of data resources to define models which represent the different construction configurations occurring in a stock.
In this work, data from the Australian Bureau of Statistics (ABS) was used to avoid shortcomings in the accessible datasets. The ABS data had useful attribute information and did provide some high-level insights into the Australian and NSW housing stock. However, there was a limitation in accessibility of ABS data in address level. This limitation could affect examining the co-occurrence or clustering of building features in individual buildings. In order to facilitate a purely data-driven approach, a hybrid method was followed in this research. A high-level ABS data analysis was combined with the expert engagement processes to identify the highly common typologies in stock.

In this study, the key data from Australian Bureau of Statistics (ABS) database for the Australian housing stock was collected and analysed. Initial typology outline was digested based on dwelling types and external wall materials, and was reviewed by experts through housing typologies development project (Daly et al., 2016) workshop. However, the outcome of the project was augmented with ABS common attributes and detailed matrix of attributes, including dwelling structure, materials of external wall, internal wall and roof, floor types, ceiling insulation, number of rooms, level of airtightness, window to wall ratio, glazing types, orientation and floor area, all prepared for common typologies to employ in building energy performance analysis.

4.7 Chapter summary

This chapter has implications in characterising the current state of the existing residential building stock and in defining the range of existing typologies in Australia. It has employed a hybrid approach to identify the Australian housing attributes and housing typologies. In this chapter, available data on Australian Bureau of Statistics (ABS) housing databases were collected and analysed, with considering the three categories as construction details, construction materials and energy system details. This was conducted in order to determine the common attributes of the Australian building stock. The initial typology outline was defined as seven typologies by using the outcome of ABS building analysis for the current housing stock.
Initial typology outline was then used as an input in Housing Typologies Development project (Daly et al., 2016) to be reviewed and augmented with experts’ knowledge. The result of Housing Typologies Development project (Daly et al., 2016) was re-evaluated with the ABS data and three common typologies were identified: i) Detached Brick Veneer ii) Detached Double Brick iii) Detached Lightweight Cladding. For the purposes of developing the representative dwelling energy simulation models, a detailed matrix of attributes was developed which represents a unique set of potential building configurations for each typology.

This chapter has justified statistical and qualitative analysis for identifying the range of housing typologies and developing a detailed matrix attributes to be employed in building energy performance analysis. Development of the energy simulation model and evaluation of current thermal energy performance of representative dwelling types will be discussed in Chapter 5.
Chapter 5: Development and thermal performance analysis of representative residential simulation models

5.1 Introduction

Previous studies have shown the necessity of making improvements to the energy efficiency of the currently available building stock in order to rapidly reduce greenhouse gas (GHG) emissions (IPCC, 2014, Stern, 2006). However, the selection of the optimal retrofitting strategy for dwellings is a complex task which requires significant knowledge and expertise (Ma et al., 2012). Each dwelling in an existing stock will have a unique combination of form, fabric and operation, which will influence the energy performance and optimal upgrade strategies. Many studies (Chidiac et al., 2011, Sehar et al., 2012) have utilised stock aggregation techniques to simplify the assessment of optimal retrofit strategies for housing stocks. ‘Archetypal’ or ‘Representative’ buildings have been employed previously as a tool to provide generic energy efficiency assessments of existing building stocks. The purpose of a representative building is to represent the energy performance of a typical building in a segment of the building stock (Theodoridou et al., 2011, Korolija et al., 2013).

The objective of this chapter was to develop a set of representative dwelling simulation models based on the results of the quantitative and qualitative characterisation of the Australian residential dwelling stock presented in Chapter 4. Then, thermal performance assessment of the developed representative dwelling simulation models, as well as of a highly efficient retrofitted house, was undertaken to quantify the potential for energy improvement of typical dwellings in Australia. The simulation models were also used to analyse the effect of floor area on the total thermal energy requirements of models.
5.2 Method

Building simulation models were developed based on the statistical review of dwelling attributes, presented in Chapter 4. For all generic simulation models, the Taguchi method and the Analysis of Variance (ANOVA) process were used in order to identify the key building attributes that influence heating and cooling requirements of models. The Taguchi is an approach that provides a predictive knowledge of a complex and multi-variable process with an efficient and effectively reduced number of trials. It has been employed in the field of Building Performance Simulation (F. Chelela, 2007, Plessis et al., 2011, Yi et al., 2015) in order to reduce a required number of simulations, find the optimum solution and assess the influence of each parameter. Analysis of Variance (ANOVA) is a variance based way that estimates the error variance and determines the significant contribution of the variables in order to achieve faster and easier approximation.

The key attributes that influenced the energy most were used to define a reduced number of representative building simulation models for a quantified sub-set of the existing building stock. The developed representative dwelling simulation models were then used to quantify the current thermal performance of dwellings by the assessment of the thermal energy requirements in order to maintain indoor comfort conditions within an acceptable range. In addition, the impact of floor area on the total heating and cooling energy requirements was quantified. The method employed for this chapter is summarised in Fig 5.1.
5.2.1 Design of experiment

In Chapter 4, the available data from the ABS housing datasets were collected and analysed to determine the most common attributes of the Australian building stock in conjunction with the dwelling typology definition undertaken by (Daly et al., 2016). Previous studies (Wong, 2013, Ren et al., 2012, Warren-Myers et al., 2012) have used ABS data to understand the relationships between building typology and sustainable renovation outcomes in Australia. The inability to access data at the property address level, due to privacy concerns, is a major barrier to the use of ABS data to analyse building types and potential energy efficiency measures. This prevents the consideration of cross-correlation and clusters of multiple attributes for
particular buildings. Therefore, for the purposes of dwelling thermal performance, it is necessary to create a simulation model to represent each unique set of potential building configurations. This will represent the full range of construction types. However, this process would result in a large number of building models. So, by recognizing that certain attributes will have less significant effects on performance, the total number of representative simulation models can be reduced. To reduce the total number of simulation models and prioritize the attributes for representative models, principles from the Taguchi and ANOVA methods (Roy, 1990, Yang and Tarng, 1998, Lam et al., 2016, Ćuković Ignjatović et al., 2016) have been used.

Design of Experiment Taguchi mix-mode design method was used to reduce the required model runs, as described in Section 3.7.1. This method uses a fractional factorial order layout, termed Orthogonal Arrays (OA) (Yang and Tarng, 1998), to reduce the number of simulations required for exploring the influence of building model attributes. As an example, to test the sensitivity of nine variable design attributes, a traditional full factorial design would require 19683 model runs with 3 levels of available values, while with the Taguchi design, the required number of model runs was only 27. The variable design attributes and possible values for each variable (termed levels) were developed based on the typology matrix of attributes presented in Section 4.5, and are given in detail in Table 5.1. This study, in fact, explored nine attributes, with 2 or 3 levels for each variable, and with total runs of 36 in each iteration. Using the Taguchi method allowed the attributes to be weighted equally and assessed independently of all other factors. The Taguchi method also applies the signal-to-noise ratio (S/N), a measure of robustness that aims to minimize the effect of noise and optimise the process performance (Zahraee et al., 2015). In this study, the delta S/N ratio, which is the difference between the maximum and minimum average signal-to-noise ratios for the attributes value levels, was used to determine the building attributes that have levels with relatively similar impact on the thermal performance of models (low delta S/N ratio) in five different iterations. For example, the influences of roof attribute values (tile and metal) variation with delta S/N ratio of 1.05 were found to be relatively similar on the thermal energy requirements of the model. ANOVA was also performed in order to determine the contribution of each attribute to the simulated total thermal energy demand. Mean of Means, which is an average respond for each combination of control factor levels in
the design, is also presented to observe the impact of attributes in energy. The decision about the significance of attributes or their effects on total thermal energy requirement of a model was made based on the p-value ($p$-value>0.05) (Fisher and Nig, 1950, Rumsey, 2016) and delta S/N ratio (delta S/N<2) of each levels of the attribute. It should be noted that Minitab software 17 (Minitab Statistical Software Support, 2016b) was employed for statistical analysis of this study.

Table 5.1: Matrix of attributes used for development of representative dwelling simulation models.

<table>
<thead>
<tr>
<th>Model input factor</th>
<th>Model construction variable input levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>Brick veneer</td>
</tr>
<tr>
<td></td>
<td>Double brick</td>
</tr>
<tr>
<td></td>
<td>Fibro</td>
</tr>
<tr>
<td>Floor</td>
<td>Slab on Ground (SOG)</td>
</tr>
<tr>
<td></td>
<td>Suspended Timber</td>
</tr>
<tr>
<td>Roof</td>
<td>Steel sheet</td>
</tr>
<tr>
<td></td>
<td>Clay Tile</td>
</tr>
<tr>
<td>Ceiling</td>
<td>Gypsum board no insulation</td>
</tr>
<tr>
<td></td>
<td>Gypsum board With poor insulation</td>
</tr>
<tr>
<td>Bedrooms</td>
<td>Two–Three</td>
</tr>
<tr>
<td>Airtightness</td>
<td>Poor–Medium</td>
</tr>
<tr>
<td>Orientation</td>
<td>North-East-South West</td>
</tr>
<tr>
<td>NatHERS Climates</td>
<td>5/6/7</td>
</tr>
<tr>
<td>Floor area</td>
<td>78 m²-122 m²-156 m²</td>
</tr>
</tbody>
</table>

5.2.2 Building performance simulation approach and assumptions

DesignBuilder V4, a graphical user interface for the Energy Plus simulation engine, was used for the building thermal energy simulations in this chapter. The assessment of energy performance was based on the energy required to maintain the models in the thermally acceptable range for 24 hours per day.

The process of converting the ABS data into the selected construction types and simulation models required the following assumptions:

- As mentioned in Section 3.7, a basic three bedrooms, timber frame detached house plan from the NSW government housing provider (Thomas, 2011) was used for building configurations in this study. The floor plan was adjusted to give a window-to-wall ratio (WWR) of 15%, average ceiling height of 2.55 meters and then perturbed to create three floor areas (78 m², 122 m² and 156m²). The floor plan and a 3D view of it are shown in Fig 5.2 and Fig 5.3, respectively. A summary of the floor areas for each zone of 78 m² case can be found in Table 5.2.
Fig 5.2: Floor plan of a representative dwelling simulation model as visualised in DesignBuilder.

Fig 5.3: 3D view of a representative dwelling simulation model as visualised in DesignBuilder.

Table 5.2: Floor area and volume of representative dwelling simulation models.

<table>
<thead>
<tr>
<th>Zones</th>
<th>Floor Area(m²)</th>
<th>Volume(m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Living Room &amp; Kitchen</td>
<td>32.83</td>
<td>83.72</td>
</tr>
<tr>
<td>Bedroom 1</td>
<td>8.94</td>
<td>22.89</td>
</tr>
<tr>
<td>Bedroom 2</td>
<td>12.4</td>
<td>31.63</td>
</tr>
<tr>
<td>Bedroom 3</td>
<td>10.27</td>
<td>26.18</td>
</tr>
<tr>
<td>Laundry</td>
<td>5.08</td>
<td>12.94</td>
</tr>
<tr>
<td>Bathroom</td>
<td>4.36</td>
<td>11.12</td>
</tr>
<tr>
<td>Corridor</td>
<td>4.55</td>
<td>11.59</td>
</tr>
<tr>
<td>Total</td>
<td>78.43</td>
<td>200.07</td>
</tr>
<tr>
<td>Conditioned Area</td>
<td><strong>64.44</strong></td>
<td><strong>164.42</strong></td>
</tr>
</tbody>
</table>

- As briefly discussed in Chapter 4, privacy concerns with the ABS data prevent from obtaining the property address level. Therefore, cross-correlation and clusters of multiple attributes for particular buildings were not
possible. The generic plan was modified to reflect the full range of identified dwelling attributes.

- Two typical floor types, suspended timber and slab on ground (SOG), are considered in each model. Timber floor is assumed to be an open suspended timber floor, 0.5 m above ground level and the slab on ground is assumed to be 0.1 m cast concrete on ground. The full description of construction attributes implemented in the current study is shown in Table 5.3.

Table 5.3: Matrix of attributes used for representative dwelling simulation models development with Taguchi method. Material thermal properties are sourced from (AIRAH, 2013).

<table>
<thead>
<tr>
<th>Model input factor</th>
<th>Model variable input levels</th>
<th>Model constant input levels</th>
<th>R-Value (m²K/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>Brick veneer</td>
<td>Detached</td>
<td>0.534</td>
</tr>
<tr>
<td>External wall</td>
<td>Double brick</td>
<td>-</td>
<td>0.679</td>
</tr>
<tr>
<td></td>
<td>Fibro</td>
<td>-</td>
<td>0.437</td>
</tr>
<tr>
<td>Internal wall</td>
<td>Gypsum board</td>
<td></td>
<td>0.319</td>
</tr>
<tr>
<td>Floor</td>
<td>Slab on Ground</td>
<td>-</td>
<td>0.287</td>
</tr>
<tr>
<td></td>
<td>Suspended Timber</td>
<td>-</td>
<td>0.439</td>
</tr>
<tr>
<td>Roof</td>
<td>Steel sheet</td>
<td>-</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>Clay Tile</td>
<td>-</td>
<td>0.370</td>
</tr>
<tr>
<td>Ceiling</td>
<td>Gypsum board no insulation</td>
<td>-</td>
<td>0.347</td>
</tr>
<tr>
<td></td>
<td>Gypsum board With poor insulation</td>
<td>-</td>
<td>1.34</td>
</tr>
<tr>
<td>Floor area</td>
<td>78 m²-122 m²-156m²</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Bedrooms</td>
<td>Two-Three</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Airtightness</td>
<td>Poor-Medium</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Orientation</td>
<td>North-East-South West</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Window to Wall ratio</td>
<td>15%</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Glazing</td>
<td>Single glazed</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>NatHERS Climates</td>
<td>5/6/7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thermostat setting</td>
<td>Winter 20°C for 24 h/day</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Summer 24.5°C for 24 h/day</td>
<td></td>
<td></td>
</tr>
<tr>
<td>COP</td>
<td>1</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Occupants</td>
<td>1</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Energy supply</td>
<td>Electricity</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

- The thermal and energy performance of a building is heavily dependent on the local climatic conditions. Hence, an efficient house design must respond to the local climate. For the current study, three major climates of New South Wales (NSW) in Australia have been used for modeling. These climates are Climate Zone 5, Zone 6 and Zone 7, which are warm temperate, mild temperate and cold temperate respectively. Weather data for use in the representative models were taken from Mascot (climate zone 5), Nowra...
(climate zone 6) and Goulburn (climate zone 7). Details of climate analysis are discussed in Section 3.6.1 and Section 3.6.2.

- The Airtightness of the modelled buildings was defined by using the crack templates within the DesignBuilder software. Five levels of airtightness were defined as very Poor, Poor, Medium, Good and Excellent. In this case, every surface in the model has a crack and its size (characterised by flow coefficient and exponent) is specified according to the DesignBuilder cracks database (DesignBuilder, 2015).

- It is a challenge to explore the effect of occupants on the thermal performance of houses and this requires detailed information. The periods of occupation and the zones in which these periods occur are the main parameters for establishing the occupancy scenario. Whilst establishing occupancy scenarios may provide some information on the effects of occupancy on energy performance, there is a high degree of uncertainty associated with this parameter. To minimise the uncertainty associated with household occupancy for this study, constant occupancy was assumed as one occupant, twenty-four hours per day, seven days a week (24/7). The focus of the current study was to investigate the effect of building envelope on the thermal performance of houses, rather than how occupants influence the performance of a house. This method could embrace the energy overload estimation issue whilst it helped to investigate the energy required to keep different dwellings in comfort zones in the same situation.

- By the use of climatic building design, thermal comfort could be provided with minimal consumption of energy which is, after all, the main purpose of developing any energy efficient building. A crucial point to be borne in mind is that the occupants’ comfort should not be sacrificed to reduce energy consumption. In this study, the NatHERS indoor comfort set points, which vary according to climate zone, were utilised (NatHERS, 2012). The total heating and cooling demand to keep the internal spaces within the comfortable range of 20° to 24.5° for all hours of the year was the set point considered for this work. The bathroom, laundry and corridor were considered service areas and therefore did not receive any heating or cooling.
Heating was available to the conditioned zones when the zone temperature was below the heating thermostat setting (20\degree) from March to October. Cooling was activated when a zone temperature was above the thermostat setting (24.5\degree) for the rest of the year. Natural ventilation was activated when the zone temperature was above the outdoor temperature, and a new temperature was calculated. However, if the conditioned zone is yet to fall outside the comfort levels, the openings are closed off and cooling becomes activated. Activation modes settings are shown in Table 5.4. The annual thermal energy required was expressed in kWh /annum.

Table 5.4: Heating, cooling and natural ventilation activation modes settings for representative simulation models.

<table>
<thead>
<tr>
<th>Activation mode</th>
<th>Month</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating</td>
<td>March-Oct</td>
<td>$T_{\text{indoor}} &lt; 20$</td>
</tr>
<tr>
<td>Cooling</td>
<td>Nov-March</td>
<td>$T_{\text{indoor}} &gt; 24.5$</td>
</tr>
<tr>
<td>Natural ventilation</td>
<td>Oct-May</td>
<td>$T_{\text{indoor}} &gt; T_{\text{outdoor}}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$T_{\text{outdoor}} &lt; 24.5$</td>
</tr>
</tbody>
</table>

- The thermal performance of the representative dwelling simulation models was also evaluated in terms of annual Discomfort Degree Hours (DDH) calculated in the free-running operation mode (i.e. no mechanical heating or cooling). Such an evaluation is achieved by calculating the number of hours when natural ventilation cannot provide the comfort temperature range inside the dwellings. Heating discomfort degree hours are calculated by subtracting the minimum heating thermostat setting (20\degree) from the hourly free running simulation temperature (indoor temperature - 20\degree), and Cooling discomfort degree hours by subtracting the simulation temperature from minimum cooling thermostat setting (24.5\degree c) (24.5\degree - indoor temperature) throughout a year.
5.2.3 Solar Decathlon House energy simulation model development

The Solar Decathlon House (SD) is an ultra-sustainable retrofitted dwelling which was the winner of Solar Decathlon House (SD) competition in China in 2013. It is located in Innovation campus of University of Wollongong (IFH, 2014). The aim of this house was to upgrade an existing building to inspire Australian homeowners as well as the local and national building industry in order to accelerate the development and adoption of advanced building energy technology in new and existing homes. In this study, thermal performance of Solar Decathlon House (SD) was examined and compared with representative dwelling simulation models to investigate the potential of energy retrofitting in existing dwellings.

Solar Decathlon House is a detached house with a total area of 89 m². The house dimension is 12.495 m×7.475m with an internal height of 2.4 m. The house landscape plan and floor plan have been shown in Fig 5.4.

Fig 5.4: Solar Decathlon House a. landscape plan b. floor plan (IFH, 2014).

In this study, energy simulation model was created in Designbuilder, based on detail of dwelling construction characteristic and energy simulation run in climate zones similar with representative dwelling simulation models to analyse the thermal performance of Solar Decathlon House (SD). Details of Solar Decathlon House (SD) construction characteristics and basic developed Designbuilder model have been shown in Table 5.5 and Fig 5.5.
Table 5.5: Material thermal properties used for Solar Decathlon House simulation model development, sourced from (IFH, 2014).

<table>
<thead>
<tr>
<th>Model input factor</th>
<th>Model construction variable input levels</th>
<th>R-Value (m²K/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>Fibro With insulation</td>
<td>4.2</td>
</tr>
<tr>
<td>Internal wall</td>
<td>Gypsum board With insulation</td>
<td>3</td>
</tr>
<tr>
<td>Floor</td>
<td>Suspended Timber With insulation</td>
<td>8.6</td>
</tr>
<tr>
<td>Roof</td>
<td>Steel sheet With insulation</td>
<td>3</td>
</tr>
<tr>
<td>Ceiling</td>
<td>Gypsum board With insulation</td>
<td>8.2</td>
</tr>
<tr>
<td>Bedrooms</td>
<td>Two</td>
<td></td>
</tr>
<tr>
<td>Airtightness</td>
<td>Good</td>
<td></td>
</tr>
<tr>
<td>Glazing</td>
<td>Double Argon filled glazed</td>
<td></td>
</tr>
</tbody>
</table>

Fig 5.5: Solar Decathlon House DesignBuilder 3D simulation model.
5.3 Results, analysis and discussions

5.3.1 Design of experiment (Taguchi) and ANOVA methods analysis

A number of representative dwelling simulation models for the Australian residential stock have been created for this study based on the ABS housing data review. In this chapter, the results of simulations exploring the sets of the most common attribute combinations (see variable parameters in Table 5.1) are presented. To ensure an accurate analysis, important variables such as size, orientation, and climatic data were considered in design attributes (Sadeghifam et al., 2015).

