LOW CARBON LIVING CRC

RP2002:

Integrated Energy, Transport, Waste and Water (ETWW) Demand Forecasting and Scenario Planning for Precincts.

Final Report.

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    - CSIRO,
    - The University of New South Wales,
    - South Australian Government's Department of Planning, Transport and Infrastructure,
    - South Australian Government's Department of Environment, Water and Natural Resources,
    - South Australian Urban Renewal Authority (RenewalSA),
    - SA Water,
    - Sydney Water,
    - AECOM.
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Peer Review Statement

The CRCLCL recognises the value of knowledge exchange and the importance of objective peer review. It is committed to encouraging and supporting its research teams in this regard. The author(s) confirm(s) that this document has been reviewed and approved by the project's steering committee and by its program leader. These reviewers evaluated its:

- originality
- methodology
- rigour
- compliance with ethical guidelines
- conclusions against results
- conformity with the principles of the Australian Code for the Responsible Conduct of Research (NHMRC 2007),

and provided constructive feedback which was considered and addressed by the author(s).

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Executive Summary

Demand estimation for services and facilities is an important component of urban development, being required for the determination of the level of provision and coverage of infrastructure and related facilities to serve the needs of present and future populations. Demands and associated cabin impacts for the domains of energy, transport, waste and water (ETWW) are significant to planning agencies, infrastructure providers and operators and private developers who all need to deliver services and resources to urban precincts.

This research project, conducted for the Low Carbon Living Cooperative Research Centre, has developed a tool for integrated demand and carbon impact forecasting of ETWW demand at the precinct level, which supports scenario planning for alternative precinct development plans. This unique approach allows for interactions between the different demand domains and can accommodate the impacts of population changes, socioeconomic variables and household behaviour change in demand forecasting. Research efforts and the resulting tool has a focus on residential precincts in a mixed-use precinct context, providing a scientific and efficient basis for the assessment of the overall carbon impacts of urban developments or redevelopments. A broad range of demand estimates and related carbon impact estimates can be achieved at high levels of accuracy with scenarios recognising the inter-domain demand relationships that occur at a household level.

The developed integrated demand estimation approach allows for the accurate estimation of the core ETWW demands and subsequent carbon impacts at a household and at a precinct level. The approach also identifies commonalities in data requirements and model formulation between the four forecasting domains. In this way overall carbon impacts of urban developments or redevelopments can be assessed more accurately, effectively and efficiently. Resulting demand forecasting can account for the integrated impacts of solar energy generation and battery storage, increased water recycling and rainwater use, alternative transport fuels including electric vehicles and strategies to encourage increased recycling behaviour and the transport of waste. Climate change effects are also considered directly through future year temperature and precipitation estimates and indirectly through changes to the water supply mix or seasonal needs for energy and water. Carbon emissions performance of the precinct is a key focus and the research considers the impact of scopes 1 and 2 emission types. The tool provides a platform for testing a variety of forecast scenarios to account for a variety of such forecast scenario options.

Model forecasts are demonstrated through case-study applications for the Lochiel Park and Tonsley precincts. Scenarios incorporate the on-ground development properties and proposed masterplan documentation for the sites with population type estimations based on Mosaic household typologies. Scenario inclusions are made for options such as electric vehicle adoption, water supply alternatives and activity change such as increased work-form-home activity. Interpretation of input datasets and output results is assisted with the use of a Geographic Information System (GIS) to represent this information spatially. Through these case studies, the model demonstrates its ability to deliver the practitioner with 'what-if' type scenario investigations important to policymaking and planning for future urban development. The user is ultimately able to explore combinations to achieve a low-carbon precinct development.

Contributors to the research project include:

- Supervisors, leadership team and researchers: Em. Prof. Michael AP Taylor, Prof. Rocco Zito, Dr. Nicholas Holyoak, Prof. John Boland, Prof Peter Newton,
- Research team: Mr Steven Percy (PhD candidate), Dr. Michalis Hadjikakou, Mr He (PhD candidates) and Dr. Ivan Iankov.

1 The Cooperative Research Centre for Low Carbon Living and Research Program-2

International research suggests that the determination of possible pathways for carbon reduction in the built environment is now essential. The Cooperative Research Centre for Low Carbon Living (CRCLCL) is specifically researching the underlying principles of low carbon living in the Australian context, addressing the unique requirements of the Australian climate, construction practices, demographics and policy environment. The CRC's three research programs engaged to deliver a low carbon built environment are:

- Program 1: Integrated Building Systems. Developing new low-carbon products and services, and finding ways to communicate best practice design through rating tools, standards and display homes.
- Program 2: Low Carbon Precincts. Creating new planning techniques, models and data for delivering low carbon developments at a precinct scale. Communicating best practice in sustainable city planning through precinct design and assessment tools
- Program 3: Engaged Communities. Creating a new community appetite for low carbon living, through strategies for social networking, education and media. Communicating the vision of a prosperous, liveable and sustainable society to business and government through living laboratories and economic modelling

All eight CRC impact pathways fall under three research programs representing specific areas in which the CRCLCL expects to transform the low carbon built environment.

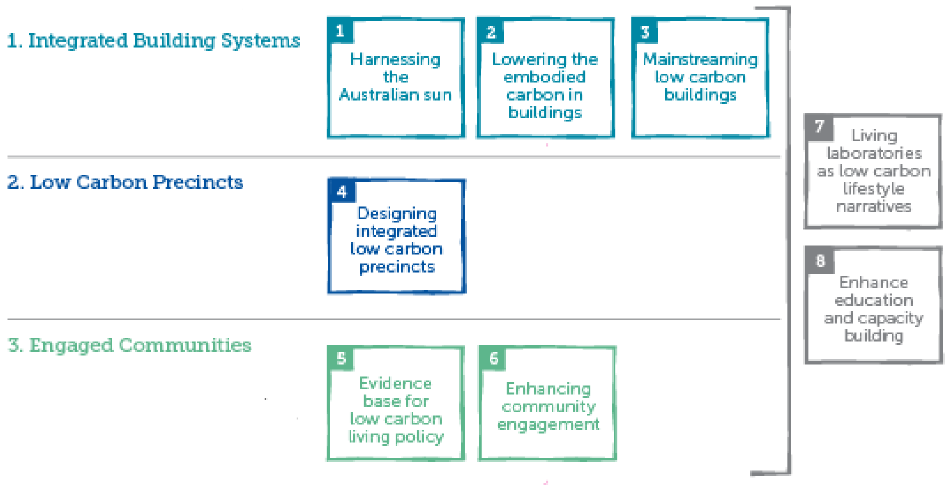


Figure 1.1: CRCLCL Impact Pathways and research programs.