To minimise the overall number of required simulation runs, a Taguchi experimental order layout was used to prioritise the building attributes, shown in Table 5.1, whilst considering the most possible combinations of building stock characteristics.

Taguchi fractional factorial design uses orthogonal arrays (OA) to pull full information out of all factors that affect the performance parameter. This was done by running a small number of experiments (Mohan et al., 2005). Taguchi method chose an adequate fraction of the combinations selected from all possibilities.

Building simulation models were created for a number of different combinations of the attributes, as shown in Table 5.6. This table displays the results of the first iteration of Taguchi mix-mode method (five attributes with 2 levels of variation and four attributes with 3 levels of variation) based on a developed matrix of attributes. Each model run had a unique combination of design attribute values. The predicted total heating and cooling energy requirements for each configuration in Table 5.6 is shown in “Total energy” column.
The influence of the attributes on total heating and cooling demand of the modelled dwellings were analysed and compared in order of relative contribution to mean S/N ratio and Mean of Means, shown in Fig 5.6 and Fig 5.7. For the purpose of minimising the cooling and heating loads, the calculation of S/N ratio is based on the situation “Smaller is better” for energy performance.

As shown in Fig 5.6, the main effect of S/N ratio graph shows how each factor affects the response characteristic (S/N ratio, means, slopes, standard deviations). A main effect exists when different levels of each attribute affect the response differently. The results of Fig 5.6 indicate a very low variance (approximately 2

1: Timber: Suspended Timber; SOG: Slab On Ground
2: W/O: Without insulation; poor: poor level (R=1.34) of insulation respectively
3: BV: Brick Veneer; DB: Double Brick; LW: Lightweight cladding (fibre-cement sheeting)
4: Confirmation test: optimal combination of parameters and their levels with minimum required thermal energy
values) regarding the influence of the roof type, number of bedrooms, orientation, and airtightness attributes value levels on the total thermal performance of models. The Mean of Means graph, as shown in Fig 5.7, confirms that attribute values with low S/N ratio variance also affect the energy in a similar way as well. It was found that the variation of these attributes values does not have a significant influence on the thermal energy requirements when modelling existing residential buildings.

![Mean of Means graph](image)

**Fig 5.6: Main effects plot for S/N ratio.**

![Mean of Means graph](image)

**Fig 5.7: Main effects plot for Means.**

The results of the ANOVA are also presented in Table 5.7. Approximately 90% of the thermal energy demand of the typical building model was found to be directly associated with the floor types, building size, climate, level of ceiling insulation and wall material attributes. This suggests that attributes with insignificant variables,
which have similar effects on the response, could be potentially accumulated into a single variable for future works. The details of the ANOVA from Taguchi order layout analysis with the delta S/N ratio for the first trial is also presented in Table 5.7.

Table 5.7: ANOVA with Taguchi delta Signal to Noise (S/N) Ratio table for the 1st iteration.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>DF</th>
<th>Seq SS</th>
<th>Contribution percentage</th>
<th>F-Value</th>
<th>P-Value</th>
<th>Delta S/N Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor Types</td>
<td>1</td>
<td>1033893564</td>
<td>36.56%</td>
<td>108.61</td>
<td>0</td>
<td>6.92</td>
</tr>
<tr>
<td>Floor Area</td>
<td>2</td>
<td>805091010</td>
<td>28.47%</td>
<td>48.61</td>
<td>0</td>
<td>6.61</td>
</tr>
<tr>
<td>Climate</td>
<td>2</td>
<td>471233060</td>
<td>16.66%</td>
<td>24.75</td>
<td>0</td>
<td>4.08</td>
</tr>
<tr>
<td>Ceiling Insulation</td>
<td>1</td>
<td>170956279</td>
<td>6.05%</td>
<td>17.96</td>
<td>0</td>
<td>3.13</td>
</tr>
<tr>
<td>Wall Types</td>
<td>2</td>
<td>84021898</td>
<td>2.97%</td>
<td>5.12</td>
<td>0.015</td>
<td>2.85</td>
</tr>
<tr>
<td>Airtightness</td>
<td>1</td>
<td>24936630</td>
<td>0.88%</td>
<td>2.62</td>
<td>0.12</td>
<td>0.37</td>
</tr>
<tr>
<td>Orientation</td>
<td>2</td>
<td>14375700</td>
<td>0.51%</td>
<td>1</td>
<td>0.385</td>
<td>0.37</td>
</tr>
<tr>
<td>Number of Bedrooms</td>
<td>1</td>
<td>13306219</td>
<td>0.47%</td>
<td>1.4</td>
<td>0.25</td>
<td>1.12</td>
</tr>
<tr>
<td>Roof Types</td>
<td>1</td>
<td>588123</td>
<td>0.02%</td>
<td>0.06</td>
<td>0.806</td>
<td>1.05</td>
</tr>
<tr>
<td>Error</td>
<td>22</td>
<td>209432552</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>35</td>
<td>2827835034</td>
<td>7.41%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

To test the effect of ignoring low impact attributes (i.e. when the ANOVA returned a p-value > 0.05) with low variance (delta S/N<2) and to rate them as constant in the representative dwelling simulation models, four iterations for the attributes that had the lowest impact (roof types, number of bedrooms, orientation, and airtightness) had been simulated with the removal of one of the insignificant factors in each trial. This strategy allowed the observation of any errors. In Fig 5.8a and Fig 5.8b, the effect of each attribute on contribution percentage and S/N ratio at different levels of each iteration from first to fifth is reported.

![Fig 5.8](image)

**Fig 5.8:** a. Main effect plots for contribution percentage and b. Delta S/N ratio.
Details of the ANOVA from Taguchi orders layout analysis with the delta S/N ratio for the fifth iteration is also presented in Table 5.8. The percentage contribution and delta S/N ratio of remaining attributes after the elimination of insignificant factors showed that the removal of insignificant factors has a small impact on the remaining factors (see Fig 5.8a and Fig 5.8b). In additions, the effect was less than 2% in all cases.

Table 5.8: ANOVA with Taguchi delta Signal to Noise (S/N) Ratio table for the 5th iteration.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>DF</th>
<th>Seq SS</th>
<th>Contribution percentage</th>
<th>F-Value</th>
<th>P-Value</th>
<th>Delta S/N Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor Types</td>
<td>1</td>
<td>1192375055</td>
<td>35.33%</td>
<td>141.08</td>
<td>0</td>
<td>7.18</td>
</tr>
<tr>
<td>Size</td>
<td>2</td>
<td>1071500209</td>
<td>31.75%</td>
<td>63.39</td>
<td>0</td>
<td>6.79</td>
</tr>
<tr>
<td>Climate</td>
<td>2</td>
<td>571939780</td>
<td>16.95%</td>
<td>33.84</td>
<td>0</td>
<td>4.47</td>
</tr>
<tr>
<td>Ceiling Insulation</td>
<td>1</td>
<td>165351974</td>
<td>4.90%</td>
<td>19.56</td>
<td>0</td>
<td>2.73</td>
</tr>
<tr>
<td>Wall Types</td>
<td>2</td>
<td>145868910</td>
<td>4.32%</td>
<td>8.63</td>
<td>0.001</td>
<td>2.42</td>
</tr>
<tr>
<td>Error</td>
<td>27</td>
<td>228189956</td>
<td>6.76%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>35</td>
<td>3375225883</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.3.2 Final representative dwelling simulation model types

The process described in the previous section effectively reduced the number of attributes requiring further investigation, and allowed the creation of twelve representative simulation models for the retrofit analysis stage, which were then modelled for the listed building size and local climates, namely:

**Type A.**

Brick veneer wall with suspended timber floor without ceiling insulation.

Brick veneer wall with suspended timber floor with ceiling insulation.

**Type B.**

Brick veneer wall with slab on ground floor without ceiling insulation.

Brick veneer wall with slab on ground floor with ceiling insulation.

**Type C.**

Double brick wall with suspended timber floor without ceiling insulation.

Double brick wall with suspended timber floor with ceiling insulation.
**Type D.**

Double brick wall with slab on ground floor without ceiling insulation.

Double brick wall with slab on ground floor with ceiling insulation.

**Type E.**

Lightweight wall with suspended timber floor without ceiling insulation.

Lightweight wall with suspended timber floor with ceiling insulation.

**Type F.**

Lightweight wall with slab on ground floor without ceiling insulation.

Lightweight wall with slab on ground floor with ceiling insulation.

For the purpose of comparative performance analysis, the representative dwelling types with 78 m$^2$ floor area and poor ceiling insulation (first group of each category) were used as the representative dwelling simulation base cases.

The full design attributes of representative dwelling simulation models were also given in detail in Table 5.9.

**Table 5.9: Design attributes of representative dwelling simulation models.**

<table>
<thead>
<tr>
<th>Design Attributes</th>
<th>Type A</th>
<th>Type B</th>
<th>Type C</th>
<th>Type D</th>
<th>Type E</th>
<th>Type F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>Detached</td>
<td>Brick veneer</td>
<td>Brick veneer</td>
<td>Double brick</td>
<td>Double brick</td>
<td>Fibro</td>
</tr>
<tr>
<td>External wall</td>
<td>Brick veneer</td>
<td>Brick veneer</td>
<td>Double brick</td>
<td>Double brick</td>
<td>Fibro</td>
<td>Fibro</td>
</tr>
<tr>
<td>Internal wall</td>
<td>Gypsum board</td>
<td>Gypsum board</td>
<td>Gypsum board</td>
<td>Gypsum board</td>
<td>Gypsum board</td>
<td>Gypsum board</td>
</tr>
<tr>
<td>Floor</td>
<td>Suspended Timber</td>
<td>Slab on Ground</td>
<td>Suspended Timber</td>
<td>Slab on Ground</td>
<td>Suspended Timber</td>
<td>Slab on Ground</td>
</tr>
<tr>
<td>Roof</td>
<td>Clay Tile</td>
<td>Clay Tile</td>
<td>Clay Tile</td>
<td>Clay Tile</td>
<td>Clay Tile</td>
<td>Clay Tile</td>
</tr>
</tbody>
</table>

**Ceiling**

Gypsum board no insulation

Gypsum board With poor insulation

<table>
<thead>
<tr>
<th>Bedrooms</th>
<th>Three</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airtightness</td>
<td>Poor</td>
</tr>
<tr>
<td>Window to Wall ratio</td>
<td>15%</td>
</tr>
<tr>
<td>Glazing</td>
<td>Single glazed</td>
</tr>
<tr>
<td>Orientation</td>
<td>North Entry</td>
</tr>
<tr>
<td>Floor area</td>
<td>78 m$^2$</td>
</tr>
</tbody>
</table>
The effect of floor area in total dwelling thermal and the influence of retrofitting in dwellings without ceiling insulation are assessed separately in Section 5.3.4, Section 6.3.1.1 and Section 6.3.2.

5.3.3 Thermal performance evaluation of models

Energy efficient buildings should provide thermal comfort with minimum consumption of energy. This can largely be achieved by employing locally appropriate climate responsive building design measures based on the location of the dwelling. It is important to balance the thermal comfort of occupancy with energy requirements. Thus, thermal comfort should be at the core of any assessment that aims to evaluate the efficiency of a particular building. The objective of this section is to evaluate the current thermal performance of both developed representative dwelling simulation models and a model of a highly efficient house. The purpose of this evaluation is to investigate the potential improvement opportunity for an existing dwelling in comparison with the best practice example of a deep energy retrofit. This section presents the thermal performance of representative dwelling simulation models and Solar Decathlon House (SD) simulation model in free running and conditioned modes.

The highly efficient house model was created based on the details of UOW ‘Illawarra Flame’, which won the Solar Decathlon House competition in China 2011 (IFH, 2014), and was available to the author.

5.3.3.1 Definition of thermal comfort

Many researches in the field have defined thermal comfort in various ways (Fanger, 1970, Givoni, 1976, Hensen, 1990, Watt, 1963). On a general level, thermal comfort is defined as “that condition of mind which expresses satisfaction with the thermal environment” (ASHRAE, 2004). As people vary biologically from each other, there cannot be a universal comfort level that satisfied everyone at the same time in the same climate. As a consequence, there needs to be a set of pre-established subjective criteria that could lay optimal comfort. For instance, Fanger (1970) defines the optimal thermal condition as the specific condition in which the largest percentage of a group feel thermally comfortable. From another point of view, the thermal optimum is achieved when there is no driving impulse to alter the environment by behavior. Giovani (1976), for instance, interprets the optimal
thermal state as one wherein there is no displeasure or discomfort caused by heat or cold. It can, therefore, be concluded that no all-encompassing definition of comfort can be agreed upon, owing to the fact that people have different preferences in relation to various climates which affect the overall perception of thermal comfort. However, if 80% - 90% of people feel thermally comfortable, then a subjective standard can be devised and accepted. In this study, thermal comfort is considered to be a condition which maintains indoor temperature, according to the Nathers comfort set points for each climate (NatHERS, 2012).

Building thermal performance can be evaluated in free-running operation mode using annual Discomfort Degree Hours (DDH), based on the boundaries of the thermal comfort zone. This is calculated from a combination of ‘heating and cooling discomfort hours’. ‘Heating’ discomfort hours for the building in free running mode and heating energy requirements for a conditioned building are indicators of a winter building performance. Likewise, ‘cooling’ discomfort hours and cooling energy requirements have been determined to investigate summer performance in this study.

Total annual Discomfort Degree Hours (DDH) for the representative dwelling simulation models (Types A to F) and Solar Decathlon House (SD) for the main three climate zones have been investigated and shown in Fig 5.9. These graphs demonstrate that discomfort hours are significantly reduced in representative dwelling simulation models with slab on ground floor type (Type B, Type D and Type F) in comparison with suspended floor type models (Type A, Type C and Type E) in every climate. In spite of the fact that the Solar Decathlon House (SD) has a suspended floor, its thermal performance or discomfort degree hours is close to the slab on ground models due to the highly insulated floor. Solar Decathlon House (SD) has also lower cooling discomfort degree hours than model Type F (Fibro with SOG) in all climates. Heating-discomfort degree hours increase from Mascot to Goulburn climate in every model due to the colder climate of Goulburn. This change is more significant in the Solar Decathlon House (SD) in comparison with a slab on ground models. The degree of discomfort in dwellings with same wall materials and different floor types is also different by a factor of two in all cases. This proves the importance of floor types on thermal demand of residential building in NSW.
In this analysis, double brick, brick veneer and fibro models with slab on ground perform better compared to suspended floor models. However, the thermal performance of slab on ground models is close to Solar Decathlon House (SD) which has a highly insulated suspended floor. Thermal performance has the potential to improve by minimising the overall discomfort degree in all cases especially in the model with suspended floor type.

The annual thermal performance of Type A (Brick veneer-suspended floor) and Type B (Brick veneer-slab on ground) models as well as the Solar Decathlon House (SD) simulation model in a free running mode in climate zones 5, 6 and 7 have been analysed in terms of temperature frequency distribution, shown in Fig 5.10. Type A has the lowest annual thermal performance in the selected climates since it has the highest distribution of air temperatures below 22°-24° centigrade and expectedly the highest discomfort degree hours (DDH) among these models. A comparison between Type B and Solar Decathlon House (SD) shows that SD should have lower DDH in Mascot which makes it more desirable in this climate but may not be better in Nowra and Goulburn. Although Solar Decathlon House (SD) house provides the highest probability of 22°-24° centigrade air temperature in Nowra and Goulburn, it also has a high probability of air temperatures below 16° centigrade in those climates. A
comparison between the thermal performance of houses with slab on ground floor and Solar Decathlon House (SD) house illustrates that the houses with SOG floor (Type B, Type D and Type F) are sometimes able to achieve a comparable or better performance than Solar Decathlon House (SD) construction, particularly when they are in free running mode.
Fig 5.10: Total annual temperature frequency distribution of representative dwelling simulation models Type A, Type B and Solar Decathlon House in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn.

The annual temperature frequency box plots for the models are also shown in Fig 5.11a, Fig 5.11b and Fig 5.11c for every climate. The box plots indicate that the simulation models with different wall materials (brick veneer, double brick and
fibro) and same floor types are performing more closely in terms of temperature frequency than the models with same wall materials and different floor types. This is mainly due to lower heat transfer through a slab on ground than a suspended timber floor as well as the effect of floor thermal mass in the overall thermal performance of dwellings.

a. Climate zone 5-Mascot
b. Climate zone 6-Nowra

c. Climate zone 7-Goulburn

Fig 5.11: Annual temperature plot boxes of representative dwelling simulation models in climate a. Zone 5-Mascot, b. Zone 6-Nowra and c. Zone 7-Goulburn.
The box plots in Fig 5.11 a and c also show Type D (Double brick with slab on ground floor) in Mascot climate and Type E (Fibro with suspended timber floor) in Goulburn climate have respectively the highest and lowest thermal comfort among representative dwelling simulation models with thermal comfort for 45% and 11% of the time. Fig 5.12 illustrates the weekly temperature of Type D plot boxes and Type E for the hottest and coldest week of the year in Mascot and Goulburn climate zones. Results of these plot boxes show that Type D and Type E are experiencing comfortable internal conditions 37% and 7% of the time in the hottest week of summer, while in winters’ coldest week, the comfortable period drops to 4% and 6% in Mascot and Goulburn climate zones, respectively.

The results of thermal comfort analysis endorse the vitality of improvement in representative dwelling types due to an increase in the number of hours during a year in which dwellings experience a comfort temperature.

Fig 5.12: Winter and summer design week temperature plot box of representative dwelling simulation models in climate Zone 5-Mascot and Zone 7-Goulburn.

The thermal performance of the models was also evaluated in a conditioned mode in terms of annual energy and particularly in terms of the aggregation of the heating and cooling energy required to maintain indoor temperatures within the
comfort air temperature settings (as defined by NatHERS, 2012). Annual required energy expressed in kWh/annum is used as an indicator of thermal performance in the conditioned operation mode. Fig 5.13 shows the amount of total energy required to maintain indoor condition within the comfort zone in all models in the three climates. Double brick, brick veneer and fibro simulation models with slab on ground floor (Type B, Type D and Type F) achieve a substantially greater thermal performance, requiring approximately 200% less energy than suspended floor type models (Type A, Type C and Type E). The total energy required to maintain the indoor temperature in the comfort zone for Solar Decathlon House (SD) is also, in most cases, about 25% to 65% below the representative dwelling simulation models with slab on ground and over 100% below the models made by suspended floor in the same climate. This level of energy requirement variance between representative dwelling simulation models and Solar Decathlon House (SD) model confirms poor thermal performance of existing dwellings in the current stock, and the substantial potential to improve dwellings to achieve higher thermal comfort. This result also demonstrates that total energy requirement is strongly influenced by the local climate.

Fig 5.13: Total annual heating and cooling requirement for representative dwelling simulation models in three climates.

As described in Section 5.3.2, Type A, Type C and Type E are models made by Brick veneer, Double brick and Fibro with suspended floor constructions and ceiling insulation, respectively, while Type B, Type D and Type F are models made by Brick veneer, Double brick and Fibro with slab on ground floor and ceiling insulation.
Solar Decathlon House (SD) is also a highly efficient retrofitted house with a suspended floor.

In this section, the annual thermal performance of representative dwelling simulation models with constant ceiling insulation level was compared with the Solar Decathlon House (SD) model in terms of DDH, annual temperature frequency distribution and the total required loads to maintain the indoor temperature in comfort compliance set points. Overall, the results of this analysis show a high potential of thermal performance improvement in representative dwelling types in comparison with the highly efficient Solar Decathlon House (SD). The influence of floor types on the total thermal performance of dwellings has been detected through this process. In addition, dwellings with double brick and fibro wall materials are shown to have the highest and lowest thermal performance respectively, among models with the same floor types.

5.3.4 Analysis of dwelling floor area

In this section, the influence of the floor area of the dwelling on the total heating and cooling performance of models in different climates is investigated. The thermal performance of dwellings must be predicted or adjusted by a factor that increases the energy load of buildings with larger floor area and decreases the energy load of buildings with smaller floor area. This is, of course, in proportion to the total building surface area to floor area ratios of a range of dwellings in particular climate zones.

In this study, floor area of the representative dwelling simulation models has been modified to different sizes from 78 m$^2$ to 156 m$^2$. These simulation models were run to assess the effect of floor area on the total thermal performance of the dwellings and to derive a simple area correction estimation method for the main three climates of this study. In this section, the results of developed representative dwelling simulation models (Type A and Type B) have been presented as examples and the rest of models are presented in Appendix A.

The adjusted annual energy requirement of the representative dwelling simulation models can be estimated based on recognised area correction factors. Area correction factors are calculated based on the growth percentage of representative simulation model floor area. In calculation when a model area is
larger than 78 m$^2$ calculated value is positive and adding while smaller model area value is negative and subtracting from area correction estimation models.

In this work, the total energy requirements (kWh) are considered instead of kWh/m$^2$. As a large dwelling has a smaller ratio of total surface area to floor area, its rating will tend to be better by kWh/m$^2$ while these dwellings will consume more energy than small dwellings if everything else is equal (NatHERS, 2012).

The effect of floor size growth in representative dwelling simulation models in the main climate zones is shown in Fig 5.14. As can be seen in the graph, floor area has a different effect on each representative dwelling type and climate. Type A, the suspended floor case, has been significantly affected by an increase in floor size. On the other hand, in Type B, slab on ground case, the slope of the change in energy consumption is less than that of Type A (Fig 5.14.). Colder climates are more sensitive to change in floor size than warmer ones for both types of dwellings.

![Fig 5.14: Influence of floor area growth in total thermal performance of representative dwelling simulation models in main climate zones. Floor Area growth percentage: 0%=78 m$^2$, 20%=~94 m$^2$, 40%=~110 m$^2$, 60%=~125 m$^2$, 80%=~141 m$^2$ and 100%=~156 m$^2$).

The result of floor size growth indicates a linear relationship between total energy requirement and floor area in both dwelling types and every climate. The study, however, does not cover designs with extremely high building parameters. For example, a highly glazed building may or may not have linear relationships with changes of floor area, but these cases have been excluded from this work. Linear relationship helps to use line slope equation, as shown in Equation 5.1, for developing area correction estimation and to identify the thermal performance of
dwelling simulation models with different sizes. Table 5.10 shows the area correction estimation model factors for each type in the three climates.

\[ y = ax + b \]  \hspace{1cm} (5.1)

\( a \) and \( b \) are constant values that depend on types and climates, \( x \) is a variable based on floor area growth percentages.

Table 5.10: Area correction estimation models based on representative dwelling types and climate zones.

<table>
<thead>
<tr>
<th>Climate</th>
<th>Dwelling type</th>
<th>( \alpha ) value</th>
<th>( \beta ) value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>7971.9</td>
<td>10910</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>1275.3</td>
<td>3488.2</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>8515</td>
<td>9230</td>
</tr>
<tr>
<td>Zone 5-Mascot</td>
<td>D</td>
<td>978</td>
<td>2490</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>8920</td>
<td>13059</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>1744</td>
<td>5214</td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>9492.9</td>
<td>12530</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>1651.3</td>
<td>4202.9</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>9727</td>
<td>10541</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>1317</td>
<td>2978</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>10938</td>
<td>15319</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>2347</td>
<td>6498</td>
</tr>
<tr>
<td>Zone 6-Nowra</td>
<td>A</td>
<td>14407</td>
<td>19238</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>2868.6</td>
<td>7121.7</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>13284</td>
<td>17140</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>2433</td>
<td>5673</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>15911</td>
<td>22740</td>
</tr>
<tr>
<td></td>
<td>F</td>
<td>3706</td>
<td>9758</td>
</tr>
<tr>
<td>Zone 7-Goulburn</td>
<td>A</td>
<td>2394</td>
<td>26008</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>4640.8</td>
<td>6945.8</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>13284</td>
<td>17140</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>F</td>
<td>3706</td>
<td>9758</td>
</tr>
</tbody>
</table>

Therefore, area correction estimation models can be used to explore the thermal performance of a variety of representative dwelling simulation models with different floor area than base case models in specified climates. Floor area growth percentage between similar representative dwelling base case model and bigger size model is calculated and applied to appropriate area correction estimation models to achieve a larger size thermal performance value.

However, an estimation error can be observed in some situations. This method is not working for attached units, townhouses or terrace houses, which share areas of walls, roofs or floors with other units, or areas which have no net heat loss or gain. When houses share building elements with other units, the area correction is not appropriate because the assumption about smaller units having larger surface areas is not true (Chen, 2011). Correction area estimation model is just a simple solution to give a general idea about the thermal performance of models that have a bigger floor area than base case models.
5.4 Discussion and limitations

In general, in terms of thermal energy performance, the building envelope elements behave differently based on the location, climatic conditions and physical properties of the building. The development of representative dwelling simulation models or the archetype approach have been used by a number of authors to model energy and resource quantities and impacts; from a study at a regional level by Lechtenböhmer and Schüring (2011) to more recent studies at urban scales by Firth et al. (2009) and Shimoda et al. (2004). The number of archetypes used in published research varies from as few as two to several thousand, and often data from actual buildings are used.

In this study, the influence of the main construction attributes on predicted energy consumption was explored in order to develop representative dwelling simulation models which cover a large proportion of the detached houses within the residential stock. These houses have substantially different energy performance characteristics. In this work, the role of occupant behaviour was not considered. Occupancy was represented as a single occupant constantly, and internal heat gains such as the use of domestic equipment, water-heating metric, and lighting were not considered. Furthermore, the annual energy requirement (kWh/annum) has been used as an indicator for the evaluation of the thermal performance of houses in the conditioned operation mode to maintain the modelled indoor temperature within pre-defined compliance set points. The thermal performance of representative dwelling simulation models is investigated for base case models as single floor area size; however, for different floor areas, a simple correction process has been defined.

In using Taguchi and ANOVA methods, there is a quantification of “Error”, which refers to errors caused by uncontrollable factors (noise) and are not included in the experiment. Shahavi et al. (2015) advises that the “Error” value should be less than 50% to consider the results reliable. In this study, errors of uncontrollable factors in all trials were less than 10%, suggesting that nearly all significant factors have been considered, and the errors in developing the Taguchi experiments were not significant. Confirmation test, which is defined as the optimal combination of process parameters and their levels, was also run for each case in order to verify the result of the minimum thermal energy expectation. Taguchi design was used.
primarily to study the main effect of building attributes on the value of the annual thermal energy requirements.

5.5 Chapter summary

Representative dwelling simulation models are particularly helpful in stock aggregation to make future projections. It supports analysis of the existing stock by making assumptions regarding changes in the housing stock and energy retrofit measures.

In this chapter, building simulation, Taguchi and ANOVA methods were applied to evaluate the influence of typical attributes on dwelling thermal performance (heating and cooling loads) and to filter out those attributes that have an insignificant effect on the calculated annual thermal energy requirement. This process led to the development of a series of representative dwelling simulation models for a large part of the housing stock in Australia. The result showed that floor type, building size, climate, level of ceiling insulation and wall materials have a substantial contribution to the thermal performance of dwellings, and they should be explicitly specified in models that represent the stock of existing buildings in Australia. Then, building simulation models were developed for defined representative dwelling types in order to evaluate their temperature fluctuations and their thermal loads in free running and conditioned mode, respectively. It also provided a comparison between the thermal performance of the derived representative dwelling simulation models and a highly efficient Solar Decathlon House (SD) to assess and demonstrate the necessity of improving the existing residential building. The influences of floor area on total thermal energy requirements of the representative dwelling simulation models were assessed and a simplified way was suggested to consider the impact of floor area.

This chapter has justified the development of twelve main types of representative simulation models which represent existing house of Australians is functioning relatively low in thermal energy performance. Evaluation of current thermal energy performance of representative simulation models also shows the high potential of improvement in these dwelling. This potential can be achieved through envelope retrofitting. Potential retrofitting measures and effective strategies to reduce the total
energy consumption of representative dwelling simulation models will be discussed in chapter 6.
Chapter 6: Assessment and prediction of annual heating and cooling demand in representative Australian residential dwellings

6.1 Introduction

One of the most popular ways of assessing energy and load features of buildings is sensitivity analysis (Athienitis, 1989, Buchberg, 1969, Lomas and Eppel, 1992, Daly et al., 2014, Thomas, 2011) which may be used to decide on viable design variables and conditions to improve building energy performance.

The present chapter focused on the application of sensitivity analysis to the energy performance improvement parameters in the representative dwelling simulation models developed in chapters 4 and 5. One of the purposes of the analysis in this chapter is to evaluate the importance and impact of input design parameters on the energy performance of models. This chapter was also presented the development of energy prediction models from building energy performance simulation results in order to approximately work out the energy loads of dwellings. Energy prediction models are created based on the building parameters that most strongly influence the annual thermal energy demand of residential buildings. The regression analysis was undertaken in three major climate zones across New South Wales (NSW). This chapter presents information regarding i) the identification of key building design variables using Differential Sensitivity Analysis, ii) the development of simple energy prediction models using regression analysis and the Taguchi Method, and iii) the evaluation of the developed energy prediction models.

In addition, the capability of the proposed methodology in development of energy prediction models was also examined by applying the methodology in a calibrated simulation model of an existing residential building.
6.2 Method

Sensitivity analysis was employed in this study in order to explore the sensitivity of simulated annual space heating and cooling energy requirements in changes of building envelope parameters. It was tested in a range of representative dwelling types that were developed for the current research (Chapter 5). The amount of energy needed to maintain indoor comfort conditions within the recommended set points (NatHERS, 2012), as discussed in Section 5.2.2, was the output variable. In this study, simulations were undertaken for three major climate zones across NSW. Parametric energy analysis was undertaken to explore the design parameters that were found to be influential. The Taguchi Method was used in order to reduce the modelling cost of the parametric analysis. A simple energy prediction model was then developed from the results of the parametric analysis for each building type in order to estimate the annual building energy consumption of the representative dwelling simulation models for NSW climate zones.

The process followed to develop the representative building types for the existing building stock has been reported previously in Chapter 4. For the current chapter, the representative dwelling types, which were modelled in Chapter 5, are used for analysis too; namely:

- Brick veneer wall with suspended timber floor with ceiling insulation.
- Brick veneer wall with slab on ground floor with ceiling insulation.
- Double brick wall with suspended timber floor with ceiling insulation.
- Double brick wall with slab on ground floor with ceiling insulation.
- Lightweight wall with suspended timber floor with ceiling insulation.
- Lightweight wall with slab on ground floor with ceiling insulation.

The representative dwelling simulation models significantly influence the outcomes of this work, as they form the foundation of all the subsequent analyses. The baseline building energy performance simulation models which are based on the representative dwelling types, required a number of assumptions regarding the generic building thermal properties. The key assumptions were outlined and described in Section 5.2.2. DesignBuilder, a graphical user interface for the
EnergyPlus simulation engine was used to calculate the idealized annual heating and cooling building loads, which serve as the relevant building energy performance metrics. Applicability of the regression model development method on a calibrated simulation model of a real building was also examined. The overall processes used in this chapter are shown in Fig 6.1.
6.2.1 Differential sensitivity analysis

To quantitatively assess the sensitivity of the space heating and cooling demand of dwellings to different design parameters, it was useful to consider the relative influence of these input parameters.

In this study, following the procedures outlined in Chapter 3, a Differential Sensitivity Analysis (DSA) was conducted. Since this study has the purpose of testing the sensitivity of a building’s energy use to the value of user assumptions, rather than a probability distribution of an uncertain input, DSA was a proper analysis. The Differential Sensitivity Analysis (DS) is appropriate because it supplies critical information about a parameter’s sensitivity at a single point in the parametric space. DSA, nevertheless, does not offer any information about the areas that fall outside the parametric range of a certain number of simulations unless, of course, the data could be linearly extrapolated (Bertagnolio, 2012). This was appropriate, as this study tested the uncertainty of predicted building energy use to a known range of commonly assumed values for various inputs.

The models were initially simulated using the base-case of representative dwelling simulation model inputs. The critical parameters were then varied one by one while the other parameters were kept constant for three climate zones in NSW.

The non-dimensional influence coefficient (IC) was used as a comparison index to measure the effect of improvement design parameters on dwelling envelope. It has been investigated as below in Equation 6.1.

\[
\text{Influence Coefficient} = \frac{\Delta OP}{\Delta IP} = \frac{\% \text{ Change in output}}{\% \text{ Change in input}}
\]  

(6.1)

Where \( \Delta IP \) and \( \Delta OP \) refer to changes in input and output parameters, respectively; \( IP_{bc} \), \( OP_{bc} \) are the base case values for output and input.

Drawing comparisons between parameters, a number of limitations were factored in depending on a calculated influence coefficient. The influence coefficient was calculated with the base assumption that the variance of the output in relation to a change in input would be almost linear (Simm et al., 2011). The minimum and maximum values for each parameter of interest in this study are given in Table 6.1. It was also assumed that with any deviation from linearity, errors would ensue. The
coefficient of determination ($R^2$) value can be calculated as a check for linearity of each input parameter. In a building energy performance simulation, there is a limit to each parameter’s range of realistic values; so the percentage change to the input parameter will be restricted distinctly for each input.

The predicted total building space heating and cooling demand for each case and the average influence coefficient across each parameter range were calculated. Table 6.1 displays high, moderate, and low values of the input parameters; the output parameter was the total building energy consumption. Input values, to use in a Differential Sensitivity Analysis (DSA), were categorised into three scenarios based on potential energy intensity impact on the dwelling. “High scenario” presents input values with a potential resultant of maximum energy intensity, “Moderate scenario” present input values with the potential resultant of average energy intensity and “Low scenario” present input values with potential resultant of minimum energy intensity.

The input parametric range was determined based on the following data sources: Section J in the Building Code of Australia (ABCB, 2015), the default values included in AIRAH guides (AIRAH, 2013), market products (knauf insulation, 2016), and previously published input values from Australian studies (Branz Ltd, 2014, Tony isaacs consulting, 2009, Belusko and Timothy, 2011, DOIIS, 2013).

The representative dwelling simulation models were first simulated with the base inputs, and then the parameters of interest were varied one after another while the other parameters remained the same. The total building energy consumption was calculated for each case, and the average influence coefficient across each parameter range was calculated. The coefficient of determination ($R^2$) was also calculated to test the assumption of linearity. Cases with the value of $R^2$ less than 0.7 (Daly et al., 2014) were taken to indicate that the assumption of linear response may not hold, and that further investigation would be required to understand the interaction between parameters.
Table 6.1: Representative dwelling simulation model inputs and parametric range for sensitivity analysis.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Representative model inputs</th>
<th>Sensitivity analysis ranges</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>High scenario</td>
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<td>Wall brick veneer R-value (m²K/W)</td>
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<td>0.5</td>
</tr>
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<td>Floor R-value (m²K/W)</td>
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<td>0.4</td>
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<td>Roof R-value (m²K/W)</td>
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<tr>
<td>Ceiling R-value (m²K/W)</td>
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<td>0.3</td>
</tr>
<tr>
<td>Internal wall R-value (m²K/W)</td>
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<td>0.5</td>
</tr>
<tr>
<td>Glazing types U-value (W/m²K)</td>
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<td>5.8</td>
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<td>Window frame U-value (W/m²K)</td>
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<td>5.9</td>
</tr>
<tr>
<td>Airtightness</td>
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<td>Very Poor</td>
</tr>
<tr>
<td>Occupant number</td>
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<td>0</td>
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<tr>
<td>Openable window area (%)</td>
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<td>25</td>
</tr>
<tr>
<td>South eaves (m)</td>
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<td>0</td>
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<tr>
<td>East-west eaves (m)</td>
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<td>0.1</td>
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<tr>
<td>Window awning (m)</td>
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</tr>
<tr>
<td>WWR (%)</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

All models have similar parameter input values except for wall materials in base case models. R-value of 0.534 (m²K/W) for brick veneer, 0.679 (m²K/W) for double brick veneer and 0.437 (m²K/W) for fibro are used for wall material in the base case models.

6.2.2 Development of energy prediction models

There have been a number of previous studies using simple two-parameter regression analysis technique for the energy analysis of buildings, pre- and post-retrofits (Lam et al., 2004, Lam et al., 2010, Lam et al., 2002, Ben-Nakhi and Mahmoud, 2004). A multiple regression technique was adopted in the present study to develop simple energy prediction models for representative dwelling types in three climates. The methodology and regression coefficients used in this study are valid only in configurations with parameters within the employed range. On the contrary, the building parameters that were applied to the representative dwelling simulation models ranged broadly in proportion to house configurations. The data, used in this work were collected from certain types of buildings and locations. It should be noted that other locations and types of buildings (namely townhouses, duplex houses and apartments) would possibly produce different regression coefficients. Nevertheless, the overarching trends apparent in this study might be
applicable to other residential models on the condition that the limitations of the current study are carefully and sufficiently considered.

6.2.2.1 Taguchi method

The main parameters of design features simulated in the sensitivity analysis were carefully selected for the parametric simulations. Table 6.2 lists the six major parameters and ranges which were selected to appropriate variation by the simulation software. These parameters were considered likely to have a significant impact on the thermal performance of dwellings.

An ideal database for the multiple regression analysis should be comprised of simulated annual building total space heating and cooling energy requirements covering possible combinations of the main highly influential parameters (Lam et al., 2010). This process could result in several thousands of simulations and therefore the Taguchi order layout was used to reduce the required model runs. As discussed before, this method uses a fractional factorial test design, termed Orthogonal Arrays (OA) (Yang and Tarng, 1998) and covers a high energy number of parameter sets. In this study, the Taguchi Orthogonal Arrays design order layout led to a total of 450 simulation runs: five different values for six design input parameters were found to be the most influential as a result of the differential sensitivity analysis described in Section 6.2.1. The resulting six most influential parameters are shown in Table 6.2 and will be reiterated in the results section of this chapter. It should be noted that these parameters are relevant to the climates of this study from NSW. A similar procedure could be followed for other climates, but the resulting parameters are likely to be different. The likely effect of these parameters was observed from the sensitivity analysis.
Table 6.2: Summary of base-case values and ranges for the representative dwelling simulation models load input parameters.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Abbr.</th>
<th>Representative model inputs</th>
<th>1st-Lower value</th>
<th>2nd</th>
<th>3rd-Mid value</th>
<th>4th</th>
<th>5th-Higher value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall (brick veneer) R-value (m²K/W)</td>
<td>WI</td>
<td>0.5</td>
<td>0</td>
<td>1.5</td>
<td>2</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>Floor R-value (m²K/W)</td>
<td>FI</td>
<td>0.4</td>
<td>0</td>
<td>1</td>
<td>1.5</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>Ceiling R-value (m²K/W)</td>
<td>CI</td>
<td>1.3</td>
<td>0</td>
<td>2.5</td>
<td>3.5</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Glazing types U-value (W/m²K)</td>
<td>G</td>
<td>Single (5.8)</td>
<td>Single (5.8)</td>
<td>Single Low E (3.78)</td>
<td>Double Low E (2.6)</td>
<td>Double Low E Argon (1.7)</td>
<td></td>
</tr>
<tr>
<td>Airtightness</td>
<td>Ar</td>
<td>Poor</td>
<td>Very Poor</td>
<td>Poor</td>
<td>Medium</td>
<td>Good</td>
<td>Excellent</td>
</tr>
<tr>
<td>WWR (%)</td>
<td>W</td>
<td>15</td>
<td>10</td>
<td>15</td>
<td>25</td>
<td>35</td>
<td>45</td>
</tr>
</tbody>
</table>

6.2.2.2 Multiple regression models

The regression analysis aims to forecast the impact that the dependent variables could have on energy consumption as a retrofitting. It can predict one variable based on the knowledge of another variable when observing building energy performance and this is indirectly related to the design parameters.

In this study, a multiple linear regression model was selected and developed with ANOVA for predicting the total annual heating and cooling energy requirements of representative dwelling simulation models in the three climates of the study.

The general form of energy equation that has been used in this study is shown in Equation 6.2:

\[ E = K + (a \text{Parameter } 1) + (b \text{Parameter } 2) + (y \text{Parameter } n) \]  \hspace{1cm} (6.2)

Where \( E \) = total annual heating and cooling and \( K \) = regression constant

In this study, the regression analysis was performed on a statistical package of Minitab 17 software (Minitab Statistical Software Support, 2016d). Energy equations were determined for the annual building energy load of each representative dwelling simulation model in every climate.

Multicollinearity between variables has been considered by using the variance inflation factor (VIF). VIF assesses how much the variance of an estimated regression coefficient increases if parameters are correlated (Martz, 2013). Multicollinearity was not detected as it will be described in Section 6.3.2.1. The
results are, therefore, assumed to have a linear dependence on the parameters in the final regression models.

### 6.2.3 Regression models evaluation

A key step in developing the model is the verification process. In this process anticipated performance deviation from a regression model and a real data is determined.

In this chapter, an independent set of simulation results was used to verify the predictions of the energy prediction models. Thirty-five simulation runs have been undertaken for each model in three climates. A random numerical experiment was carried out by using the random number generator in Microsoft Excel to generate six sets of input design parameters for simulations. The sets of randomly generated input variables, from which the 35 different simulation models, were developed, and the results of simulations have been compared with the results of the regression prediction models. These simulation models were independent of those used in the development of the energy prediction models.