The *Low Carbon Precincts* program focuses on reducing the carbon footprint of our urban systems, with key consideration being given to integrating the interlinked aspects of energy, water, waste, transport and buildings. The challenge is to reduce the carbon footprint of precinct infrastructure through the development of better tools and planning techniques that will make low carbon infrastructure valuable and desirable to the buyer. As a result, low carbon precincts will be transformed into highly desirable lifestyle options. Improved planning of precincts will allow carbon footprint to be reduced to zero in the longer term, at the same time as quality of life continues to grow. The program is developing new knowledge and tools that enable the design of, and stimulate the market for, low carbon infrastructure at the precinct scale. This will facilitate property developers and local government partners providing low carbon infrastructure development as well as redevelopment and retrofitting at the planning point of delivery. The workflow structure for the Low Carbon Precincts program is indicated in Figure 1.2. It includes six connected work packages, which also link to the other programs in the CRC.

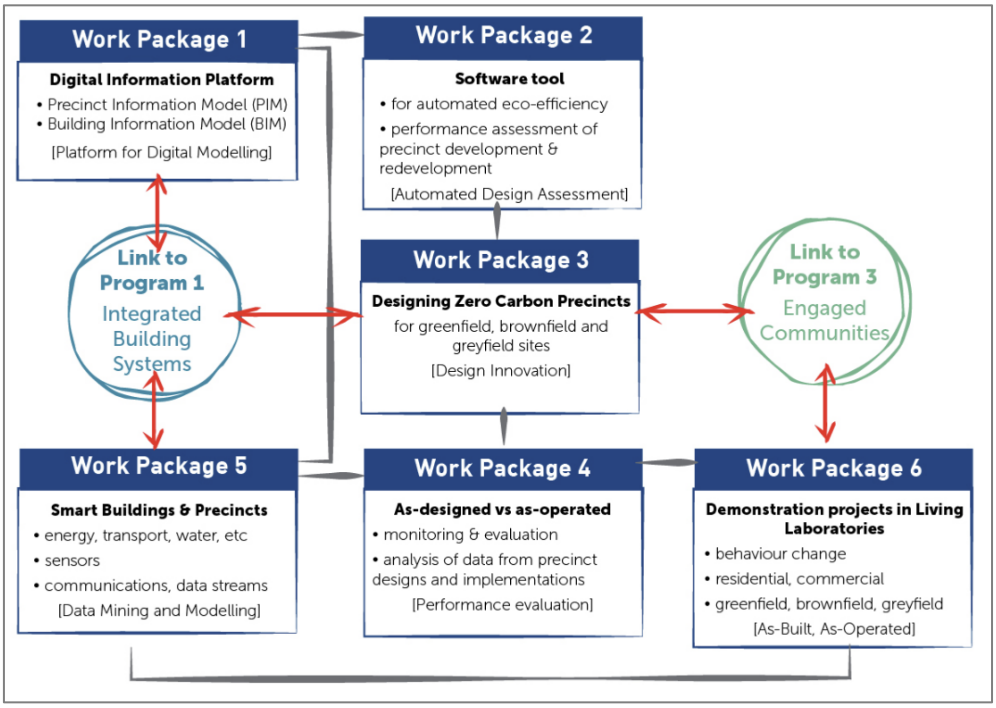


Figure 1.2: Workflow structure for Low Carbon Precincts.

Work package 2 within Program 2 therefore offers an environment to perform research into the development of a tool for integrated demand forecasting of Energy, Transport, Waste and Water (ETWW) generation demand at the precinct level, which supports scenario planning for alternative precinct development plans.

2 Research Project Context: RP2002

A number of forecasting and software tools already exist in the ETWW domains with a range in application scale, operational ease and purpose. Tools and methods applied to the ETWW domains have been developed and used largely in isolation from each other without integration and recognition of the demand interactions that occur at a household and also at a precinct scale. For energy, software such as the Gridlab-D modelling platform (Chassin et al, 2008) and CSIRO developed AccuRate software (Chen and Chan, 2015) offer demand forecasting platforms. In the water domain there are packages such as Innovyze (2016) and SimulAlt demand-supply water simulation model (Government of South Australia, 2011). Established transport demand models such as MASTEM (Holyoak et al, 2005) and software packages like Cube (Citilabs, 2011) and AIMSUN software (Casas et al, 2011) provide modelling and simulation potential in that domain. On the other hand, few waste production software models currently exist, with most approaches based on unique research applications.

Advances have been made over the past decade in tools for the performance assessment of buildings in terms of energy, carbon, water, building materials and indoor environments. Newton et al (2013) detailed outcomes of the CRC's research project RP2001 in which a scoping study was undertaken to identify the requirements for a design assessment tool for precincts for evaluating the carbon intensity and other features of built environments. This research investigated a number of tools at three levels of approach as frameworks and principles, assessment systems and rating systems. Included in assessment of precinct assessment tools are those developed by partner organisations of the CRC: LESS (Hassell), MUtopia (University of Melbourne), PrecinX (NSW Government) and SSIM (AECOM).

Newton et al (2013) concluded that most demand estimation procedures in assessment tools "*are rudimentary and lack transparency (in relation to algorithms used, model assumptions and baseline data)*". In response to this identified need, recommendations were made for a research project to "provide more advanced and scientifically validated models for use in precinct assessment tools." In addition this research needed to address the complex factors that interact to drive demand across the range of environmental loads, making use of CRC research outcomes such as those from the living laboratories and likewise potential for these living labs to act as test-beds for its algorithms, and a path to the existing precinct assessment tools. CRC Research Project RP2002 was developed to this end.

This research into integrated demand forecasting for energy, travel, water and waste generation at the precinct level has provided a tool to accurately estimate precinct-level cabin impacts. The method has delivered this tool for the simultaneous estimation of the demands for energy consumption, travel, water consumption and waste disposal facilities by households in residential areas of Australian cities, implemented as a software tool for use by:

- planning agencies,
- infrastructure providers,
- infrastructure operators,
- private developers,
- researchers and others.

The research output of the project is a practical tool which is transparent, flexible, utilised by a range of operators, operated without the need for specialised input datasets and benefitting from existing and available operational data. It can recognise the impacts of voluntary behaviour change by households, useful in the assessment of the total demands in the planning, design and evaluation of residential developments, including their carbon impacts. Further, it can cater for the interactions in the demands for the four precinct infrastructure domains of energy, transport, waste and water.

Structured with a residential focus, it is possible to assess not only the physical structure of the precinct but also variations to resident populations and socio-demographics. Carbon impacts of non-residential land uses are also estimated as forecasting techniques go beyond the household to recognise other land uses, green areas and precinct-scale infrastructure. The result is a software tool for integrated demand and carbon impact assessment and scenario evaluation with specific technology and behaviour-based forecast scenario inclusions.

As a CRC-based research project, involvement of project industry partners in all stages of model development and application has been essential to deliver a practical tool with relevant and useful outcomes. The CRC industry partners associated with this research are:

- The University of South Australia,
- CSIRO,
- The University of New South Wales,
- South Australian Government's Department of Planning, Transport and Infrastructure,
- South Australian Government's Department of Environment, Water and Natural Resources,
- South Australian Urban Renewal Authority (RenewalSA),

- SA Water,
- Sydney Water,
- AECOM.

Associated with each of the four demand forecasting domains were PhD candidate and post-graduate researchers, affiliated with Australian institutions. These researchers were:

- Energy: Steven Percy (PhD candidate, University of Melbourne/CSIRO): Demand forecast process combined with battery solar optimisation model.
- Transport Nicholas Holyoak (Post-doctoral Fellow, Flinders University), Michael Taylor (Emeritus Professor, University of South Australia) (Rocco Zito, Professor, Flinders University), Branko Stazic (Research Associate, Flinders University) Ivan Iankov (PhD candidate, University of South Australia): Macro and 'nano' scale demand representations for internal and external precinct-travel.
- Water Michalis Hadjikakou (Post-doctoral Fellow, University of New South Wales): Water demand forecasting using a linear mixed modelling approach.
- Waste He He (PhD candidate, University of South Australia): Regression and factor analysis based forecasts of waste production.

The ETWW research has therefore been a collaborative effort, requiring input from many individuals representing private organisations, public organisations and academia. It has required the sharing of resources as primarily data resources, with information relating to current modelling and forecasting data needs. Often this has been part of the in-kind contributions from industry partners along with expert opinion and advice and feedback on topics such as tool functionality and forecast scenarios. The project leadership team, individual researchers and industry representatives have met on a regular basis throughout the project life with regular and documented project steering committee meetings (six in total over the life of the project) and workshops. Reports developed as part of these workshop exist as:

- Beatty, Kate; Berry, Adam; Delvin, John; Donaldson, Phil; Holyoak, Nick; Iankov, Ivan; Lehmann, Steffen; Newton, Peter; Oxlad, Lindsay; Philp, Michelle; Parasad, Deo; Taylor, Michael; Thomas, Nick; Ting, Jason Wiedmann, Tommy; Zaman, Atiql; Zito, Rocco (2013) Project Workshop No.1: Initial Workshop Summary Report
- Dr. Nicholas Holyoak, Professor Michael Taylor, Dr Adam Berry, Associate Professor Tommy Wiedmann, Mr Fernando Gamboa, Mr John Devlin (2014), Energy, Transport, Waste and Water (ETWW) Demand Forecasting and Scenario Planning for Precincts - Workshop 2 - Establishing a framework for integrated ETWW demand forecasting
- Dr. Nicholas Holyoak (2014) Energy, Transport, Waste and Water Demand Forecasting and Scenario Planning for Precincts: Workshop 3 - Model specification, development and integration.
- Nicholas Holyoak, Steven Percy, Ivan Iankov, Michalis Hadjikakou, He He (2015) Energy, Transport, Waste and Water Demand Forecasting and Scenario Planning for Precincts: Workshop 5 - Research Development and Scenario Specification.
- Nicholas Holyoak, Michalis Hadjikakou, Steven Percy, Ivan Iankov, He He (2016) Energy, Transport, Waste and Water Demand Forecasting and Scenario Planning for Precincts. Workshop 6 - The Development and Application of the ETWW Model Foundation Version 1.0 as a Prototype.

3 Overview of Forecasting Approach

Forecasting the future demands associated with residential precincts is a necessary process to deliver adequate services and resources whilst minimising the subsequent carbon impacts during the everyday activities of the population. Accurate forecasting processes need to account for not only the physical attributes of the built environment and technologies but also the nature of residential population types. Core demand forecasting domains associated with Energy, Transport, Waste and Water (ETWW) have significant impacts on the overall carbon production associated with the precinct as a whole. Planning agencies, private developers, infrastructure providers and operators all stand to benefit from detailed, accurate and integrated forecasting based on readily available input data sources.

The ETWW model operation involves the definition of precinct variables, internal and external routines, data management and display environments and output summaries as depicted in Figure 3.1. Research conducted in the individual domains has provided much of the model 'engine' with integration between domains and feedback processing loops. A GIS environment is utilised for data management, processing and display purposes associated with input and output data archives, including the final demand and carbon impact results. The model also has potential pathways to connect with other CRC for Low Carbon Living research, particularly in terms of precinct-level data across all aspects. Operation processes within the ETWW model are illustrated in the following figure with latter paragraphs detailing these core components.