### 6.2.4 Energy prediction method validation

A critical part of building retrofitting analysis is to validate the developed energy prediction models. Many studies have used a calibrated simulation model to analyse the potential effects of various building energy efficiency measures for existing buildings (Fumo, 2014, Wei et al., 2014, ASHRAE, 2013). This method is to tune the inputs in a building energy model in order to achieve a close match between measured and modelled energy data. However, using calibrated simulation outputs of energy model based on measured energy data in representative dwelling simulation models is nearly impossible due to lack of specific building measured data. In this section, the methodology used for developing the energy prediction models in representative dwelling types was again used in an existent highly efficient house to examine the validity of the energy retrofitting application of this study. To evaluate the reliability of the method, firstly, energy model of the case study (Solar Decathlon House), as described in Section 5.2.3, was created in DesignBuilder and simple energy prediction model of it was obtained by following the process described in Section 6.2.2. In this way, an energy prediction model was developed based on identified high influential parameters that were defined in Section 6.31. Secondly,
the Solar Decathlon House (SD) simulation model was calibrated with recorded temperature data for a short period, as it will be explained in Section 6.3.4.2. The calibrated simulation model inputs were refined based on inputs of a simulation model that used for development of energy prediction model such as occupancy, thermostat set points, window control, air condition control and COP. The refined model was re-simulated to predict the annual total heating and cooling demand of Solar Decathlon House (SD) model in Mascot climate. Thirdly, series of random simulations were then undertaken and then the results were compared with the prediction of the regression model.

The simple process distilled in this section is shown in Fig 6.2

Fig 6.2: Energy prediction method validation process.
6.2.4.1 Development of Solar Decathlon House regression model

Solar Decathlon House (SD), at the University of Wollongong, was used as a case study to develop a simplified energy equation that predicts the thermal demand (heating and cooling) and assesses the capability of used methodology in this study. Solar Decathlon House (SD) is a highly efficient house that won Solar Decathlon House competition in China in 2013. A simulation model was developed by using the DesignBuilder program based on real construction characteristics as listed in the manual of the Solar Decathlon House (SD). In this study, energy simulation database was required to develop a simplified energy prediction model for a case study. Creation of the energy database based on five different parameters (identified in Section 6.3.1) required a large number of simulations. To tackle this problem, Taguchi fractional factorial order layout, termed Orthogonal Arrays (OA), was again proposed for the Solar Decathlon House (SD) model in Mascot climate. The required energy database was created by running less number of simulations to develop the energy prediction model. The regression analysis was used for development of the simplified energy prediction model based on highly influential parameters listed in Section 6.2.1. The parameters that were used for the development of energy prediction model for the Solar Decathlon House are shown in Table 6.3.

Table 6.3: Summary of base-case values and ranges for the Solar Decathlon House simulation model, load input parameters.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Abbr</th>
<th>1st-Lower value</th>
<th>2nd</th>
<th>3rd-Mid value</th>
<th>4th</th>
<th>5th-Higher value (Solar Decathlon House model inputs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall R-value (m²K/W)</td>
<td>W1</td>
<td>1.5</td>
<td>2</td>
<td>2.5</td>
<td>3</td>
<td>4.27</td>
</tr>
<tr>
<td>Floor R-value (m²K/W)</td>
<td>FI</td>
<td>1</td>
<td>1.5</td>
<td>2.5</td>
<td>3</td>
<td>8.6</td>
</tr>
<tr>
<td>Ceiling R-value (m²K/W)</td>
<td>CI</td>
<td>2.5</td>
<td>3.5</td>
<td>5</td>
<td>6</td>
<td>8.2</td>
</tr>
<tr>
<td>Glazing types U-value (W/m²K)</td>
<td>G</td>
<td>Single (5.8)</td>
<td>Single Low E (3.78)</td>
<td>Double Low E (3.16)</td>
<td>Doubl e Low E (2.6)</td>
<td>Double Low E Argon (1.35)</td>
</tr>
<tr>
<td>Airtightness</td>
<td>Ar</td>
<td>Very Poor</td>
<td>Poor</td>
<td>Medium</td>
<td>Good</td>
<td>Excellent</td>
</tr>
</tbody>
</table>
6.2.4.2 Development of Solar Decathlon House calibrated energy simulation model

In order to examine the validity of the developed energy prediction method in practice and to evaluate the building energy simulation skill of the researcher (author) in producing the accurate simulation energy models, a calibrated simulation model was required. The focus of the calibration was on the Solar Decathlon House (SD) simulation model with regards to the recorded experiment data as free-running to obtain simple calibrated simulation model.

In this effort, the created Solar Decathlon House (SD) simulation model, described in Section 5.2.3, was reviewed again to accurately match with existing house specification in DesignBuilder. A weather file was also generated based on the recorded outdoor temperature and wind speed for the house site by using the Element software. The average measured Solar Decathlon House (SD) indoor temperature was used to be compared with the DesignBuilder simulation indoor temperature result over the period of seven days.

Calibration process of Solar Decathlon House energy simulation model

To obtain calibrated energy simulation model, a number of model revisions were required. “A number of iterative process steps were required to meet the acceptance criteria and satisfy the analyst(s)” (Raftery et al., 2011). These steps depend on “the size and complexity of the modelled building and systems and the amount of information available at each stage of the calibration process”. In this study, the Solar Decathlon House (SD) energy simulation model, described in Section 5.2.3, was modified and re-examined to achieve a calibration, according to the outcome of simulations. The definitions of modelling that was examined are:

- Geometrical details
- Constructional details
- Glazing and frame properties
- Internal contents (thermal mass)

In order to deliver precise weather data over the course of the study, the weather station was set up next to the house to measure temperature and wind speed. The
weather data file was generated based on outdoors dry-bulb temperature and wind speed by the Element software. Elements (Big Ladder Software 2016) is a free, open-source, cross-platform software tool for creating and editing custom weather files for building energy modelling. However, no wind direction and solar radiation measurements were available for this location. Thus, instead, the typical means of wind and solar radiation parameters from Nathers (NIWA, 2012) for climate zone 5-Mascot were used.

Data analysis

In this work, average hourly indoor and outdoor temperatures were used for 7 days during 11/11/2014 to 18/11/2014. The used sensors were Clipsal 5031RDTSL-WE C-Bus temperature sensors that are wall mounted and connected digitally over the C-Bus network with Resolution ± 0.5°C and Accuracy ± 1°C. During the period of the measurement, the house was unoccupied, the HVAC system was off and the windows were closed to reduce the uncertainties of the calibration as much as possible.

Mean Bias Error (MBE) and Cumulative Variation of Root Mean Squared Error (CVRMSE) values were calculated using the following Equations 6.3 and 6.4 formulas:

\[
CVRMSE = \sqrt{\frac{\sum_{i=1}^{N_p}((M_i-S_i)^2/N_p}{M_p}}}
\]  

(6.3)

\[
MBE = \frac{\sum_{i=1}^{N_p}(M_i-S_i)}{\sum_{i=1}^{N_p} M_i}
\]

(6.4)

Where \(M_i\) and \(S_i\) are measured and simulated data at instance \(i\), respectively; \(p\) is the interval (e.g. monthly, weekly, daily & hourly), \(N_p\) is the number of values at interval \(p\) and \(M_p\) is the average of the measured data.
6.2.4.3 Method verification-Analysis of Solar Decathlon House energy prediction model vs calibrated simulation model

To determine the reliability of the developed energy prediction model in anticipating energy performance of the Solar Decathlon House (SD), an independent set of simulation results was used from the calibrated model to verify its predictions. Twenty-five simulation runs were undertaken for Solar Decathlon House (SD) model in Mascot climate. The random number generator in Microsoft Excel was used to generate five sets of input design parameters for simulations which were independent of those used in the development of the regression model. In order to evaluate the reliability of Solar Decathlon House (SD) energy model prediction, the results of the regression prediction model for sets of variables were compared with the outcome of calibrated simulation model with similar sets of simulations.

6.3 Results and discussion

6.3.1 Differential sensitivity analysis of parameters influencing the thermal performance of houses

In this study, a Differential Sensitivity Analysis (DSA) was conducted following the procedure outlined in Section 6.2.1. Types A to F representative dwelling simulation models with insulation, as defined in the previous chapter, were analysed to investigate the relative impact of different design parameters on the total energy consumption. The outcomes of simulations were comparatively reported for each parameter in all representative dwelling simulation models in all three climates. To evaluate the relative influence and to check for linearity of each parameter under consideration, the absolute influence coefficient and the coefficient of determination ($R^2$) were calculated. From combining the extreme parameters values, the scenarios with the highest and lowest annual energy requirements were also investigated on representative dwelling simulation models.

6.3.1.1 Sensitivity analysis of improvement parameters

In the following section, the effect of changes to input improvement parameters, as shown in Table 6.1, on the thermal performance of representative dwelling simulation models will be summarised for the three climates of this study.
Ceiling insulation

Using bulk ceiling insulation has improved the thermal performance in all types of representative dwelling simulation models (refer to Fig 6.3). Improvement has been more effective in models with slab on ground floor than with suspended timber floor. Adding ceiling insulation of R-value 1 (m²K/W) to an uninsulated ceiling of a representative dwelling (low energy scenario, R-value of ceiling is 0.3 (m²K/W)) can give an average reduction of the annual energy requirements from 15% to up to 35% for suspended timber and slab on ground dwellings, respectively. This reduction increases from 25% and 50% when enhancing the ceiling insulation resistance up to R-value 6 (m²K/W) in the representative dwelling simulation models. As expected, adding the ceiling insulation has a greater effect on improving the thermal performance of dwellings that are uninsulated and located in cold climates compared to other climates. The annual thermal performance of dwellings with slab on ground was improved by approximately 2 times more than the thermal performance of dwellings with suspended timber floor in all three climates.

As a result, using ceiling insulation has a potential to reduce the annual energy requirements in conditioned houses.

Fig 6.3: Effect of ceiling insulation on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.
Wall insulation

As shown in Fig 6.4 and as expected, wall insulation would decrease the annual energy requirements in all cases in every climate. The simulation results indicate that the thermal performance of representative dwelling simulation models, from high scenario (uninsulated wall, R-value of wall is 0.4 (m²K/W)) to medium scenario (R-value of wall is 2.4 (m²K/W)) can be improved for up to 45% in fibro wall, 30% in brick veneer wall and 25% in double brick for both floor type houses and for every climate. The changes in the wall insulation influence the heavyweight houses by less fluctuating indoor temperatures (e.g. lower peaks) than in lightweight houses due to the effect of thermal mass. The addition of R-value 6 (m²K/W) insulation to the uninsulated external walls (high scenario, R-value of wall is 0.4 (m²K/W)) resulted in an average annual thermal performance improvement from 22% to 55% in fibro, 10% to 35 % in brick veneer and 10% to 30% in double brick dwellings with suspended timber and slab on ground floor types, respectively. The proportion of annual thermal performance improvement in upgrading the dwellings with external wall insulation of R-value 2 (m²K/W) (medium scenario) to R-value 6 (m²K/W) l (low scenario) was also less than the average of 11% in all houses.

Lightweight dwelling in particular, such as the fibro types, benefits more than heavyweight houses (brick veneer and double brick) from the addition of external wall insulation. As expected, the effect of wall insulation in the annual energy requirements was more significant in colder climates in all models.
Floor insulation

Dwellings with slab on the ground floor have the highest thermal performance (Willrath, 1998). In this study, the slab on ground cases were removed from floor insulation analysis due to the impossibility of floor retrofitting action in this type. The timber floors were assumed to be suspended about 60 cm above the ground. In these cases, insulation was added to the bottom of the timber floor.

As shown in Fig 6.5, the thermal performance of the representative dwelling simulation models showed significant sensitivity towards the addition of under-floor insulation. The insulated houses (medium scenario, R-value of floor is 2.4 (m²K/W)) with double brick, brick veneer and fibro wall constructions had up to 33%, 26% and 20% less thermal energy requirements than uninsulated houses (high scenario, R-value of floor is 0.4 (m²K/W)) in every climate. However, the potential for the thermal performance improvement, from adding the layer of insulation, in a dwelling can be reduced by the existence of prior floor insulation.
Fig 6.5: Effect of floor insulation on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Roof insulation**

A pitched roof receives no insulation or layer of reflective foil in current typical constructions. The effects of insulation in the pitched roof are shown in Fig 6.6. It can be seen that adding the roof insulation (low scenario, R-value of roof is 4.4(m²K/W)) in uninsulated roof (high scenario, R-value of floor is 0.4(m²K/W)) has the potential to reduce the annual heating and cooling by up to 15% with slab on ground floor and by approximately 7% in suspended timber floor houses.

Increasing the roof insulation to levels greater than those of R-value 2 (m²K/W) did not result in significant improvement of the thermal performance of all types of models in every climate. Employing ceiling insulation could have a higher potential than roof insulation to affect the annual thermal performance of dwellings.
Fig 6.6: Effect of floor insulation on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Glazing types**

The thermal performance of the representative dwelling simulation models was calculated for a range of glazing types based on U-value from 5.19 (W/ m²K) to 1.7 (W/ m²K) and also based on SHGC from 0.81 to 0.69. Fig 6.7 shows the outcome of changes in the thermal performance when all glazing changed from single glazing to other types that were specified in Table 6.1. It demonstrates that all representative dwelling simulation models have the same pattern in their annual thermal performance in response to the application of different glazing types. The replacement of glazing in a dwelling with single glazed windows (high scenario-U-value of glazing is 5.8(W/ m²K) and SHGC is 0.819) to double glazed (medium scenario- U-value of glazing is 3.1(W/ m²K) and SGHC is 0.76) resulted in an average reduction of the annual thermal requirements by 11.3% in slab on ground and 3% in suspended floor dwellings in every climate. This reduction can reach 19.5% and 5% if they are upgraded from high scenario (U-value of 5.8 (W/ m²K) and SHGC of 0.819) to low scenario (U-value of 1.7 (W/ m²K) and SHGC of 0.69) for slab on ground and suspended floor dwellings, respectively. The double brick and fibro models have the highest and lowest reduction in the annual energy.
requirements, respectively. This result noted that the windows type could be an effective improvement parameter for retrofitting existing dwellings.

![Graph showing the effect of window type on annual thermal performance](image)

**Fig 6.7:** Effect of window type on the annual thermal performance of representative dwelling simulation models with WWR of 15% in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Window frame U-value (W/m²K)**

The impact of the window frame in the total thermal performance of dwellings depends on different parameters like size of the frame. The effect of different window frames in representative dwelling simulation models was examined and presented in Fig 6.8. The analysis of this figure shows the minor influence of window frames in the annual energy requirements of the representative dwelling simulation models. Therefore, frame type can be neglected from the list of significant building envelope parameters, required for the development of simplified annual heating and cooling regression models.
Fig 6.8: Effect of window frame U-value on the annual thermal performance of representative dwelling simulation models with WWR of 15% in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Airtightness**

The annual thermal performance of conditioned houses is declining when infiltration rate increases. In this study, three different infiltration rates were included in the simulations for determining the impact of infiltration rate in the dwelling annual heating and cooling requirements. Infiltration rate increased from very poor to excellent as defined by the crack templates in the DesignBuilder. In this study, every surface in the model has a crack and its size (characterised by flow energy coefficient and exponent) is specified by the DesignBuilder cracks database (DesignBuilder, 2015).

Improving airtightness levels boosts the thermal performance of the representative dwellings for all types of houses in every climate, as shown in Fig 6.9. The analysis shows that with improved airtightness, the annual thermal performance of the houses with slab on ground is enhanced by up to 50% and those with suspended timber floor by up to 35%. As expected, improvement of airtightness had a greater effect on reducing the annual thermal loads in the colder climates of NSW.
By improving infiltration rate from “Very Poor” (high energy scenario) to “Excellent” (low energy scenario), the energy intensity of double brick dwellings with suspended timber floor (Type C) and slab on ground floor (Type D) became lower than that of brick veneer houses with the same floor types, on average by 3% and 13%, respectively. Double brick houses, Type C and Type D, also had an average 5% and 20% less energy intensity than fibro houses (Type E and Type F) in same climates, respectively. This outcome shows the high impact of airtightness improvement in dwelling thermal performance.

Fig 6.9: Effect of airtightness on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Openable window area (%)**

The openable window area is defined as a percentage that the total window area can be opened. By increasing the percentage of openable window area, a house’s annual thermal performance could be affected. As shown in Fig 6.10, an increase from 25% to 75% on the openable window area resulted in a slight reduction of annual energy requirements. So, this parameter was not considered further in this study. However, this reduction can be more significant if seasonal energy requirements or free running modes are investigated for potential improvements in
the performance of houses in the summer. However, a detailed analysis of natural ventilation and window control strategies is beyond the scope of this study.

Fig 6.10: Effect of openable window area (%) on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Number of occupants**

Different studies probed the effect of the number of occupants, for example, family size (de Meester et al., 2013) and occupants’ behaviour (Motuziene and Vilutiene, 2013, Yu et al., 2011), on the energy consumption of a building. In this study, the effect that the number of occupants has on the total energy requirements of the representative dwellings has been examined (refer to Fig 6.11). The results showed that the number of occupants, from dwelling with no occupants (high scenario) to four occupants (low scenario), had a moderate effect on the total energy load of houses. This has been up to 27% in slab on ground floor and 10% in suspended timber floor.
Fig 6.11: Effect of number of occupants on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Eaves (m)**

Shading provided by overhangs was studied and its effect on energy intensity was calculated in this study. Eaves effect was simulated first for the south and then tested in both east and west facades of the representative dwelling simulation models.

Adding an overhang in south caused a slight reduction in annual thermal performance of all models as shown in Fig 6.12. Changing the width of eaves from 0.4 to 1.5 m had the influence of up to 5% in intensifying the model energy.

The same overhang in east and west did not influence on the annual thermal performance, but a slight improvement was observed in thermal performance in fibro cases (Type E and Type F), as shown in Fig 6.13. As the effect of solar loads on the lightweight material is usually more than heavyweight materials, these results are significantly different. Eaves in east and west of fibro dwellings could reduce the solar loads and therefore cooling loads. The influence of eaves was detected insignificant in representative dwelling simulation models and neglected from...
further analysis. However, eaves could be useful for different houses if they are designed in relation to window area and orientation.

**Fig 6.12:** Effect of south eaves on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Fig 6.13:** Effect of east and west eaves on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.
**Internal wall insulation**

Internal walls are mainly built as two layers of plasterboard with no additional insulation. The effect of internal wall insulation in representative dwelling simulation models has been reported in Fig 6.14. It was found that the thermal performance in all representative dwelling simulation models with both floor types were not considerably affected (less than 1%) by adding internal wall insulation in every climate. However, it is possible that the effect of internal walls would be more significant if we changed the wall materials instead of adding the insulation in conditioned houses (Kordjamshidi, 2011). This parameter was removed from list of improvement parameters for further analysis in this study.

![Effect of internal wall insulation on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.](image-url)
Window awning (m)

The use of window awnings could, in some cases, improve building’s thermal energy performance. Simulations were done for three sizes of external window awnings in the representative dwelling simulation models. The energy simulations were divided into two categories; first, east and west facades; and second, north and south. The result of east-west awning simulations showed a minor potential in the reduction of energy intensity in every model in all climates (reductions were up to 3%) (Fig 6.15).

The setting of different window awning in south and north facades also produced close patterns as east and west awnings affect the annual thermal performance of dwellings, as shown in Fig 6.16. The results revealed that 1 m awning (low energy scenario) could influence total energy intensity of a dwelling with no awnings (high energy scenario) by up to 1% in every climate. This might have happened due to the availability of north facade eaves. It should be noted that even though window awnings were not an appropriate improvement technique for the developed representative dwelling simulation models in this study, they might be helpful for other models with different configurations.
Fig 6.16: Effect of north and south awnings on the annual thermal performance of representative dwelling simulation models in climate Zone 5-Mascot, Zone 6-Nowra and Zone 7-Goulburn. Types A to F refer to the construction types that described in Section 6.2.

**Window to wall ratio (%)**

The impact of window to wall ratio (WWR) was studied in Fig 6.17. A series of energy simulations was undertaken, in which the window areas in four facades increased from 15% to 30% and to 75%.

The analysis shows that increasing the percentage of the window area to 30% results in an insignificant variation in the annual thermal performance of the models in every climate. Increasing the window to wall ratio significantly increased the energy requirements of double brick houses by up to 200%, brick veneer houses by up to 150%, and fibro houses by up to 50%. In addition, the effects of WWR are greater in models with slab on ground floor than models with suspended timber floor. Increasing the window area in heavyweight houses reduces the effect of the mass by accelerating heat transfer.

A smaller window area is more appropriate for improving the thermal performance of a conditioned house. WWR should be considered as significant parameters for the thermal performance of dwellings.
6.3.1.2 Analysis of influence coefficients

The annual energy intensities of the simulation models were found and discussed in Section 6.3.1.1 for the improvement design parameters with a range of different input values in the main three climate zones of Australia. To quantitatively assess how sensitive the total building energy use would be to changes in the input design parameters, the absolute influence coefficient (IC) was determined.

Table 6.4, Table 6.5 and Table 6.6 present the calculated absolute influence coefficients (IC). The highlighted values with an $R^2$ of less than 0.7 indicate that the total energy consumption was not represented by the changes to the input parameter and further examination would be required to characterise the influence of that input variable on energy consumption. Fig 6.18, Fig 6.19 and Fig 6.20 also illustrate the same information as Table 6.4, Table 6.5 and Table 6.6 but in a way that influence coefficients could be more easily compared amongst building types. In general, “the larger the IC, the more important the design parameter would be as it tends to exert greater influence on the energy use of the building” (Lam et al., 2010).
<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Type A</th>
<th>Type B</th>
<th>Type A</th>
<th>Type B</th>
<th>Type A</th>
<th>Type B</th>
<th>Type A</th>
<th>Type B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Climate 5</td>
<td>Climate 6</td>
<td>Climate 7</td>
<td>Climate 5</td>
<td>Climate 6</td>
<td>Climate 7</td>
<td>Climate 5</td>
<td>Climate 6</td>
</tr>
<tr>
<td>Airtightness</td>
<td>0.2586</td>
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<td>0.5159</td>
<td>0.4061</td>
<td>0.40316</td>
<td>0.5159</td>
<td>0.4061</td>
</tr>
<tr>
<td>WWR</td>
<td>0.1498</td>
<td>0.1443</td>
<td>0.1095</td>
<td>0.3628</td>
<td>0.3257</td>
<td>0.2241</td>
<td>0.3628</td>
<td>0.3257</td>
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<tr>
<td>Ceiling insulation</td>
<td>0.1160</td>
<td>0.1321</td>
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<td>0.2979</td>
<td>0.3189</td>
<td>0.3531</td>
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<tr>
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<td>0.0619</td>
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<td>0.1923</td>
<td>0.1838</td>
<td>0.2209</td>
<td>0.1923</td>
</tr>
<tr>
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<td>0.0472</td>
<td>0.0445</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Wall insulation</td>
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<td>0.0485</td>
<td>0.0495</td>
<td>0.0537</td>
<td>0.0485</td>
<td>0.0495</td>
</tr>
<tr>
<td>Openable window</td>
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<td>0.0100</td>
<td>0.0044</td>
<td>0.0111</td>
<td>0.0036</td>
<td>0.0085</td>
<td>0.0111</td>
<td>0.0036</td>
</tr>
<tr>
<td>Number of occupants</td>
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<td>0.0097</td>
<td>0.0489</td>
<td>0.0465</td>
<td>0.0354</td>
<td>0.0489</td>
<td>0.0465</td>
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<td>0.0045</td>
<td>0.0035</td>
<td>0.0103</td>
<td>0.0105</td>
<td>0.0130</td>
<td>0.0103</td>
<td>0.0105</td>
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<tr>
<td>East-West awning</td>
<td>0.0343</td>
<td>0.0002</td>
<td>0.0200</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>South eaves</td>
<td>0.0033</td>
<td>0.0024</td>
<td>0.0047</td>
<td>0.0127</td>
<td>0.0076</td>
<td>0.0075</td>
<td>0.0127</td>
<td>0.0076</td>
</tr>
<tr>
<td>Internal partition</td>
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<td>0.0009</td>
<td>0.0019</td>
<td>0.0001</td>
<td>0.0009</td>
</tr>
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<td>0.0005</td>
<td>0.0005</td>
<td>0.0000</td>
<td>0.0015</td>
<td>0.0029</td>
<td>0.0000</td>
<td>0.0015</td>
</tr>
<tr>
<td>North-South awning</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.0002</td>
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<td>0.0000</td>
<td>0.0000</td>
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</table>

Table 6.5: Influence coefficients of input parameters for representative dwellings Type C and Type D.

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<tr>
<th>Parameters of interest</th>
<th>Type C</th>
<th>Type D</th>
<th>Type C</th>
<th>Type D</th>
<th>Type C</th>
<th>Type D</th>
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<tbody>
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<td></td>
<td>Climate 5</td>
<td>Climate 6</td>
<td>Climate 7</td>
<td>Climate 5</td>
<td>Climate 6</td>
<td>Climate 7</td>
</tr>
<tr>
<td>Airtightness</td>
<td>0.2953</td>
<td>0.2704</td>
<td>0.3181</td>
<td>0.7156</td>
<td>0.5788</td>
<td>0.5166</td>
</tr>
<tr>
<td>WWR</td>
<td>0.1893</td>
<td>0.1870</td>
<td>0.1364</td>
<td>0.5095</td>
<td>0.4655</td>
<td>0.2883</td>
</tr>
<tr>
<td>Ceiling insulation</td>
<td>0.1260</td>
<td>0.1443</td>
<td>0.1296</td>
<td>0.3882</td>
<td>0.4311</td>
<td>0.3359</td>
</tr>
<tr>
<td>Glazing u-value</td>
<td>0.0476</td>
<td>0.0719</td>
<td>0.0727</td>
<td>0.3095</td>
<td>0.2744</td>
<td>0.2261</td>
</tr>
<tr>
<td>Floor insulation</td>
<td>0.0468</td>
<td>0.0548</td>
<td>0.0497</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Wall insulation</td>
<td>0.0170</td>
<td>0.0184</td>
<td>0.0205</td>
<td>0.0502</td>
<td>0.0510</td>
<td>0.0574</td>
</tr>
<tr>
<td>Openable window</td>
<td>0.0219</td>
<td>0.0109</td>
<td>0.0044</td>
<td>0.0189</td>
<td>0.0135</td>
<td>0.0128</td>
</tr>
<tr>
<td>Number of occupants</td>
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<td>0.0101</td>
<td>0.0117</td>
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<td>0.0748</td>
<td>0.0498</td>
</tr>
<tr>
<td>Roof insulation</td>
<td>0.0074</td>
<td>0.0084</td>
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<td>0.0159</td>
<td>0.0167</td>
<td>0.0126</td>
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<tr>
<td>Window frame</td>
<td>0.0011</td>
<td>0.0063</td>
<td>0.0022</td>
<td>0.0155</td>
<td>0.0175</td>
<td>0.0143</td>
</tr>
<tr>
<td>East-West awning</td>
<td>0.0029</td>
<td>0.0002</td>
<td>0.0020</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>South eaves</td>
<td>0.0050</td>
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<td>0.0136</td>
<td>0.0107</td>
</tr>
<tr>
<td>Internal partition</td>
<td>0.0022</td>
<td>0.0027</td>
<td>0.0028</td>
<td>0.0010</td>
<td>0.0025</td>
<td>0.0032</td>
</tr>
<tr>
<td>East-West eaves</td>
<td>0.0010</td>
<td>0.0009</td>
<td>0.0004</td>
<td>0.0091</td>
<td>0.0082</td>
<td>0.0072</td>
</tr>
<tr>
<td>North-South awning</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
Table 6.6: Influence coefficients of input parameters for representative dwellings Type E and Type F.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Type E</th>
<th>Type F</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Climate 5</td>
<td>Climate 6</td>
</tr>
<tr>
<td>Airtightness</td>
<td>0.2122</td>
<td>0.1812</td>
</tr>
<tr>
<td>WWR</td>
<td>0.0985</td>
<td>0.0911</td>
</tr>
<tr>
<td>Ceiling insulation</td>
<td>0.0980</td>
<td>0.1102</td>
</tr>
<tr>
<td>Glazing u-value</td>
<td>0.0489</td>
<td>0.0546</td>
</tr>
<tr>
<td>Floor insulation</td>
<td>0.0349</td>
<td>0.0367</td>
</tr>
<tr>
<td>Wall insulation</td>
<td>0.0279</td>
<td>0.0303</td>
</tr>
<tr>
<td>Openable window</td>
<td>0.0172</td>
<td>0.0056</td>
</tr>
<tr>
<td>Number of occupants</td>
<td>0.0070</td>
<td>0.0069</td>
</tr>
<tr>
<td>Roof insulation</td>
<td>0.0058</td>
<td>0.0060</td>
</tr>
<tr>
<td>Window frame</td>
<td>0.0022</td>
<td>0.0028</td>
</tr>
<tr>
<td>East-West awning</td>
<td>0.0028</td>
<td>0.0002</td>
</tr>
<tr>
<td>South eaves</td>
<td>0.0014</td>
<td>0.0007</td>
</tr>
<tr>
<td>Internal partition</td>
<td>0.0013</td>
<td>0.0015</td>
</tr>
<tr>
<td>East-West eaves</td>
<td>0.0027</td>
<td>0.0025</td>
</tr>
<tr>
<td>North-South awning</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

So far, a total of six significant design parameters were identified: airtightness, level of ceiling insulation, floor insulation and wall insulation, window types and window-to-wall ratio (WWR). There was a marked decrease in the influence coefficient for the rest of the input parameters. However, parameters rank varied depending on types and locations. These six most influential parameters directly influenced the energy consumption of representative dwelling simulation models, while the remaining inputs had a second-order effect on them.

![Fig 6.18: Influence coefficients of variables for representative dwelling types A to F in climate Zone 5-Mascot.](image)
Fig 6.19: Influence coefficients of variables for representative dwelling types A to F in climate Zone 6-Nowra.

Fig 6.20: Influence coefficients of variables for representative dwelling types A to F in climate Zone 7-Goulburn.
6.3.1.3  Energy sensitivity of building modelling inputs

The predicted annual energy consumptions for a number of input variables that result in the highest and lowest thermal energy needs were also calculated and shown in Fig 6.21. The maximum and minimum values of parameters, from Table 6.1, were combined to create representative dwelling simulation models with ‘low energy’ and ‘high energy’ scenarios.

Combining the parameters that result in the highest thermal energy needs are more than twice when combining the parameters that result to the lowest calculated thermal needs. While the all-high and all-low parameter inputs were selected to be extreme values, they could often be observed in the Australian residential building stock. Given the magnitude of predicted savings generally expected for energy efficient retrofits, this was considered a significant difference.

It should be noted that the COP was assumed as 1, having a better comparison scale between all scenarios.
6.3.2 House thermal performance prediction using regression model

In the previous section, the Differential Sensitivity Analysis (DSA) identified the range of parameters that have the highest influence in annual thermal energy requirement of representative dwelling simulation models. The result of this investigation was used to develop the multivariate regression models for the energy prediction of representative dwelling types in this section.

According to Thornton et al (1998), “multivariate regression analysis is one of the most widely used statistical techniques for predicting the effect of variables in every field. Applications of regression are numerous and occur in the building performance research, whether it is based on experimental or simulated data” (Thornton et al., 1998, Ben-Nakhi and Mahmoud, 2004). Also, exclusive application of regression analysis to simulated data underpins the development of some current rating tools (for example FirstRate, the mandated house energy rating tool in the state of Victoria, Australia) and the regulatory impact studies that support them (Energy Efficient Strategies, 2002). In this study, a multivariate regression analysis was used to estimate the contribution of each significant design parameter to the overall thermal performance improvement of residential houses. The example of NSW was selected in this study, but the process of developing such regression models could be expanded and applied in a similar way elsewhere.

6.3.2.1 Multiple regression analysis

Energy simulation models were created for the different combinations of influential parameters resulted (Table 6.4, Table 6.5 and Table 6.6), based on Taguchi experiment order layout. Table 6.7 shows an example of simulation designs for building Type A and provides a summary of the Taguchi fractional factorial design order layout for six parameters with five levels of variation. In Taguchi design order layout, each model run had a different combination of design parameter variables for creating the database.
Table 6.7: Taguchi orders layout for building type A-climate 5 (ranges were shown in Table 6.2).

<table>
<thead>
<tr>
<th>Run order</th>
<th>Floor Insulation (FI)</th>
<th>WW R (W)</th>
<th>Ceiling Insulation (CI)</th>
<th>Airtightness (Ar)</th>
<th>Wall Insulation (WI)</th>
<th>Glazing Type(G)</th>
<th>Total Heating and Cooling demand (kWh/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No insulation</td>
<td>10%</td>
<td>No insulation</td>
<td>Very Poor</td>
<td>No insulation</td>
<td>Single</td>
<td>14005.76</td>
</tr>
<tr>
<td>2</td>
<td>R 1</td>
<td>15%</td>
<td>R 2.5</td>
<td>Very Poor</td>
<td>R 1.5</td>
<td>Single Low E</td>
<td>8679.95</td>
</tr>
<tr>
<td>...</td>
<td>R 1.5</td>
<td>15%</td>
<td>No</td>
<td>Medium</td>
<td>R 2.5</td>
<td>Double Low E</td>
<td>7568.47</td>
</tr>
<tr>
<td>...</td>
<td>R 1.5</td>
<td>35%</td>
<td>R 6</td>
<td>Good</td>
<td>R 1.5</td>
<td>Single</td>
<td>8666.82</td>
</tr>
<tr>
<td>24</td>
<td>R 1</td>
<td>45%</td>
<td>R 3.5</td>
<td>Excellent</td>
<td>R 2.5</td>
<td>Single</td>
<td>9901.14</td>
</tr>
<tr>
<td>25</td>
<td>R 1.5</td>
<td>10%</td>
<td>R 5</td>
<td>Excellent</td>
<td>R 3</td>
<td>Single Low E</td>
<td>3240.19</td>
</tr>
</tbody>
</table>

The total simulated annual building energy consumption data (E) were regressed against the 6 main input parameters (ranges described in Table 6.2) in dwellings with suspended timber floor (Type A, Type C, Type E) and 5 main input parameters in dwellings with slab on ground models (Type B, Type D, Type F) as shown in Equations 6.5:

\[ E (\text{total annual heating + cooling (kWh)}) = A \text{ (Constant value)} + FI (\text{Floor Insulation}_{1st-5th}) + CI (\text{Ceiling Insulation}_{1st-5th}) + WI (\text{Wall Insulation}_{1st-5th}) + Ar (\text{Airtightness})_{1st-5th} + W (\text{WWR})_{1st-5th} + G (\text{Glazing type})_{1st-5th} \]

Or

\[ y(x_1, x_2, ..., x_n) = \beta_0 + \sum \beta_j x_j \]

Where y is the predicted total annual heating, cooling, or total energy, x_j represents the value of design parameter and \( \beta_j \) is the corresponding regression coefficient.

The regression analysis produced linear regression coefficients for a series of parameters, which were derived influential from the sensitivity analysis. The regression can predict the energy consumption as a function of the key building envelope parameters.

Table 6.8 to Table 6.13 show a summary of the resulted regression coefficients (i.e. A, FI to G) for building types A to F (see Table 6.2 for details and corresponding units of the design variables). In this analysis, same as in Capozzoli et al. (2009), "multivariate linear regression was performed on results for a total of heating and cooling energy with respect to each of the six (6) main independent parameters".
It can be seen that the coefficient of determination $R^2$ varies from 0.88 to 0.97 in all models and locations.

Table 6.8: Multiple regression coefficients for Type A-brick veneer with suspended timber floor.

<table>
<thead>
<tr>
<th>Parameter Ranges</th>
<th>Climate</th>
<th>Airtightness</th>
<th>Glazing Types</th>
<th>Ceiling Insulation</th>
<th>Wall Insulation</th>
<th>Floor Insulation</th>
<th>WWR</th>
<th>Regression $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st-Lower value</td>
<td>5</td>
<td>2729</td>
<td>506.6</td>
<td>2169</td>
<td>392.6</td>
<td>2255</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>2732</td>
<td>617</td>
<td>2825</td>
<td>503.2</td>
<td>2841</td>
<td>-2535</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>5299</td>
<td>868.6</td>
<td>3972</td>
<td>979</td>
<td>4120</td>
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<td></td>
</tr>
<tr>
<td>2nd</td>
<td>5</td>
<td>265.7</td>
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<td>29.28</td>
<td>-232.4</td>
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<tr>
<td></td>
<td>6</td>
<td>299</td>
<td>136.9</td>
<td>-420.5</td>
<td>24.55</td>
<td>-196.5</td>
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<tr>
<td></td>
<td>7</td>
<td>641.5</td>
<td>214.1</td>
<td>-619.6</td>
<td>-35.83</td>
<td>-257.3</td>
<td>-1720</td>
<td></td>
</tr>
<tr>
<td>3rd-Mid value</td>
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<td>-581.6</td>
<td>-4.34</td>
<td>-517.3</td>
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</tr>
<tr>
<td></td>
<td>6</td>
<td>-454.1</td>
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<tr>
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<td>36.61</td>
<td>-991</td>
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<td>-992</td>
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<tr>
<td>4th</td>
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<td>-1134</td>
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<td>-627.8</td>
<td>-159.9</td>
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<td></td>
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<tr>
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<td>-1136</td>
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<td>-232.9</td>
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<tr>
<td></td>
<td>7</td>
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<td>-345</td>
<td>-1151</td>
<td>-382.1</td>
<td>-1121</td>
<td>1484</td>
<td></td>
</tr>
<tr>
<td>5th-Higher value</td>
<td>5</td>
<td>-1475</td>
<td>-440</td>
<td>-633.2</td>
<td>-257.6</td>
<td>-888.6</td>
<td>2729</td>
<td></td>
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<tr>
<td></td>
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</table>

Table 6.9: Multiple regression coefficients for Type B-brick veneer with slab on ground floor.

<table>
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<th>Parameter Ranges</th>
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<th>Airtightness</th>
<th>Glazing Types</th>
<th>Ceiling Insulation</th>
<th>Wall Insulation</th>
<th>Floor Insulation</th>
<th>WWR</th>
<th>Regression $R^2$</th>
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Table 6.10: Multiple regression coefficients for Type C-double Brick with suspended timber floor.

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<th>Climate</th>
<th>Airtightness</th>
<th>Glazing Types</th>
<th>Ceiling Insulation</th>
<th>Wall Insulation</th>
<th>Floor Insulation</th>
<th>WW R</th>
<th>Regression R²</th>
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<tbody>
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<td>1st-Lower value</td>
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<td>1753</td>
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<td>2100</td>
<td>-1997</td>
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<tr>
<td></td>
<td>6</td>
<td>2699</td>
<td>530.2</td>
<td>2286</td>
<td>516.4</td>
<td>2625</td>
<td>-1997</td>
<td>0.973</td>
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<td>7</td>
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<td>886</td>
<td>2877</td>
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<td>3988</td>
<td>-2268</td>
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<td>82.81</td>
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<td>6.352</td>
<td>-232.5</td>
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<td>6</td>
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<td>-220.8</td>
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Constant value
5 - 6872
6 - 7424
7 - 11395

Table 6.11: Multiple regression coefficients for Type D-double Brick with slab on ground floor.

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<th>Glazing Types</th>
<th>Ceiling Insulation</th>
<th>Wall Insulation</th>
<th>WWR</th>
<th>Regression R²</th>
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<td></td>
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<td>329</td>
<td>1753</td>
<td>307</td>
<td>-815</td>
<td></td>
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<td></td>
<td>7</td>
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<td>538</td>
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<td>692</td>
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<td>-209.4</td>
<td>-100</td>
<td>-583.4</td>
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</tr>
<tr>
<td></td>
<td>6</td>
<td>227</td>
<td>176</td>
<td>-311</td>
<td>29</td>
<td>-711</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>351</td>
<td>233</td>
<td>-466</td>
<td>18</td>
<td>-939</td>
<td></td>
</tr>
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<td>-76.1</td>
<td>468.5</td>
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</tr>
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<td></td>
<td>6</td>
<td>-793</td>
<td>-159</td>
<td>-431</td>
<td>-137</td>
<td>486</td>
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</tr>
<tr>
<td></td>
<td>7</td>
<td>-1031</td>
<td>-208</td>
<td>-693</td>
<td>-249</td>
<td>700</td>
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<tr>
<td>5th-Higher value</td>
<td>5</td>
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<td>-275.9</td>
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<td>-117.2</td>
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<td></td>
<td>6</td>
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<td>-291</td>
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<td>881</td>
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<td>-1202</td>
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<td>-947</td>
<td>-275.1</td>
<td>1001</td>
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</table>

Constant value
5 - 2281.6
6 - 2644.2
7 - 4555.2
In other words, by

Multicollinearity increases the standard error of the coefficients. Increased standard errors, in turn, suggest that coefficients for some independent variables may not be found to be significantly different from 0. In other words, by
overinflating the standard errors, multicollinearity makes some variables statistically insignificant when they should be significant” (Akinwande et al., 2015). “Without multicollinearity (and thus, with lower standard errors), those coefficients might be significant”. One way to measure multicollinearity is the variance inflation factor (VIF), which assesses how much the variance of an estimated regression coefficient increases if predictors are correlated. In this study, the variance inflation factors (VIF) were in all cases less than 1.6. This indicates an insignificant correlation between the regression model parameters (i.e. because if VIF values are less than 5 (Martz, 2013).