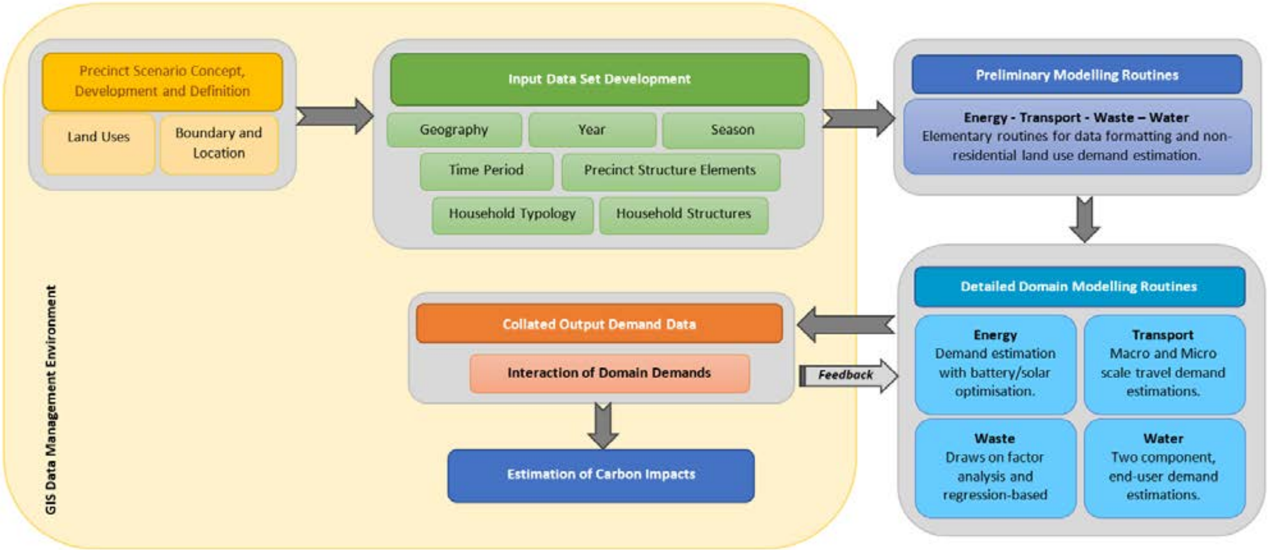


Figure 3.1: ETWW model operational flowchart.

Scenario definitions are the first step in the ETWW model operation with the need for details on the precinct 'concept' including land uses and household typologies involved with other land uses for education, retail, commercial, public space etc. Physical attributes of the precinct with respect to support infrastructures, the boundary definition or size of the precinct and location within Australia are required in preparation for the development of detailed input data sets. Assembly of scenario components in a GIS environment is the first stage of this data accumulation.

Input data required by model components is compiled for all precinct forecast scenarios, as required by all of the forecasting domains. Some data may be specific to individual domains (such as the transport network configuration), with other core inputs (such as number of household residents) having multiple domain applications. Greatest attention is paid to defining the household in detail with other inputs for non-household related land uses that are regarded as precinct structure elements such as green space and commercial land uses. Timing components including the forecast year/s, the season and forecast period (which may be a day or a peak period during the day) are defined. Household typologies align with Mosaic household typologies developed by Experian (2013) and housing types relate to the physical attributes of the house including structure type, number of bedrooms and solar generation capacity.

The Mosaic dataset (Experian 2013) is an important component in the ETWW forecasting routine as it provides the model and domain-specific routines with a means to classify household types. According to the Mosaic household segmentation, any Australian household can be classified as one of 49 unique segments (Experian, 2013), existing under 13 overarching groups. This Mosaic code allocation can then be related to detailed choice, preference and census-like demographic information through the 'Grand Index' and a 'Household Expenditure' tables. For the ETWW project, it is therefore possible to utilise the Mosaic household classifications to allocate a precinct (either existing or planned) with household population types and support this typology with data to describe the household (i.e. information on income, residents, vehicles, bathrooms, bedrooms, etc.).

Code ID	*Description*		Code ID	*Description*		Code ID	*Description*
A01	*Suburban Elite*		**E18**	*Moving Minerals*		**I35**	*University Diversity*
A02	*Successful Spending*		**E19**	*Crops and Country*		**J36**	*Paddock Views*
A03	*Long term Luxury*		**E20**	*Working the Land*		**J37**	*Aussie Grit*
A04	*Financially Savvy Families*		**F21**	*Family Connections*		**K38**	*Sensible Seniors*
B05	*Educated Savers*		**F22**	*New Bubs, New Burbs*		**K39**	*Silver and Pearls*
B06	*Maturing Assets*		**F23**	*Regional Relations*		**K40**	*Community Conservatives*
B07	*Commuting Communities*		**F24**	*Tykes and Takeaways*		**K41**	*End of the Road*
B08	*Multicultural Wealth*		**G25**	*Backyard Pride*		**K42**	*Constant Struggle*
B09	*The Good Life*		**G26**	*Out on the Edge*		**L43**	*Pride and Perseverance*
C10	*Stylish Pursuits*		**G27**	*Suburban Backbone*		**L44**	*Trucks and Tools*
C11	*Inner City Aspirations*		**G28**	*Local Focus*		**L45**	*Labouring Lay-bys*
C12	*Wireless and Wealthy*		**G29**	*Spirited Solos*		**L46**	*Simple Living*
C13	*Professional Views*		**H30**	*Cultural Fusion*		**M47**	*Assisted Elders*
C14	*Leased Lifestyles*		**H31**	*Extended Ethnicities*		**M48**	*Been Around The Bush*
D15	*Coastal Contentment*		**H32**	*Multicultural Mix*		**M49**	*Armchair Blues*
D16	*Ageing Gracefully*		**I33**	*Education Generation*			
E17	*Greener Pastures*		**I34**	*Roaring Twenties*			

Table 3.1: Mosaic household classifications.