6.3.3 Model verification: building energy performance simulation results vs. regression model predictions

Verification with results of independent EnergyPlus determines the efficiency of using the regression model in place of direct simulation. This approach is similar in process to the building envelope trade-off option in (ASHRAE, 2007); both perform regression on many building energy simulations to obtain simplified equations.

In order to verify the reliability of the regression models, sets of independent simulations were run and comparisons were made between the simulated annual total space heating and cooling requirements with the results of the regression models. Fig 6.22, Fig 6.23 and Fig 6.24 show the results of the comparison and it can be observed on a general level that the results of the regression models match well with the simulation results. The most significant deviations between the two types of results are in the range of 15%, with the cases of climate 7 (Goulburn) having slightly larger data scattering. It is envisaged that the developed regression models can be used to estimate the likely energy savings/penalty associated with certain design changes during the retrofitting design stage when different building schemes and design concepts are being considered. However, the development of these models is based on the specific building types and climates of this study and their application should not be generalised and considered as an equivalent alternative to the dynamic building energy simulation models for other building types and climates.
Fig 6.22: Comparison between regression-predicted and EnergyPlus-simulated annual total space heating and cooling energy requirements of representative dwelling simulation models for Types A to F based on 35 sets of random inputs for Mascot-Climate zone 5.
Fig 6.23: Comparison between regression-predicted and EnergyPlus-simulated annual total space heating and cooling energy requirements of representative dwelling simulation models for Types A to F based on 35 sets of random inputs for Nowra-Climate zone 6.
Fig 6.24: Comparison between regression-predicted and EnergyPlus-simulated annual total space heating and cooling energy requirements of representative dwelling simulation models for Types A to F based on 35 sets of random inputs for Goulburn-Climate zone 7.
6.3.4 Energy prediction method validation

In this section, first, a multivariate regression model was developed for Solar Decathlon House (SD) simulation model. This helps to estimate the overall thermal performance of a house, as described in Section 6.2.4.1. Second, simple temperature calibration was done for the Solar Decathlon House (SD) simulation model, as explained in Section 6.2.4.2. Third, a calibrated simulation model was used for running sets of simulations and its outcome was compared with regression model outcome for method validation purposes, as described in Section 6.2.4.3.

6.3.4.1 Solar Decathlon House regression analysis

Based on Taguchi experiment order layout and for the required energy database, Solar Decathlon House (SD) simulation models were created for different combinations of selected parameters (Table 6.3). Table 6.14 shows a summary of the Taguchi fractional factorial order layout for five parameters with five levels of variations. As mentioned before, in Taguchi design order layout, each model run had a different combination of design parameters for creating the database.

The total simulated annual building energy consumption data were regressed against the five main input parameters for Mascot climate zone. The regression, based on this database, produced linear regression coefficients, which were proportional to each parameter’s sensitivity to energy use. It also can predict the energy consumption as a function of the key parameters. Table 6.15 shows a summary of the resulted regression coefficients (i.e. A, FI to G) for Solar Decathlon House (SD) simulation model. In this analysis, same as Capozzoli et al. (2009), multivariate linear regression was performed on the results for the total of heating and cooling energy, with respect to each of the 5 main independent parameters. It can be seen that the coefficient of determination $R^2$ is 0.89 for Mascot.

Table 6.14: Taguchi orders layout for Solar Decathlon House in Mascot climate zone. (Ranges were shown in Table 6.3).

<table>
<thead>
<tr>
<th>Run order</th>
<th>Floor Insulation (FI)</th>
<th>Ceiling Insulation (CI)</th>
<th>Airtightness (Ar)</th>
<th>Wall Insulation (WI)</th>
<th>Glazing type(G)</th>
<th>Total Heating and Cooling demand (kWh/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>R 8.6</td>
<td>R 8.2</td>
<td>Good</td>
<td>R 4.3</td>
<td>Double Low E Argon</td>
<td>1741.4</td>
</tr>
<tr>
<td>2</td>
<td>R 1</td>
<td>R 2.5</td>
<td>Good</td>
<td>R 1.5</td>
<td>Single Low E</td>
<td>4890.7</td>
</tr>
<tr>
<td>...</td>
<td>R 8.6</td>
<td>R 8.2</td>
<td>Medium</td>
<td>R 2.5</td>
<td>Double</td>
<td>5024.5</td>
</tr>
<tr>
<td>...</td>
<td>R 8.6</td>
<td>R 6</td>
<td>Very poor</td>
<td>R 4.3</td>
<td>Double Low E</td>
<td>7582.8</td>
</tr>
<tr>
<td>24</td>
<td>R 8.6</td>
<td>R 5</td>
<td>Excellent</td>
<td>R 1.5</td>
<td>Single</td>
<td>3147</td>
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<tr>
<td>25</td>
<td>R 1</td>
<td>R 5</td>
<td>Excellent</td>
<td>R 2</td>
<td>Single</td>
<td>4862.9</td>
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</tbody>
</table>
Table 6.15: Multiple regression coefficients for Solar Decathlon House (SD) simulation model in Mascot climate Zone-5.

<table>
<thead>
<tr>
<th>Parameter Ranges</th>
<th>Airtightness</th>
<th>Glazing Types</th>
<th>Ceiling Insulation</th>
<th>Wall Insulation</th>
<th>Floor Insulation</th>
<th>Regression R²</th>
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</thead>
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<td>429.1</td>
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<td>52.6</td>
<td>147.2</td>
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<td>3rd-Mid value</td>
<td>-534.2</td>
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<td>-42.7</td>
<td>-9.3</td>
<td>-154.8</td>
<td>0.89</td>
</tr>
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<td>4th</td>
<td>-1216.8</td>
<td>-42.8</td>
<td>-0.6</td>
<td>-142.6</td>
<td>-253.7</td>
<td></td>
</tr>
<tr>
<td>5th-Higher value (Solar Decathlon House model inputs)</td>
<td>-1079.3</td>
<td>-486.4</td>
<td>-100.6</td>
<td>-424.4</td>
<td>-770.4</td>
<td></td>
</tr>
</tbody>
</table>

Constant value 4677.3

In addition, the variance inflation factor (VIF) was calculated less than 2.5 for Solar Decathlon House model which indicates an insignificant correlation between the regression model parameters (i.e. because VIF values are less than 5 (Martz, 2013).

6.3.4.2 Solar Decathlon House model calibration analysis

Building energy simulation calibration is a relatively challenging practice in the real world. In this study, simple model calibration was run for aligning indoor air temperature from the energy simulation model with the measured data. The initial simulation model was created according to the building manual and program defaults where design information was unavailable.

In the initial calibration process stage, several inconsistencies were identified between the simulation run and the measurement results, as shown in Fig 6.25.

![Fig 6.25: Initial model energy-simulation temperature data vs measured data.](image)
Raftery et al. (2011) strongly recommend to having an error check in the calibration process. Several error checks have been run for Solar Decathlon House (SD) simulation model and the details were corrected based on a site visit. Wall constructions and material properties were again updated. Internal loads were again checked and the source of load was found from control box in the house.

The CVRMSE\textsubscript{(hourly)} and MBE are calculated for pre and post revision and are presented in Table 6.16.

Table 6.16: Summary of Solar Decathlon House simulation model revisions.

<table>
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<th>MBE</th>
<th>CVRMSE\textsubscript{(hourly)}</th>
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<td>Initial model</td>
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<td>7%</td>
</tr>
<tr>
<td>Final model</td>
<td>1%</td>
<td>4%</td>
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</tbody>
</table>

The results of Table 6.16 show that the acceptance criteria (the ASHRAE hourly calibration criteria) for this project are met at every stage of the iterative process. ASHRAE Guideline 14 defines the acceptable limits for calibration to hourly data as within ±10% MBE and ≤30% CVRMSE\textsubscript{(hourly)} measured at a utility level (ASHRAE, 2002, Raftery et al., 2011). However, the author continued the calibration process to have a more reliable calibrated model despite the results meeting the acceptance criteria. Fig 6.26 shows the acceptable outcome of the final simulation temperature outputs vs measured data.

![Final simulation temperature data vs measured data](image)

Fig 6.26: Final simulation temperature data vs measured data.

The results still show a degree of discrepancy between measured and simulated values. This might be caused by poor estimates for some parameter values. However, some of this is due to the unpredictable operation of the building or the assumptions.
and simplifications made by the simulation engine. A thorough discussion of the simplifications and assumptions made by whole building energy simulation tools can be found in recent research (Maile, 2010).

In addition, the most currently available stringent acceptance criteria focus only on comparing indoor temperature between the model and the real building. However, there is no guarantee that any particular solution is a fair representation of how the building actually operates (Raftery et al., 2011).

6.3.4.3 Method verification

In order to verify the reliability of the proposed methodology, sets of independent simulations were run and comparisons were made between the simulated annual total space heating and cooling requirements of Solar Decathlon House (SD) calibrated simulation model and the result of the regression models. Fig 6.27 shows the results of the evaluation and it can be observed that the results of the regression model were well-matched with the simulation results. The most significant deviations between the two types of results were below 20% data scattering. The results also showed that the effectiveness of using the regression model instead of a direct simulation, which is the ultimate goal of this work. It is envisaged that the developed methodology in this study is valid and regression models can be used to estimate the likely energy savings/penalty associated with certain design changes during the retrofitting design stage. This will occur if different building schemes and design concepts are being considered. As mentioned before, the development of regression models is based on specific building types and climates of this study and their application should not be generalised and considered as an equivalent alternative to the dynamic building energy simulation models.
Fig 6.27: Comparison between regression-predicted and EnergyPlus-simulated annual total space heating and cooling energy requirements of Solar Decathlon House calibrated simulation model based on the 25 sets of random inputs for Mascot-Climate zone 5.

6.4 Discussion and limitation

By applying various energy efficiency upgrade strategies, this work has the implications of identifying the potential energy retrofitting parameters of the current stock representative dwelling simulation models. It also intends to estimate the energy performance of a range of houses in order to cope with the challenge of the climate change. However, this approach may not offer precise results or insights into the particular challenges and possibilities for individual buildings that are significantly different from those used in this study.

The sensitivity of parameters is analysed by investigating the influence coefficients. In this study, it could be observed that parameters ranking (as seen by their impact on the heating and cooling loads) is almost the same in all the three locations. As such, the total energy sensitivity depends on the relative magnitude of the required heating and cooling. Parameters that are key in the building thermal performance represent six most sensitive out of the total 14 parameters. The use of non-dimensional influence coefficient from DSA need to be further investigated in future work. However, as much as DSA informs the sensitivity of a parameter at a single point in the parametric space, it provides no understanding of the areas that fall out of the parametric range of a number of simulation sets, except when the data could be generalised in a linear fashion. In this study, a linear relationship has been assumed between the range of the parameters and the outputs of DSA; yet the effect
of this assumption should also be tested. DSA also does not allow the interaction between parameters to be assessed. However, despite the potential for misinterpretation, a review of the previous literature indicates that influence coefficients are the useful measure available that could be employed in comparisons of a building’s energy sensitivity analysis (Daly et al., 2014, Simm et al., 2011).

The regression model is a useful tool to supply quick feedback in terms of energy requirements in retrofitting stage of buildings. Contrary to the simulations tools at hand, a regression model along with a visualization tool, can be used by a designer or building owner without the necessity of running the energy simulation for buildings that are simple in terms of energy flows (e.g. many residential buildings in Australia). The developed energy prediction models used in the current study have been limited to particular representative dwelling types and climate zones. Nevertheless, further research can probe into a new way of including parameters that include the effects on complex building geometries. The analysis indicates that in the stages of deciding a retrofit and instead of energy simulation models, a linear regression model can be a useful basis for an effective decision support tool. In addition, the regression coefficients quantify the sensitivity of total energy loads to the parameters used in building design parameters in all the three major climatic zones for six representative dwelling simulation models.

In this study, the influence of individual design parameters was analysed and reported. More sample types and over ten thousand simulations were required in order to consider the interaction effect of each parameter while it was well beyond scope of the current study. In a real-life situation, however, each parameter will probably change the effect of other parameters, which is something a designer should take into account before considering energy retrofit of buildings.

The energy prediction methodology was verified instead of regression model evaluation that affects the accuracy of representative regression models. However, this evaluation shows that correct modelling will lead to results within an acceptable range of error. In this project, method evaluation was the reasonable option due to the nature of typology models that are usually built from a range of statistical data analysis.
6.5 Chapter summary

While building performance simulation model can be an accurate quantifier of energy in a building, it is difficult to be employed in every single retrofitting project. It would be useful to have an approximate characterisation of building energy performance that could act according to changes in high influential envelope parameters. By using a building energy simulation engine, the current work leads to the development of multivariate linear regression models for a range of dwellings based on six (6) identified building design parameters.

In this chapter, building performance simulation was combined with the DSA method for the developed representative dwelling simulation models. The combination was to demonstrate a method for identifying how sensitive the predictions of thermal loads are on a number of building parameters. The six key building design parameters that were identified as high influential through Differential Sensitivity Analysis (DSA) were airtightness, window-to-wall ratio (WWR), window types, level of ceiling insulation, level of wall insulation and level of floor insulation. These parameters have a substantial contribution to the energy performance of dwelling and should be explicitly used as inputs while developing energy prediction models for residential buildings in NSW.

Simple regression models for the prediction of space heating and cooling energy requirements of representative dwelling types in the three major climates in NSW were developed by using building energy simulation and based on the findings of the sensitivity analysis. The results presented showed that the linear models with simple independent variables could predict the requirements for space heating and cooling of the residential buildings in the specific climates with acceptable error variance from the simulation predictions. A random number generator was also employed to generate random designs in order to verify the accuracy of the regression models outputs. The differences between regression-predicted and EnergyPlus-simulated annual building total heating and cooling demand were within the commonly used ranges as published by ASHRAE (ASHRAE guideline 14, 2002, Lam et al., 2010) and were less than 15%. Decisions for energy retrofits involve a certain degree of complexity and it is difficult for homeowners to have an informed opinion on the effectiveness of these retrofits without seeking advice from experts. The advice from
experts is often financially prohibitive for homeowners. Hence, this study developed regression models that suit a specific climate and building stock to enable decisions to be made for envelope retrofits.

The methodology of this study was also evaluated with a calibrated simulation model. The outcome of evaluation verified the reliability of the developed methodology. The similar methodology could be applied for the development of energy prediction models that would suit other climates and building types.

In chapter 7, the energy prediction models of the residential building types were placed into a tool to be able to provide retrofitting cost-benefit assessment carrying over time and fuel prices.
Chapter 7: Development of Cost-Benefit Decision Support Tool for Retrofits

7.1 Introduction

The assessment of building retrofitting has emerged as one of the major issues in the building industry. To simplify the retrofitting assessment process of dwellings, various cost-benefit tools have been offered (Georgopoulou et al., 2006, Nikolaidis et al., 2009, Freund, 1979). While most decision-making tools are generally well-developed tools, they are often considered as being relatively complex and mainly designed for commercial or large projects (Steskens et al., 2015). To obtain information on energy and cost-efficient retrofits in existing dwellings, a simple decision-making tool for retrofitting process is required. Simple decision-support tools can assist relevant stakeholders (e.g. occupants) in developing and designing energy and cost efficient dwelling retrofit solutions.

The objective of this chapter is to develop a simple retrofitting decision-making tool, based on the developed energy estimation models presented in Chapter 6, which offers cost-benefit assessments for representative dwelling types. This tool takes into account the current thermal performance of the building, the impact of specific envelope improvement measures on the energy consumption and associated retrofitting costs.

In addition, the developed decision-support tool is used to evaluate the cost-effectiveness of different retrofitting scenarios applied in example representative dwelling types, in terms of potential economic weaknesses (costs) and strengths (benefits) of investment alternatives. The cost-benefit analysis has been investigated in terms of initial investment cost (cost of materials and installation) and associated energy/cost saving of retrofitting scenarios. Payback period and Net Present Value (NPV) of models have also been investigated through considering the risk of fuel price changes through years.

The typical process presented in this chapter is shown in Fig 7.1.
7.2 Framework for development of retrofitting decision-support tool

The combination of findings from Chapter 5 and Chapter 6 have structured the decision-support tool that enables users to assess the cost-benefit of different retrofitting strategies in representative dwelling types.

A cost-benefit decision support tool has been developed by employing Microsoft Excel 2010 with Visual Basic for Applications (VBA). This tool has been designed to allow users to self-assess their dwellings in terms of energy consumption, as well as to select retrofitting strategies and derive the associated cost of retrofitting. This simple tool helps to identify areas for energy efficiency improvement in a range of representative dwelling types in the current stock. While the tool is not equivalent to a full-scale and comprehensive energy audit, it provides a cheap and easy way of establishing a baseline of retrofitting analysis based on pre and post retrofit.

The interface of the cost-benefit decision support tool is shown in Fig 7.2. The tool is an Excel spreadsheet-based tool and can be used to investigate the cost implications of a range of appropriate energy efficiency measures based on energy load requirements, associated capital costs of materials and labours, future energy
price scenarios and potentially achievable cost-benefit of retrofitting in different dwelling types.

Fig 7.2: Interface of a developed decision-support tool for assessing the impact of retrofitting strategies in a range of dwellings.

The tool includes four assessment sections to take the user through the steps to create the baseline, improvement strategies and cost-benefit analysis. These sections are called Property type, Property characteristics, Action planner, and Cost planner, and have been summarised below:

- The ‘Property type’ section classifies dwelling types based on a request from the user to select climate, types of wall material, and types of floor material in accordance with the result of Section 5.3.2.

- The ‘Property characteristic’ section quantifies the baseline (existing design) thermal performance of the dwelling, based on developed energy estimation models in Section 6.3.2, after the user inputs information about the resistance of ceiling insulation, resistance of wall insulation, resistance of floor insulation, level of airtightness, types of glazing and window to wall ratio.

- The ‘Action planner’ section offers a range of high influential improvement parameters that can be used in retrofitting of the dwelling based on user preference. It uses the developed energy prediction models in Section 6.3.2 to predict the effect of different improvement strategies.
on the dwelling annual energy consumption and potential achievable savings from that.

- The ‘Cost Planner’ part assesses the cost-benefit of retrofitting strategies by calculating the energy saving, the capital cost of retrofitting strategies and analysing the NPV and Payback Period in terms of different energy price scenarios from 2015 to 2036.

- In previous chapters (Chapter 5 and Chapter 6), the methodology used to create the above first three stages (Property type, Property characteristics, and Action planner) of decision-making tool was described in detail. In the following sections, the details of the ‘Cost Planner’ stage in a development of decision-making tool, which includes material cost, retail price forecast, and cost-benefit evaluation methods, are discussed.

### 7.2.1 Costing the upgrades

Building retrofit decisions mainly depend on the specific building thermal performance and targets of refurbishment. An important role in the decision-making process is striking the balance between costs and benefits of each measure (Ćuković Ignjatović et al., 2016, Nemry et al., 2010, Rysanek and Choudhary, 2013).

In this study, different sources were used to populate the material cost of retrofitting. Because of the sensitive commercial nature of the information around the volume build industry, such information is hard to access publicly. Cost information was drawn directly from the Rawlinson Construction Handbook (Rawlinsons, 2015), Cordell Housing Cost Guide (Corelogic, 2016), Sustainability Victoria Company (Sustainability Victoria, 2016), thesis (Jones, 2017), and available market suppliers (knauf insulation, 2016). The average price of resources for materials has been calculated based on cost with (material + labour) and without labour to unify the calculation when several costs are available for one material. However, costs of materials are just default inputs in a developed decision-support tool that can be changed upon market changes or user preference in future. The collected cost details of insulation materials, airtightness upgrades and window types are presented in the following sections:
7.2.1.1 Costing insulation upgrades

This study examines insulation levels for building elements, namely: (a) the external walls, (b) ceiling and (c) floor. Table 7.1 presents the implementation costs of various insulation measures. It is assumed that insulation is applied to all external walls and not to a proportion of external wall area in the representative dwelling simulation models. Floor insulation is just considered for the dwelling types with a suspended timber floor. In this study, the average cost from Rawlinson and Cordell for ceiling and wall insulation and just Cordell for floor insulation have been used in the analysis.

Table 7.1: Default capital costs of insulation materials (Rawlinsons, 2015, Corelogic, 2016).