Preliminary modelling routines exist as simpler internal models mainly for the purpose of data preparation or support procedures for the detailed domain modelling applications. Simplified calculations that add to domain-specific forecasting routines include those associated with non-residential land use estimations and data formatting with processes such as application of linear regression equations or factor matrices. Much of the preliminary modelling therefore occurs before the domain modelling processes which are more detailed in nature and can rely on external processes to complete the modelling duties. Detailed domain-specific forecast models are for:

- Energy demand - demand forecast process combined with battery solar optimisation model,
- Transport demand - macro and nano-scale model representations for external and internal precinct-travel,
- Waste production - regression and factor analysis based forecasts,
- Water demand - water demand forecasting using a linear mixed modelling approach.

Forecast demands from the detailed domain models are collated and assembled as precinct consumption and production estimates. Again, given that the integrated demand model is primarily designed for residential precincts, the focus is on the households and household typologies with other land uses also accounted for with simplified approaches. It is also noteworthy that external models can be used in isolation however the real benefit is gained when integration between the model forecasts is achieved.

Output datasets are collated within the ETWW model environment from domain-specific routines to define the consumption and production or overall demand profile of the precinct. The ETWW model then specifies the relationships that can potentially exist between the domains with relationships within the precinct demand forecasts. Potential relationships are initially reported in the Workshop 3 report on model specification, development and integration and now exist within the ETWW modal as identified in the following table.

Scenario Interaction Option	Interacting Domains
Electric vehicle ownership and use	Transport – Energy
Hot water use	Water - Energy
Evaporative cooling	Water - Energy
Rainwater tank water use	Water – Energy
Wastewater	Waste – Water
Activities from home	All Domains
Water consumption behaviour	Water – Energy
Recycling behaviour	Waste – Transport – Energy
Water supply	Water – Energy
Waste removal	Waste – Transport
Energy use behaviour	Energy
Solar panels	Energy
Battery storage	Energy
Grid energy generation	All Domains

Table 3.2: Domain interaction options in the ETWW forecast structure.

In addition to the **scenario interaction types**, the structure and development of domain modelling routines allow for the representation of the following technologies and attributes of precinct structure, both at the household and precinct scale:

- Solar electricity generation technology,
- Battery electricity storage technology,
- Various household energy efficient devices,
- Supply of energy from renewable resources,
- Household water capture and re-use,
- Various household water saving devices,
- Alternative hot water systems,
- Water-efficient green areas at the household and precinct,
- Household recycling techniques and technologies,
- Public transport and non-motorised network alternatives, both contained within and connecting to the precinct.

Other **behavioural interactions** resulting in domain demand interactions that are represented are:

- Increased recycling behaviour,
- Reduced waste production behaviour,
- Increased work-form-home behaviour,
- Increased shop-from-home behaviour,
- Reduced water consumption behaviour,
- Reduced energy use behaviour,
- Reduced transport demand behaviour,
- Mode shift behaviour.

The ETWW model processes the **domain interaction** with resulting changes to demands as appropriate. An example of an interaction is that which exists between the transport and energy domains in an electric vehicle scenario. Transport demands that include the use of electric vehicles must first be established in order to estimate the electrical energy required to fully or partially charge the electric vehicle batteries required for a day's travel. This additional energy requirement from the precinct household can then be incorporated into the energy demand model with supply of this energy possible from mains or solar produced power. Revised demand profiles then bring about the need for model re-estimations, with updates of modelling inputs supplied by the feedback routine.

Data feedback processes between the collated output information sets allows for demand interactions and their influence the forecasting process. Re-estimations of domain forecasts then accounts for the influence of other domains on consumption and production profiles to reflect scenario definitions. Following this process, final demand profiles can be submitted to carbon estimation routines.

For the transport domain, current project-related research into emission forecasting domain involves the development of generic emission rates for light vehicle traffic loads that are highly applicable to Australian conditions. The emission rates are user friendly and can be used in long term forecasting studies. A sound and robust statistical methodology is used for predicting the expected variance of the emission rates and they are reported as confidence intervals. The user of the emission rates can thus assess risk when forecasting road transport greenhouse gas emissions. Research has also determined the uptake of fuel efficient technologies, including hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV) and fuel cell vehicle (FCV) in the future light vehicle fleet.

It is likely that existing forecasting and demand estimation tools and approaches draw on common data input requirements such as basic socio-demographic and household variables, even if their estimation methods differ. Forecasting approaches are supported by databases such as Australian census data, household travel survey datasets containing revealed travel behaviour and preferences, operational and usage datasets held by providers such as Sydney Water, AGL, SA Water and waste collection agencies. Household monitoring data such as that available for the Lochiel Park precinct (Whaley et al, 2010) provides detailed energy, water, waste consumption and production information which is invaluable in the estimation of model parameters. Research currently underway by the CRC for Low Carbon Living largely associated with Program 2 on Low Carbon Precincts also offers potential for model development. For instance the Precinct Information Modelling (PIM) project on open digital information standard throughout the urban development lifecycle and Integrated Carbon Metrics with a multi-scale life cycle approach to carbon outcomes for built environments.

In some cases mature and well-researched models are utilised in forecasting routines, while in other cases new approaches have been developed. A focus of all modelling is on the household, however other land uses and activities that exists within a precinct are recognised and accommodated so that mixed use development can be considered in the precinct planning scenarios... Resulting demand forecasts can account for the integrated impacts of solar energy generation and battery storage, smart-metering, alternative transport fuels including electric vehicles, strategies to encourage walking, cycling, public transport use, increased recycling behaviour and the transport of waste. Consideration can also be given to water sensitive urban design water saving devices and use of rainwater collection and greywater recycling, and extend to potential climate change scenarios and population changes in the precinct over time.

Resulting output datasets are collated within the ETWW model environment from domain-specific routines to define the consumption and production or overall demand profile of the precinct. The ETWW model specifies the relationships that can potentially exist between the domains with relationships within the precinct demand forecasts, a process which is very much a result of the initial scenario specification.

The remainder of this report describes outcomes from the research effort into forecasting for integrated demands and carbon impacts of a precinct in the energy, transport, waste and water (ETWW) domains and how this can contribute to the assessment of policy scenarios for low carbon futures. A major component of this modelling framework includes the impacts of household behaviour change in demand forecasting. The approach also identifies commonalities in data requirements and model formulation between the four forecasting domains. In this way overall carbon impacts of urban developments or redevelopments can be assessed more accurately, effectively and efficiently.

4 ENERGY Domain Forecasting

The residential energy sector has many opportunities for emissions reduction. Emissions reduction could be through increased distributed generation and distributed storage, new demand response methods, and improved energy efficiency (Newton et al. 2011). With falling battery costs [1], battery storage is likely to be a major component of our future electricity network [2]. One barrier that is slowing the emergence of precincts with increase distributed generation and storage is the difficulty in quantifying solar and battery costs. Also required is an improved understanding of the impacts on electricity demand, network performance, potential network infrastructure savings, and emissions reductions related to distributed energy resource deployment (Kavgic et al. (2010) and Suganthi and Samuel (2012)). Without a meaningful quantification of such costs and benefits, the value proposition for emissions reduction through distributed energy and energy efficiency in residential precincts is unclear.

One tool that is required to make this assessment is a model that can accurately simulate time-series energy demand. Moreover, to estimate the impact of solar and battery systems on cost, network performance and reliability, the demand model must be able to simulate individual household demands with the required time-series complexity – estimating peaks and daily variability accurately. An electricity demand model with accurate time-series complexity can be used to evaluate the emissions reduction and costs of installing solar and battery systems in the residential sector. The demand model can also allow the design of precinct microgrid systems, providing an understanding of the optimal solar and battery capacities required to meet emissions reductions or grid autonomy constraints.

The goal of the energy demand forecasting process in the ETWW research was to simulate hourly electricity demand. The model has been developed to use a simple set of input parameters that capture the electricity load diversity of homes in Australia and capture summer and winter seasonality, yearly peak events and daily morning and afternoon peaks. Hourly demand allows the user of the model to investigate the time dependent impacts of solar, battery systems and electric vehicle use, and peak and off-peak energy costs. The model simulates the interactions between the ETWW Domains using common input parameters. Demands, after the emissions reductions from solar and battery system, are aggregated and the grid intensity conversion (AEMO, 2017) is used to estimate the carbon impact of a precinct due to electrical energy use (gCO2/kWh) for both present and future scenarios.

4.1 Energy Demand Modelling Techniques

There has been significant research effort applied to simulating electricity demand for individual or small groups of residential homes (referred to as the 'bottom-up approach'). The approach can be classified into physics-based (analytical) models [8], [9] and machine learning (statistical) models [6]. The physics-based approaches, such as the CSIRO AccuRate tool, rely on an extensive dataset containing information about the building stock, including building structure and materials, and an extensive set of inputs about the household occupancy and social demographics. An example of the systems considered in a physics-based model is shown in Figure 4.1.

For early precinct demand simulation, a complete set of such data is likely to be absent. Machine Learning approaches have been shown to be effective in navigating an absence of such detailed data. As a result, Machine Learning will be the focus of this research.

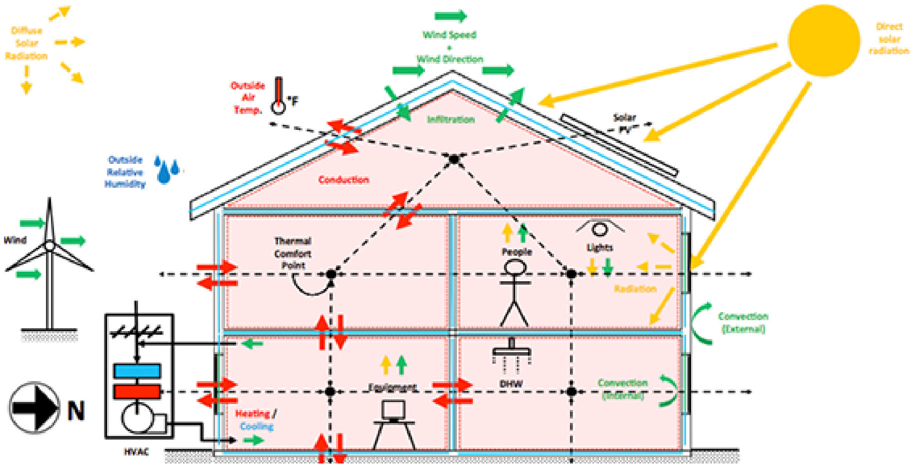


Figure 4.1: Components for consideration in physics-based model approaches.

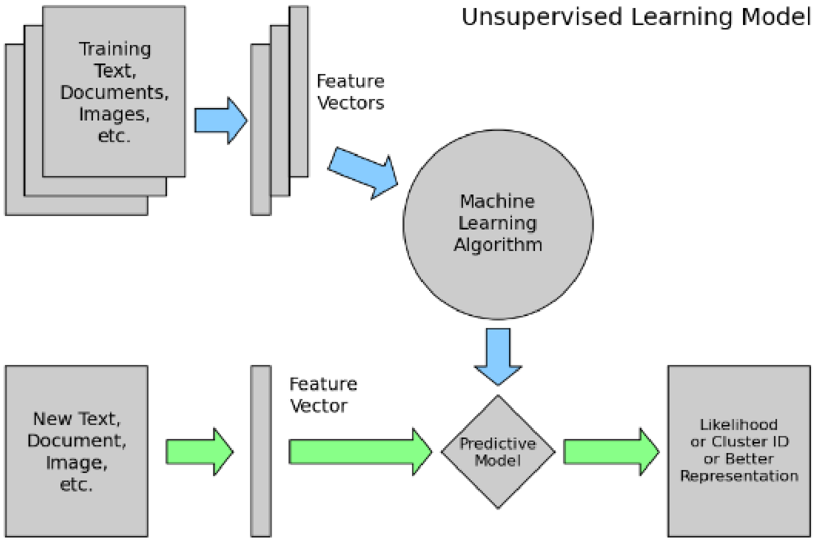


Figure 4.2: Processes involved in machine learning based model approaches.