<table>
<thead>
<tr>
<th>Material</th>
<th>Specification (R-value)</th>
<th>Default Input Cost ($AU/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ceiling Insulation</td>
<td>R 2.5</td>
<td>10.1</td>
</tr>
<tr>
<td></td>
<td>R3.5</td>
<td>12.4</td>
</tr>
<tr>
<td></td>
<td>R5</td>
<td>17.6</td>
</tr>
<tr>
<td></td>
<td>R6</td>
<td>23.1</td>
</tr>
<tr>
<td>Wall Insulation</td>
<td>R1.5</td>
<td>12.0</td>
</tr>
<tr>
<td></td>
<td>R2</td>
<td>12.9</td>
</tr>
<tr>
<td></td>
<td>R2.5</td>
<td>15.7</td>
</tr>
<tr>
<td></td>
<td>R3</td>
<td>17.5</td>
</tr>
<tr>
<td>Floor Insulation</td>
<td>R1</td>
<td>7.6</td>
</tr>
<tr>
<td></td>
<td>R1.5</td>
<td>9.7</td>
</tr>
<tr>
<td></td>
<td>R2.5</td>
<td>11.7</td>
</tr>
<tr>
<td></td>
<td>R3</td>
<td>12.8</td>
</tr>
</tbody>
</table>

7.2.1.2 Costing airtightness upgrades

One of the main reasons for energy loss and increasing emissions is air leaks from envelope of existing and new buildings (Energy saving trust, 2009).

Calculation of energy savings and the associated cost of airtightness improvements in dwellings is a difficult task due to the limited information available on the specifics of individual dwellings. In this study, a list of improvement measures of airtightness levels and their associated cost have been sourced from the Draught Sealing Retrofit Trial report published by Sustainability Victoria (2016). In this report, detailed information on the impact of draught sealing upgrades and air leakage rate is given for several houses in Melbourne.

Table 7.2 represents the list of sealing measures to apply in dwellings to gradually improve the airtightness levels. In addition, the cost of each measure has been investigated. However, the impact of the measures across different houses may
vary and this table is a very simple version of infiltration improvement. Airtightness improvement is linked to measures based on the total reduction impact of one or a series of measures.

Table 7.2: List of air leakage reduction measures and associated capital costs (Sustainability Victoria, 2016).

<table>
<thead>
<tr>
<th>Airtightness level</th>
<th>Draught sealing measure</th>
<th>Potential for Reduction (%)</th>
<th>unit</th>
<th>Cost per unit ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very poor to poor</td>
<td>General caulking</td>
<td>26.1%</td>
<td>per meter</td>
<td>2.80</td>
</tr>
<tr>
<td>Poor to Medium</td>
<td>Evaporative cooler outlets</td>
<td>20.0%</td>
<td>per outlet</td>
<td>44.90</td>
</tr>
<tr>
<td>Medium to Good</td>
<td>Exhaust fans/vents</td>
<td>15.5%</td>
<td>per fan/vent</td>
<td>47.10</td>
</tr>
<tr>
<td></td>
<td>Seal external door</td>
<td>11.9%</td>
<td>per door</td>
<td>90.10</td>
</tr>
<tr>
<td>Good to Excellent</td>
<td>Seal wall vents</td>
<td>6.7%</td>
<td>per vent</td>
<td>6.80</td>
</tr>
<tr>
<td></td>
<td>Caulking heating/cooling</td>
<td>4.1%</td>
<td>per instance</td>
<td>48.70</td>
</tr>
<tr>
<td></td>
<td>Combined</td>
<td>3.4%</td>
<td>per measured implemented</td>
<td>9.40</td>
</tr>
<tr>
<td></td>
<td>Seal chimney</td>
<td>3.1%</td>
<td>per chimney</td>
<td>48.20</td>
</tr>
<tr>
<td></td>
<td>Seal larger gap or hole</td>
<td>2.6%</td>
<td>per instance</td>
<td>27.90</td>
</tr>
<tr>
<td></td>
<td>Seal louver window</td>
<td>1.8%</td>
<td>per window</td>
<td>66.00</td>
</tr>
<tr>
<td></td>
<td>Seal downlights</td>
<td>1.5%</td>
<td>per downlight</td>
<td>16.70</td>
</tr>
<tr>
<td></td>
<td>Seal windows</td>
<td>1.0%</td>
<td>per window</td>
<td>16.90</td>
</tr>
<tr>
<td></td>
<td>Seal manhole cover</td>
<td>0.8%</td>
<td>per cover</td>
<td>22.40</td>
</tr>
<tr>
<td></td>
<td>Tape leaking ductwork</td>
<td>0.6%</td>
<td>per duct system</td>
<td>39.00</td>
</tr>
<tr>
<td></td>
<td>Seal sliding door</td>
<td>0.4%</td>
<td>per door</td>
<td>35.30</td>
</tr>
<tr>
<td></td>
<td>Caulk ceiling rose</td>
<td>0.4%</td>
<td>per rose</td>
<td>34.40</td>
</tr>
<tr>
<td></td>
<td>Seal plumbing penetrations</td>
<td>0.3%</td>
<td>per instance</td>
<td>42.40</td>
</tr>
</tbody>
</table>

7.2.1.3  Energy savings with window types

Windows replacement may not be a popular retrofitting option due to high cost while it has the potential to provide comfort and also lower the cost of energy. In this study, the replacement of single glazing windows with single low E, double glazing and double glazing low E with Argon gas has been examined. Table 7.3 presents the cost of window replacement. However, due to the difficulty of window replacement price assessment and the associated labour cost in the construction industry, all window prices are approximated from (Jones, 2017) with the addition of labour cost at about $99.64 per m². Labour cost has been added as the average price of glazing job per m² from Cordell estimator to neglect the uncertainty of required hours.
Table 7.3: Default capital costs of window materials.

<table>
<thead>
<tr>
<th>Material</th>
<th>Specification</th>
<th>Cost ($AU/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glazing Type</td>
<td>Single Low E</td>
<td>514</td>
</tr>
<tr>
<td></td>
<td>Double Glaze</td>
<td>489</td>
</tr>
<tr>
<td></td>
<td>Double Low E</td>
<td>407</td>
</tr>
<tr>
<td></td>
<td>Double Argon</td>
<td>794</td>
</tr>
</tbody>
</table>

7.2.2 Retail electricity price forecast

For the purpose of cost-benefit assessment of dwellings in a decision-making tool, the sets of the energy price prediction scenarios, including Optimistic, Neutral and Pessimistic, were developed based on future fuel price changes. For the development of electricity price prediction scenarios, relative future energy price trends from published studies which have conducted extensive modelling on future energy price outlooks for Australia (Frontier Economics Pty. Ltd, 2015, Jacobs Australia Pty Ltd, 2016), has been analysed. The Neutral energy price forecast of Jacobs and Frontier have been used to produce the Neutral energy price scenario in this study. The highest and lowest fuel price predictions of those studies were also used as the Pessimistic and the Optimistic analysis scenarios, respectively. These scenarios help to ensure that the cost analysis includes a consideration of uncertainties with regards to future energy prices.

Fig 7.3 illustrates the developed ‘Neutral’ energy price prediction scenario from Frontier and Jacobs studies. The ‘High/Strong’ and ‘Low/Weak’ energy price scenarios from Jacobs and Frontier are also illustrated in Fig 7.4. In addition, Fig 7.4 shows that the Frontier prediction has the highest and lowest ranges in prediction compared to the Jacobs energy price projection. Hence, in this study, the Frontier High and Low energy prediction for Optimistic and Pessimistic electricity prediction scenarios have been adapted.
7.2.3 Cost-benefit evaluation methods

The decision-making tool assists in analysing the effect of different retrofitting scenarios on example dwellings. The initial capital cost, the reduction in annual energy load requirement and the related energy costs were inputs for the cost-benefit evaluation method. Net Present Value (NPV) and Payback Period for retrofitting strategies are calculated based on the designed electricity price scenarios. The cost-benefit calculation for the retrofitting strategies on the representative dwelling types takes into account pre and post retrofitting conditions.
7.2.3.1 **Net present value (NPV)**

The NPV sums the discounted cash flows; it simultaneously merges and converts money (e.g. incomes, expenses, etc.) from different time periods. NPV is determined by Equation 7.1:

\[
NPV = -C_0 + \sum_{t=1}^{n} \frac{F_t}{(1+p)^t} = 0 \quad (7.1)
\]

where \( t \) is the time period, usually a year, \( F_t \) is the net cash flow for year \( t \), i.e. \( F_t = B_t - C_t \), \( B_t \) the benefit (inflows) for year \( t \), \( C_t \) the cost (outflows) for year \( t \); the value \( C_0 \) reflects the initial investment, \( p \) the cost of capital, and \( n \) is the number of years of the investment’s lifetime or, differently, the number of years for which the economic evaluation is requested.

7.2.3.2 **Payback period**

Payback period constitutes a variant of the determination of the payback period of the initial investment \( C_0 \). This method calculates how long (usually determined in years) is needed until the initial outflow \( C_0 \) of an investment by an investor is returned. The net cash flows \( F_t \) that occur due to such investment play the key role in investment recovery. However, this method cannot sensibly measure the direct “value” of a certain investment. It rather measures the time which is needed to recover the initial outflow of an investment. According to PP, the present value of the expected net cash flows \( F_t \) is calculated based on the cost of capital \( p \), and then is set equal to the initial investment \( C_0 \). The depreciated payback period is given by Equation (7.2):

\[
PP = \frac{-ln \left( \frac{1 - \frac{F_0}{F_t}}{ln(1+p)} \right)}{ln(1+p)} \quad (7.2)
\]

Where it is assumed that the net cash flows \( F_t \) remain constant for every \( t \).

For this study, it is assumed that energy-saving measures selected are to be constant during time-horizon (from 2014 to 2036) covered by the analysis. No predictions are included beyond 2036, as it is deemed that longer study periods increase uncertainty in the precision of the cost estimates due to assumptions made about cost price prediction into the future.
For the purposes of this study, the real discount rate of 4.72% (Trading economic, 1990-2017) from 1990 till 2017 is applied for analysis.

7.2.4 Retrofitting investment assessments in example representative dwelling types

To demonstrate the capabilities of the decision-making tool, this section demonstrates the economic feasibility of retrofits in example representative dwelling types. To assess the cost-benefit of retrofits in example representative dwelling types, a series of thermal performance scenarios were devised as low, moderate and high, as described in Table 7.4. The average requirement of R-value, based on Building Code of Australia (BCA), and available parameter range of this study have been considered to develop retrofitting scenarios. The low option meets insulation requirements of BCA from 1996 to 2009, the moderate option complies with BCA till 2015 and the high is a predicted scenario that could match future building regulations. Prescribed retrofitting benchmarks, as described in Table 7.4, were applied in the analysis. It should be noted that the minimum BCA requirement is applicable for new buildings only and the already built dwellings are not obligated to follow them. This study tried to meet the minimum BCA insulation requirements but for wall parameters, it was not fully followed. This is due to the nature of the existing buildings (brick veneer and double brick) which makes it very difficult to add a very thick layer of insulation to them.

Table 7.4: Summary of retrofitting scenarios.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Retrofitting scenarios input</th>
<th>Base case</th>
<th>Low option</th>
<th>Moderate option</th>
<th>High option</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ceiling R-value (m²K/W)</td>
<td></td>
<td>1.3</td>
<td>2.5</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Walls R-value (m²K/W)</td>
<td></td>
<td>0.5</td>
<td>1.5</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Floor R-value (m²K/W)</td>
<td></td>
<td>0.4</td>
<td>1</td>
<td>1.5</td>
<td>3</td>
</tr>
<tr>
<td>Window type U-value (W/m²K)</td>
<td></td>
<td>Single</td>
<td>Single low E</td>
<td>Double</td>
<td>Double Low E argon</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5.8)</td>
<td>(3.78)</td>
<td>(3.16)</td>
<td>(1.7)</td>
</tr>
<tr>
<td>Airtightness</td>
<td></td>
<td>Poor</td>
<td>Medium</td>
<td>Good</td>
<td>Excellent</td>
</tr>
<tr>
<td>WWR %</td>
<td></td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
</tr>
</tbody>
</table>

A summary of the floor areas and simulation inputs assumption for the example representative dwelling types that are used in this chapter, are presented in Table 7.5 and Table 7.6.
Table 7.5: Summary of the areas for the envelope elements of the example representative dwelling simulation model.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Unit</th>
<th>Model inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>External wall</td>
<td>m²</td>
<td>76</td>
</tr>
<tr>
<td>Floor</td>
<td>m²</td>
<td>78.4</td>
</tr>
<tr>
<td>Ceiling</td>
<td>m²</td>
<td>99.75</td>
</tr>
<tr>
<td>Glazing</td>
<td>m²</td>
<td>13.42</td>
</tr>
</tbody>
</table>

The area of the ceiling is greater than floor area because it includes the roof eves around the house.

Table 7.6: Summary of representative dwelling simulation model inputs.

<table>
<thead>
<tr>
<th>Parameters of interest</th>
<th>Unit</th>
<th>Model inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brick veneer wall R-value</td>
<td>m²K/W</td>
<td>0.5</td>
</tr>
<tr>
<td>Floor R-value</td>
<td>m²K/W</td>
<td>0.4</td>
</tr>
<tr>
<td>Roof R-value</td>
<td>m²K/W</td>
<td>0.4</td>
</tr>
<tr>
<td>Ceiling R-value</td>
<td>m²K/W</td>
<td>1.3</td>
</tr>
<tr>
<td>Internal wall R-value</td>
<td>m²K/W</td>
<td>0.3</td>
</tr>
<tr>
<td>Glazing types U-value</td>
<td>W/m²K</td>
<td>5.8</td>
</tr>
<tr>
<td>Window frame U-value</td>
<td>W/m²K</td>
<td>3.6</td>
</tr>
<tr>
<td>Airtightness</td>
<td>Level</td>
<td>Poor</td>
</tr>
<tr>
<td>Number of occupants</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Openable window area</td>
<td>Ratio %</td>
<td>50</td>
</tr>
<tr>
<td>South eaves</td>
<td>m</td>
<td>0.4</td>
</tr>
<tr>
<td>East-west eaves</td>
<td>m</td>
<td>0.1</td>
</tr>
<tr>
<td>Window awning</td>
<td>m %</td>
<td>0.0</td>
</tr>
<tr>
<td>WWR</td>
<td>Ratio %</td>
<td>15</td>
</tr>
<tr>
<td>COP</td>
<td>-</td>
<td>1</td>
</tr>
</tbody>
</table>

In addition, the initial values for the air leakage of the house are shown in Table 7.7.

Table 7.7: Quantities of default air leakage values assumption.

<table>
<thead>
<tr>
<th>Draught sealing measure</th>
<th>Unit</th>
<th>Model assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaporative cooler outlets</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Exhaust fans/vents</td>
<td>per fan/vent</td>
<td>3</td>
</tr>
<tr>
<td>Seal external door</td>
<td>per door</td>
<td>2</td>
</tr>
<tr>
<td>Seal wall vents</td>
<td>per vent</td>
<td>4</td>
</tr>
<tr>
<td>Seal windows</td>
<td>per window</td>
<td>10</td>
</tr>
</tbody>
</table>

Summary of initial investment for retrofitting scenarios (Table 7.4) in representative dwelling simulation models are presented in Table 7.8.

Table 7.8: Summary of initial investment for retrofitting options.

<table>
<thead>
<tr>
<th>Model types</th>
<th>Initial investment of retrofitting scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low option</td>
</tr>
<tr>
<td>Dwelling with suspended timber floor (Type A, Type C, Type E)</td>
<td>10789 $</td>
</tr>
<tr>
<td>Dwelling with slab on ground floor (Type B, Type D, Type F)</td>
<td>10189 $</td>
</tr>
</tbody>
</table>

To prevent repetition, only results of the cost-benefit assessment for climate zone 5-Mascot are analysed in this chapter.
7.2.4.1 Example of economic evaluation of representative dwelling types

This section demonstrates the cost-benefit assessment within a decision support tool for a range of retrofits in the representative dwelling types. The outcome of the NPV analysis of the retrofitting options of Table 7.4 for the zone 5-Mascot climate is presented in Fig 7.5, Fig 7.6 and Fig 7.7 by considering different energy price scenarios.

Growth in the NPVs’ trend could be observed for all energy price scenarios and retrofitting options across every model in a 20 year-horizon. It can be seen that the NPV can grow over time as a proportion to the energy savings. However, this growth did not yield positive values in some cases such as brick veneer and double brick with slab on ground (“Type B” and “Type D” models), respectively, due to their original/base case energy performance condition.

The results illustrate that the fibro house with suspended timber floor (Type E) and double brick with slab on ground floor (Type D) could achieve the highest and lowest NPV, respectively, in every retrofitting option and for three energy price scenarios.

The fibro house with the suspended floor (Type E) can achieve a minimum of $16518 and a maximum of $21965 total NPV in the pessimistic scenario and a minimum of $9767 and a maximum of $12267.4 NPV for the optimistic fuel scenario over 20 years. This shows that over a 20-year time horizon retrofitting options are cost-effective in comparison with capital investment which is as $10789 and $17264 for low and high retrofitting options, respectively. These results show the effect of retrofitting for different dwelling types in terms of thermal performance and cost-benefit achievement.
Fig 7.5: Influence of “Low retrofitting option” (Table 7.4) on representative dwelling simulation models with three energy price scenarios on NPV for climate Zone 5-Mascot.

Fig 7.6: Influence of “Moderate retrofitting option” (Table 7.4) on representative dwelling simulation models with three energy price scenarios on NPV for climate Zone 5-Mascot.

Fig 7.7: Influence of “High retrofitting option” (Table 7.4) on representative dwelling simulation models with three energy price scenarios on NPV for climate Zone 5-Mascot.
In addition, the significant effect of different energy price scenarios can be observed in the total NPV in all models with every retrofitting option after the first 5 years. It can be seen that the NPV of investment increases with future high-energy price scenarios whereas the low-energy price scenarios result in lower NPV.

When comparing the influence of different retrofitting options, it can be seen that the moderate retrofitting option (Table 7.4) provides the highest NPV after 5 years to 20 years, followed by the ‘high retrofitting option’(Table 7.4). Energy savings for the ‘high retrofitting option’ are between 17% and 38% greater than the savings for a ‘moderate retrofitting option’ over a 20-year period while the capital cost for the ‘high retrofitting option’ is about 45% higher than the moderate option in every model. This, in fact, makes the moderate option the most cost-effective option. It should be noted that the highest NPV occurs with the optimistic energy price scenarios. Applying the pessimistic energy price scenario makes the benefit of the high retrofitting option greater than the moderate retrofitting option especially in some models with suspended timber floor (Type A and Type C). Increasing energy price turns energy reduction into a necessity and encourages high capital investments for energy savings in dwellings. Fig 7.5, Fig 7.6 and Fig 7.7 also show that for the slab on ground models, total NPV has increased when adopting the low and moderate retrofitting options. However, the retrofits for the slab on ground models do not achieve a positive NPV except in fibro types (Type F).

Fig 7.8 represents the required payback period for every retrofitting option with three energy price scenarios for the representative dwelling simulation models in Mascot climate. The results show that the total number of years required to payback the capital investment for the (Type A, Type C and Type E) with applying the low retrofitting option is minimum 6 to 10 years in the pessimistic energy price scenario. It also shows that in order to payback the capital investment in those types (Type A, Type C and Type E) with employing the high retrofitting option requires maximum 10 to 14 years in the optimistic energy price scenario. In spite of that, the total number of years in Type B and Type D to payback the capital investment is over 22 and for Type F is around 11 to 22 years, respectively. It is also observable that the moderate option has the lowest number of years to payback the capital investment in all models in every energy price scenario. This is due to the amount of required
capital investment and achieved energy saving that provided higher NPV and lower payback time in this scenario.

The earliest payback period belonged to moderate retrofitting option by 5 years for Type E, followed by 8 years for Type A and Type C, 11 years for Type F, 22 years for Type B and over 22 years for Type D. The reason for the longer payback period of Type B and Type D is that models with the slab on ground floor had higher thermal performance in pre retrofitting stage than models with suspended timber floor.

Fig 7.8: Influence of different retrofitting options (Table 7.4)) on representative dwelling simulation models with three energy price scenarios on payback period for climate Zone 5-Mascot.

7.2.4.2 Economic evaluation of single parameters

The effects of individual parameters on the NPV and Payback Period for brick veneer with the suspended floor (Type A) dwelling have been examined and the results are presented in Fig 7.9, Fig 7.10 and Fig 7.11.