Machine learning algorithms, used for electricity demand simulation, have been summarised in numerous review articles (see [7], [14], [15]). At a high-level, as shown in Figure 4.2, the approach involves training an algorithm to generalise to a known dataset. In the case of electricity demand forecasting, the datasets are normally obtained from smart-meter measurements and household surveys. The data is processed into a form suitable for a machine learning algorithm and used to train the algorithm. Once the algorithm is trained, a new input dataset can be provided to simulate an electricity demand output. Previously in Australia, machine learning demand models have not been feasible due to the limited availability of datasets that capture a significant amount of historical energy usage data and demographic and appliance ownership information about the households. The recent release of datasets such as the Residential Building Energy Efficiency Standards and Smart Grid Smart Cities Customer Apps data has made machine learning a new possibility for this task.

For electricity demand forecasting, the most common machine learning techniques are Linear Regression [16], Artificial Neural Networks [13], [17], Support Vector Machines (SVM) [18] and Classification and Regression Trees (RT) [19]. Table 4.1 contains a summary of the advantages and disadvantages of these techniques for electricity demand forecasting.

Algorithm Type	Advantages	Disadvantages
Support Vector Machines	*Able to solve nonlinear time series problems*	*Cannot handle large datasets causing huge training times.*
Artificial Neural Networks	*Able to fit nonlinear data.*	*Unable to forecast daily variability and yearly peak events.*
Linear Regression	*Very quick to find a solution, interpretable.*	*Cannot fit non-linear trends of electricity Demand as shown in* [12]
Regression Tree	*Very quick to find a solution*	*Prone to Overfitting.*
Random Forests	*Quick to find a solution*	*Experiments showed it to be inaccurate for demand forecasting.*
Adaptive Boost Regression Tree	*Quick to find a solution Accurate in Predicting demand, including yearly peaks events and daily variability.*	*Few for this research application.*

Table 4.1: Machine learning algorithm types.

The adaptive boost algorithm applied to a regression tree (ABRT) approach has been most successful and offers advantages for an application to this research. ABRT has found use in [25] to predict energy demand for a short period into the future, achieving an R2 value of 0.9. In [12], ABRT was applied on a small set of 315 homes, to simulate residential electricity demand. This technique has been shown to model the yearly demand peaks and daily variability accurately. The ETWW electricity demand model applies the ABRT algorithm.

4.2 Training Dataset

The Smart Grid Smart Cities (SGSC) customer applications data (Smartgrid Smartcity, 2014) provides a valuable resource as training and an application dataset. It contains power consumption at 30-minute intervals for household locations in Newcastle, Lake Macquarie, Upper Hunter Non-metro and Sydney (Figure 4.3) with over 12,000 residential smart meter demand profiles.

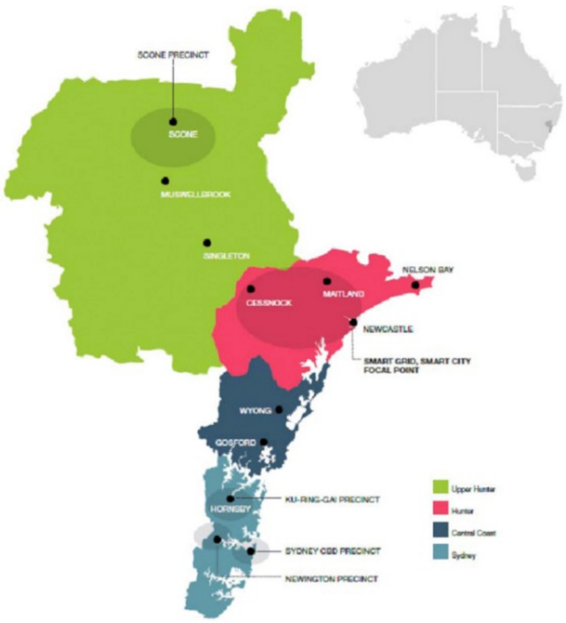


Figure 4.3: Spatial extent of the Smart Grid, Smart City dataset. (Source: "Smart Grid, Smart City: Shaping Australia's Energy Future" 2014)

In this project, a 2013 subset of 5,260 residential profiles without solar is utilised for model estimation purposes. For application purposes, the energy demand datasets acquired from the University of South Australia's Lochiel Park record database and the CSIRO RBEES data are two identified evaluation datasets. The research gains an in-depth understanding of which modelling features are required to provide accurate demand forecasts for the residential sector.

4.3 Demand Model

The first forecast version is an ABRT approach was applied to the Newcastle area. This application utilising a set of 360 demand profiles with a suite of survey responses and no solar installed, this data is split into 310 homes for training the algorithm and 50 homes for validation of the trained algorithm, or forecasting. Input data for the model *"X"* considers socio-demographics, demand or use and appliance ownership data, summarised in Equation 4.1.

$$X = \begin{bmatrix} Age\ of\ adults,\ number\ of\ occupants,\ number\ of \\ children, Income\ bracket, renting, Outside\ Temperature, \\ Weekend\ indictor,\ Day\ hour\ indicator, \\ Gas\ Usage, Has\ Gas,\ Has\ Gas\ Cooking,\ Has\ Gas, \\ Heating,\ Has\ Gas\ Hot\ Water,\ Has\ Pool\ Pump, \\ Has\ Air\ Conditioning, Number\ of\ Refrigerators, \\ Number\ of\ Rooms\ Heated, Dryer\ Usage \end{bmatrix} \quad \text{(Equation 4.1)}$$

To forecast the time series complexity, the model considers time-variable components such as weekend indicator, outside temperature and day hour indicators. The model is trained on individual home, hourly data, for one year. As shown in Figure 4.4, the model is trained using the input set X and a target set Y. Once trained, a new training set $\hat{X}_{new}$ is provided to the model to simulate an hourly demand output, $\hat{y}_{new}$.

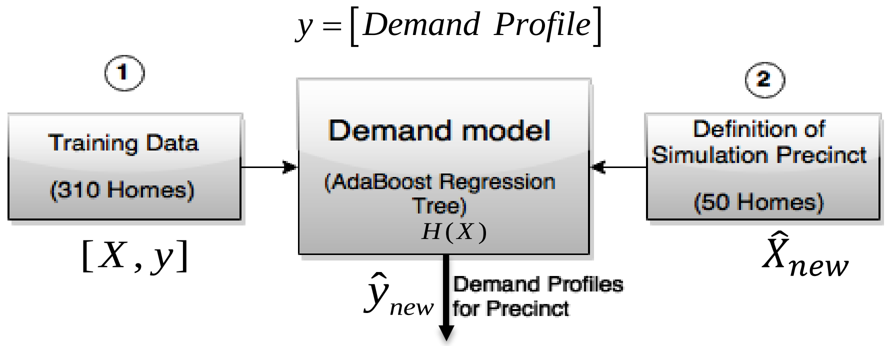


Figure 4.4: Demand model forecasting process.