The result of the analysis shows that mainly upgrading the floor insulation and ceiling insulation of base case model (Type A) constitutes choices that ensure a high NPV and a short payback period (achievable in less than 5 years). Replacing the windows does not help to achieve a positive NPV even in 20 years, because the demand for the capital investment in window upgrading is much greater than the advantage to be gained from the total energy which is saved in every future energy price scenario. The results also show that upgrading the floor insulation from base case (no insulation) to the high retrofitting option (R-value (m²K/W) of 3) can increase the NPV by about 20% more than in the low retrofitting option (R-value
Upgrading the ceiling insulation to high retrofitting option (R-value (m²K/W) of 6) can achieve NPV 23% more than base case (R-value (m²K/W) of 1.3) option in every energy price scenario. As analysed in Chapter 5, the type of floor has the highest influence on the total energy performance of dwellings, and higher levels of floor insulation can result in more energy savings.

The assessment of airtightness improvement on models proves that it is an economically effective upgrade. The result shows that increasing airtightness leads to a positive NPV in every retrofitting option through 20 years, but this benefit can triple if high retrofitting option instead of the low retrofitting option is adopted. The slope of the NPV growth in the high retrofitting option is greater than the other options because improving the airtightness from low retrofitting option to high retrofitting option includes more complex improvement measures and also saves a higher percentage of energy than the capital required.

Furthermore, it is noticeable that the installation of insulation in brick veneer wall constitutes the more economically attractive option than the option of window replacement. The total NPV of wall insulation varies from $596 to $1371 in 20 years for the pessimistic energy price scenario. However, if the wall has initially been built as the heavyweight (brick veneer and double brick), adding wall insulation would not be much economically beneficial while the addition of wall insulation for the lightweight wall (Fibro) can save more energy and will result in high NPV.
Fig 7.9: Influence of low single retrofitting parameters (Table 7.4) on payback period of Type A dwelling in climate Zone 5-Mascot, and for three energy price scenarios.

Fig 7.10: Influence of moderate single retrofitting parameters (Table 7.4) on payback period of Type A dwelling in climate Zone 5-Mascot, and for three energy price scenarios.

Fig 7.11: Influence of high single retrofitting parameters (Table 7.4) on payback period of Type A dwelling in climate Zone 5-Mascot, and for three energy price scenarios.
7.3 Discussion and limitation

A decision-making tool for building retrofitting is important as an assistance to building users when setting goals for sustainability, and for making sure that the retrofitting objectives are met throughout the renovating process (Nielsen et al., 2016). In this chapter, the retrofitting strategies for the example models have been significantly facilitated by the use of a developed decision-making tool. The tool provides results for the effectiveness of the retrofitting measures on the thermal performance and cost benefit of dwellings.

The economic assessment of different retrofitting options showed that applying retrofitting in representative dwelling simulation models could in many cases be economically beneficial.

A comparison between retrofit options shows that significant energy and economic savings can be gained (of over 80% in some cases). The achieved levels of energy performance followed by economic profit in the three-refurbishment scenarios show that energy efficiency is the clear economic way forward for the existing buildings.

An analysis of the investment costs and the respective NPV and payback periods show that the high retrofit option has the longest payback period for every energy price scenario among all cases, except for Type A (brick veneer with the suspended floor) and Type C (double brick with suspended floor). This was anticipated as high retrofitting option covers a larger scope of interventions, which are markedly more costly compared to low and moderate retrofitting options. The results of NPV analysis showed that moderate retrofit is the optimum option in representative dwelling simulation models and it has the shortest payback time as well as the highest NPV among the available options in the three energy price scenarios.

However, limitations along the way affect the results of the decision-making tool. The energy saving per year is always assumed to be constant in all analysis. Also, taking end users into account will lead to a more complete representation of residential energy uses systems.

In addition, as the discount rate has been considered a constant value, this study could be extended by considering variable discount rates in the study time-horizons.
The focus of the analysis is on heating and cooling demands and therefore the economic benefit is just calculated based on those factors. It should be noted that a prior assessment is needed in order to make a decision about which measure and retrofit option to choose for a certain building.

7.4 Chapter summary

In this chapter, a decision-making tool for the energy efficient retrofitting of dwelling has been presented. The tool is developed for building users who intend to retrofit existing dwellings and investigate the impact of specific energy efficiency measures on the total thermal performance of dwellings as well as the cost-benefit of different retrofitting strategies. An example application of the tool has also been shown in this chapter. Three different retrofitting options are designed for the example representative dwelling types by considering a combination of the investigated high influential energy-saving measures, derived from Chapter 6. Example models have been evaluated from an economic point of view with the two most popular evaluation methods (NPV and Payback Period). The outcomes have been presented in tables and figures. NPV was used as an evaluation criterion and a uniform evaluation period.

As energy prices increase, the results show that the cost savings from higher efficiency retrofits over a 20-year period will be more economical options. With the expansion of the time-horizon and the accumulation of energy savings in relation to the neutral or optimistic energy price predictions, it is noticeable that the ‘moderate’ retrofitting option is shown to be the better economic option in the vast majority of dwellings. The findings suggest that a ‘moderate’ retrofitting option is the optimal and cost-efficient standard for about 20 years with an optimistic or neutral energy price scenario. The results also demonstrate that the ‘high’ retrofitting option is the energy optimum for over 20 years’ time-horizon when high-energy prices are assumed.

The analysis of the cost-effectiveness of individual parameters provides evidence that the insulation of the floor and ceiling in representative dwelling simulation models constitutes the most effective interventions, followed by improved
airtightness and wall insulation. The replacement of windows is also proven not to be economically beneficial due to high capital cost.

In this chapter, the developed decision-making tool is a novel instrument that supports users to consider the influence of energy improvement measures on existing dwellings, the capital cost of retrofitting strategies and the associated cost savings of retrofits without conducting the complex building energy simulation models. Energy modelling software packages can help a practitioner understand the comparative performance of design alternatives. However, these softwares frequently require a high level of detail, significant time, resources, and technical expertise which are commonly beyond the knowledge of people. The tool is easy to use, with a friendly interface structure that helps achieve the energy performance goal while exploring different ranges of improvement parameters and associated costs in three climates.

The analysed retrofitting options in the example representative dwelling types can be economically feasible refurbishment scenarios for a range of dwellings in the existing housing stock in order to improve energy performance and comfort.
Chapter 8: Conclusion

The aim of this project was to develop a framework for cost-benefit assessment of retrofitting strategies in order to improve the energy performance of existing dwellings. This study was one of the very few attempts that focus on Australian housing stock. It employed both qualitative and quantitative analysis to develop representative dwelling types. It also investigated residential energy retrofits, and offered the cost-benefit decision-making tool.

In this chapter, first, a summary of the methodology steps is outlined. Then research findings and recommendations for further research are presented.

A number of distinct steps were carried out to address the aims and objectives presented in Chapter 1 (Section 1.2). The methodology used in this research (see Chapter 3) was formed to investigate the research questions from various perspectives.

The key methodology used to achieve the research objectives intended to:

1. Explain the context of retrofitting in Australian dwellings, the associated thermal performance issues and existing solutions, as well as the literature review which was provided in Chapter 2. A range of knowledge gaps in the current residential stock was identified (Section 2.3 and Section 2.4). The literature review revealed a need for more rigorous research in identifying and analysing energy retrofit strategies and their associated costs to improve performance of existing dwellings in Australia.

2. Characterise the current state of the existing residential building stock in Australia (Chapter 4) for which several Australian Bureau of Statistics (ABS) databases relating to Australian residential buildings were used (Section 4.3). However, useful ABS data were not available at address level; therefore, it was not easy to examine the co-occurrence or clustering of building features in individual buildings. In response to the lack of suitable and accessible data relating to the housing stock, this project used a hybrid approach.

A hybrid approach, which combined the output from statistical analysis of accessible databases with the input of qualitative assessment from experts and practitioners, was used to finalise the list of typologies for the current stock
(Section 4.4). The developed list of typologies was digested with the most common building attributes from ABS statistical analysis to identify the common typologies and to produce a set of ‘representative’ dwelling attribute matrix (Section 4.5).

3. Develop representative simulation models for the existing typologies in the current stock (Chapter 5). To achieve this, a detailed matrix of the dwelling construction attributes was used (Section 4.5). The Taguchi method and the Analysis of Variance (ANOVA) process were combined with a building energy simulation program in order to identify the key building attributes that influence heating and cooling requirements (Section 5.3.1). The quantification of the most influential attributes led to the development of representative dwelling simulation models for the current stock (Section 5.3.2).

Thermal performance of developed representative dwelling simulation models was then quantified by evaluating the models in free-running and conditioned modes (Section 5.3.3). The outcome of thermal performance analysis, derived from representative dwelling simulation models, was then compared to a highly efficient retrofitted house. The effects of the floor area on total thermal energy requirements of the representative dwelling simulation models assessed and the simplified area correction estimation models were also developed for considering the impact of floor area (Section 5.3.4).

4. Conduct a Differential Sensitivity Analysis (DSA) (Section 6.3.1) to assess the sensitivity of the range of design parameters on representative dwelling space heating and cooling demands by using building performance simulation (BPS). The influence coefficient was calculated for the tested variables (Section 6.3.1.2) and the most influential design parameters were identified.

5. Linear regression models, predicting the thermodynamic performance of building envelope, were developed by exploring the high influential parameters (Section 6.3.2). Building energy simulation together with Taguchi experiment order layout was used to create simulation databases needed for developing energy prediction models (Section 6.3.2.1). Random values of design parameters, which were included in the developed energy prediction models, were also generated, and the results of EnergyPlus simulations using these
parameters were used to verify the outputs of the prediction models (Section 6.3.3).

In addition, the feasibility of the designed methodology, used for the development of the energy prediction models of this study, was examined. A similar methodology was used for the development of an energy prediction model in a real building. The outcome of the building energy prediction model that was developed through this process was compared with the prediction of the calibrated simulation model (Section 6.3.4).

6. Develop a decision-making tool for assessing the energy retrofit of dwellings (Chapter 7). This tool offered the retrofitting investigation of an existing dwelling in terms of: 1. the dwelling’s current energy requirement identification, 2. the impact of specific energy efficiency measures on the total thermal performance analysis, 3. and the cost-benefit of selected strategies evaluation (Section 7.2).

To establish the cost analysis function in the decision-making tool, the cost of insulation materials, glazing types and airtightness level were provided as optional inputs (Section 7.2.1). The range of energy price scenarios included an optimistic energy price scenario, a neutral energy price scenario, and a pessimistic energy price scenario. These scenarios provided a cost-benefit of retrofitting strategies based on future energy price changes (Section 7.2.2). Finally, the economic feasibility of retrofits in representative dwelling types was also assessed (Section 7.2.3). The retrofitting decision tool was used to evaluate the cost-benefit of a series of low, moderate and high retrofitting options and a single parameter in developed representative dwelling simulation models (Section 7.2.4).

An overview of the key research findings is presented in the following section.
8.1 Research findings

8.1.1 Investigate the characteristics of the existing residential building stock in Australia in order to identify the representative dwelling types.

- Quantitative and Qualitative assessments were used to explore the physical attributes of Australian housing stock. The ABS analysis revealed that about 70% of the housing stock in Australia were occupied detached houses or bungalows, with two and three bedrooms. It was also shown that most common wall materials in dwellings were brick veneer (22%), double brick (38%) and fibro (10%). Tiles (62%) and steel (33%) were the most typical roofing materials. The vast majority of the insulated buildings have the insulation placed in the ceiling (98%) and the type of insulation is usually batts or fiberglass (62%) (Section 4.3).

- The ABS analysis was digested to define an initial typology outline of seven different dwelling types (Detached-Brick Veneer, Detached-Double Brick, Detached-Lightweight Cladding, Semi-Detached-Brick Veneer, Semi-Detached-Double Brick, Unit-Double Brick, Unit-Brick Veneer), as shown in Section 4.3.1.5. The outcome of ABS analysis and qualitative analysis was combined and resulted in three common typologies: Detached-Brick Veneer, Detached-Double Brick, Detached-Lightweight Cladding, with a detailed matrix of construction attributes in current residential stock (Section 4.5).

8.1.2 Identify the key building attributes that influence heating and cooling requirements for the development of representative dwelling simulation models.

- The outcome of the detailed attributes matrix analysis showed that substantial contributions of attributes to the thermal performance of dwellings belong to the floor type (35.33%), building size (31.75%), climate (16.95%), level of ceiling insulation (4.90%) and wall materials (4.32%). These attributes should be explicitly specified in representative dwelling simulation models (Section 5.3.1). Quantification of the key attributes that mostly influenced heating and cooling load requirements
of dwellings led to the development of twelve representative dwelling simulation models for current stock (Section 5.3.2).

- The outcome of thermal performance analysis of representative dwelling simulation models, presented in Section 5.3.3, indicated that the dwellings with different wall materials (brick veneer, double brick and fibro) and same floor types performed more consistently in terms of temperature frequency than the dwellings with similar wall materials and different floor types (slab on ground floor and suspended timber floor). It was also found that the discomfort hours were significantly lower in the dwellings with slab on ground floor (Type B, Type D and Type F) in comparison with the dwellings by suspended floor type (Type A, Type C and Type E) in every climate. The reason for this is in the lower heat transfer and higher thermal mass of dwellings with slab on ground floor than those of the dwellings with suspended timber floor. The result of free running assessment revealed that dwellings with the highest and the lowest thermal comfort hours per year belong to Type D (Double brick with slab on ground floor) in Mascot with 45% and Type E (Fibro with suspended timber floor) in Goulburn with 11% of the year hours, respectively. The outcome of thermal performance analysis of models in conditioned mode showed that double brick, brick veneer and fibro with slab on ground floor dwellings (Type B, Type D and Type F) achieve a substantially greater thermal performance, requiring approximately 200% less energy than the suspended floor type models (Type A, Type C and Type E). Analysis of the thermal performance of a highly retrofitted house (Solar Decathlon House) also demonstrated that this model with suspended timber floor required about 25% to 65% less energy than in models with the slab on ground and over 100% less than the dwellings with suspended timber floor. This comparison revealed the high potential of retrofitting in improving the thermal performance of existing residential building (Section 5.3.3).
8.1.3 Investigate the relative impact of improvement design parameters on the thermal performance of dwellings and develop the energy prediction models for representative dwelling types.

- The appropriate selection of improvement parameters has a major influence upon the thermal performance of dwellings. In section 6.3.1, the result of running Differential Sensitivity Analysis (DSA) and calculating the influence coefficient indicated that level of airtightness, window-to-wall ratio (WWR), window types and levels of ceiling, wall and floor insulations are the parameters that strongly influenced the predicted energy consumption. Hence, these parameters are necessary for the development of linear energy prediction models (Section 6.3.2).

- The outcome of model reliability analysis showed that differences between the developed regression-predicted and EnergyPlus-simulated annual thermal energy requirements were about 10%-15% (Section 6.3.3). The coefficient of determination \( R^2 \) was over 0.85, indicating a good agreement between simulation and the regression models. The outcome of reliability analysis suggested that annual heating and cooling energy requirements could be forecasted with an acceptable accuracy using the regression models.

- The methodology evaluation verified the reliability of the developed methodology with less than 20% deviation between the calibrated simulation model and the dwelling energy prediction model (Section 6.3.4).

8.1.4 Develop a cost-benefit decision-making tool for assessing the energy retrofit of a range of existing dwelling types in Australian residential stock.

- The developed energy prediction models (the result of Chapter 6) were combined with the cost of upgrades (described in Section 7.2.1) and energy price prediction scenarios (Section 7.2.2) that resulted in the development of a simple cost-benefit decision-making tool (Section 7.2). The offered tool demonstrates how different envelope improvement parameters affect the required energy to maintain indoor
comfort and the associated costs of retrofitting. The tool included four assessment sections, Property type, Property characteristics, Action planner, and Cost planner to take the user through the steps to create the baseline, improvement strategies and cost-benefit analysis for a range of dwelling types.

- The economic feasibility of retrofits in representative dwelling types with a decision-making tool, through a series of low, moderate and high retrofitting scenarios and single parameter, was also investigated. The outcome of economic feasibility analysis demonstrated that growth can happen in the NPVs trend for all energy price scenarios and retrofitting options across every model in a 20-year horizon. (Section 7.2.4.1). It was also evident that energy efficiency is the clear economic way forward for the existing dwellings. With the expansion of the time-horizon and the accumulation of energy savings in relation to the neutral or optimistic energy price predictions, the results showed that the ‘moderate retrofitting option’ is the better economic scenario in the vast majority of dwellings by having the earliest payback period time. The economic analysis also showed that the earliest payback period belonged to “moderate retrofitting option” by 5 years for Type E, followed by 8 years for Type A and Type C, 11 years for Type F, 22 years for Type B and over 22 years for Type D.

- The results also demonstrated that the ‘high retrofitting option’ is the energy optimum scenario for a time-horizon of over 20 years at high-energy prices. Energy savings for the ‘high retrofitting option’ were between 17% and 38% greater than the savings for a ‘moderate retrofitting option’ over a 20-year period while the capital cost of the ‘high retrofitting option’ is about 45% higher than the moderate option in every model. The high retrofitting option requires a payback period of 7 to 14 years in suspended timber floor models (Type A, Type C and Type E) and 15 to over 23 years in slab on ground models (Type B, Type D and Type F).
• An economic analysis of single parameters (air-tightness, window types and levels of ceiling, wall and floor insulations) was conducted. The result of the analysis showed that the insulation of floor and ceiling in representative dwelling types constitutes the most effective interventions in NPV growth by 20% and 23% respectively, followed by airtightness and wall insulation (Section 7.2.4.2). The replacement of windows is also proven to poorly return investments due to initial high capital cost.

This research has advanced the knowledge of energy retrofit for existing buildings in the Australian residential stock. It aimed to develop a decision process framework to identify a range of retrofit strategies that maximise the cost-effectiveness of upgrades, whilst preserving an acceptable level of thermal comfort for particular buildings. The use of multimethod research techniques has provided a more nuanced insight into the residential building stock and retrofitting in the Australian context. This Ph.D. is one of the few attempts that focused on the predictions of the energy load required for thermal comfort and cost assessment for Australian residential buildings and is unique in its emphasis on representative dwelling types. It is also important as it offers a cost-benefit decision-making tool (Fig 7.2) that quickly summarises the cost of different strategies and the likely benefits over a next 23 years. This tool assists building designers, experts and general users from the burden of performing a detailed dynamic simulation of the building, that requires a significant amount of experience, time, and efforts, to determine appropriate retrofit strategies and associated cost in range of dwelling types.

8.2 Recommendations for further research

Numerous research questions were identified through the course of this research, which were beyond the scope of this study. The research questions were mainly concerned with three related objectives: 1. adding to the body of and representation of existing dwelling characteristics in residential stock, 2. reducing the operational energy requirement while maintaining indoor condition in the thermal comfort setting, and 3. providing a better knowledge about the cost-benefit associated in a range of retrofit plans.
Goals are fundamentally related to the need of improving the thermal performance of existing dwellings based on different budgets. Suggested future research activities include:

- An extension of the present project would develop household profiles that synthesise age, energy bill, dwelling occupancy patterns and other demographic as well as building related data to characterise a set of householder profiles continuing the work of the present project based on existing dwelling experiment. These profiles would allow researchers and policymakers to target energy retrofit programs and policies for the final energy user: the householder.

- A similar methodology could be applied to dwellings in different residential climate zones to explore its applicability. In order to be used by different projects or users, the decision framework was coded in Microsoft Excel. This function provides the chance of change in default values such as material cost or labour fee for users. The decision tool could also be coded further to become more functional for the user, e.g. to visualise the retrofit strategies.

- The approach outlined in the method identified the retrofit of representative dwelling types. It is recommended that retrofit strategies be implemented in similar dwelling types to assess the effectiveness of measures in a different relationship between envelope attributes and energy requirements. Although investment in time and money is predicted to be high, the potential benefits are also important.

- The study was limited to post retrofitting thermal performance in conditioned houses; the differences between thermal performances of free running and conditioned model needs to be tested for strategies.

- The limitation of this study was also using the twelve typical detached houses with similar floor plans. The validity of the derived application from this study is depended on a certain type of dwelling and location relevant to the current Australian residential stock. It is recommended that further studies on other types of dwellings be undertaken.
• The result of this study demonstrated the potential of designed methodology in predicting the energy performance of dwellings. However, results also depend on the validity of climate files as well. It is recommended to run an uncertainty analysis of climate files pre energy simulation modelling.

• The study was offered the retrofitting strategies for existing dwellings through the common envelope improvement practices. It is recommended to evaluate the effect of various more advanced building envelope technologies including active and passive upgrades (ventilation wall, ventilation window and shading, energy frame, vertical garden, solar façade and adaptive solar façade).

• In this research, an economic analysis was limited to evaluate cost-benefit of retrofitting strategies in improving the energy performance of existing dwellings. It is recommended to include the co-benefits analysis (health, mortality, re-sale value, etc.) in future works.

• This study was limited to improve the thermal performance of representative dwelling types by using the energy simulation software. Implementation of some retrofits to existing houses and taking real-world measurements of energy loads to determine the benefits is recommended.
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