Aggregating households to determine precinct-level demand profiles has provided greater accuracy against the accuracy of simulating a single home. This result can be seen by the difference between simulated and measured results in Figure 4.5 (5 homes) and Figure 4.6 (47 homes). The unique way a single home uses energy is the cause of this result, the demand trends from aggregating a small number of homes, after simulation, is far easier to predict.

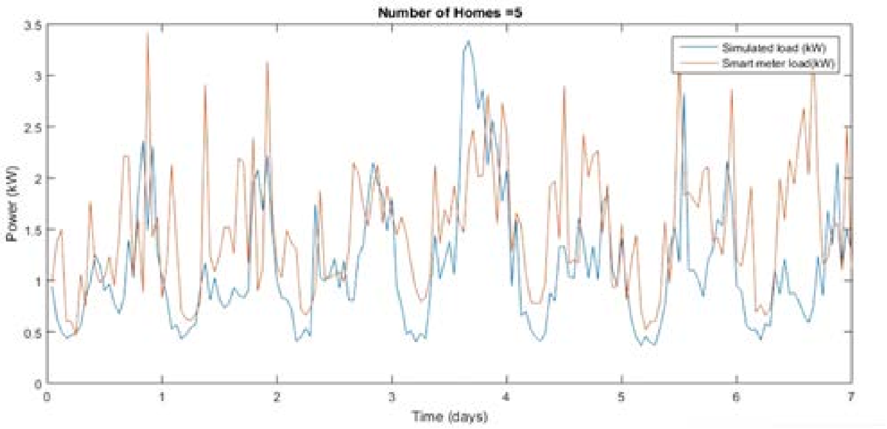


Figure 4.5: Hourly demand profile model validation for a precinct with five homes.

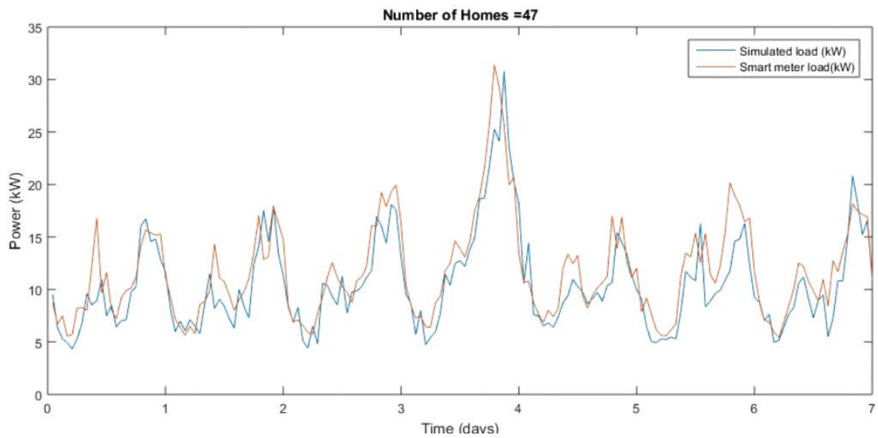


Figure 4.6: Hourly demand profile model validation for a precinct with 47 homes.

4.4 Mosaic Australia Consumer Segmentation

This section provides a description of the final ETWW mode. This applies Mosaic datasets with household typologies and associated socio-demographic attributes to assist in defining precinct populations when household surveys are not available. The Mosaic classification is therefore used to describe the socio-demographic components of input data X in the forecasting processes, as noted previously. The next stage of the model prediction details the method for connecting the Mosaic data to the model as an input (Figure 4.7).

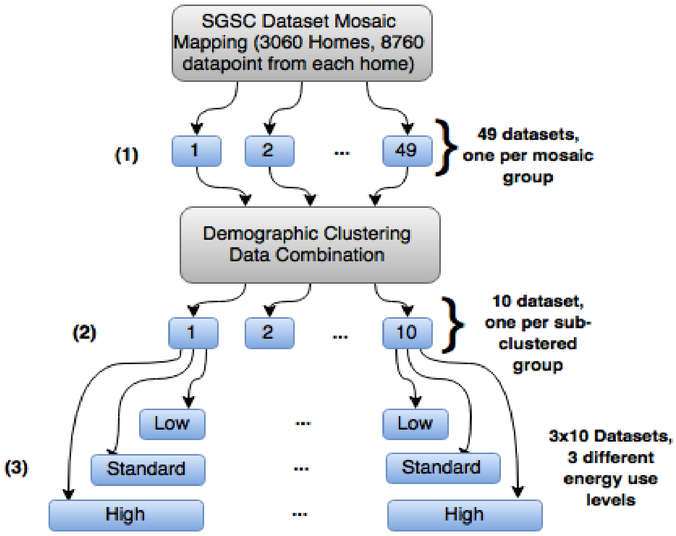


Figure 4.7: Data flow for clustering Mosaic household type data about energy user types.

There are three steps involved in this forecasting process. Step 1 is the allocation of a Mosaic type to the SGSC homes using one of the 49 Mosaic household typologies. Step 2 involves a K-means clustering algorithm to group homes that are similar for demographic indicators that impact energy consumption. The original 49 type datasets are clustered into ten datasets. Each one of these ten then generates a demand model and depending on the Mosaic type in question; forecasting will use one of these. Step 3 divides demand into groups that relate to user types. The ten model data sets then recognise three subsets of user, and so they are provided with a further low user, standard user and extreme user, as depicted by the user profiles and red-boxed use levels in Figure 4.8. This process provides the model with effectively (10 x 3 =) 30 demand training input vectors and 30 sub-models as a result of demand modelling.

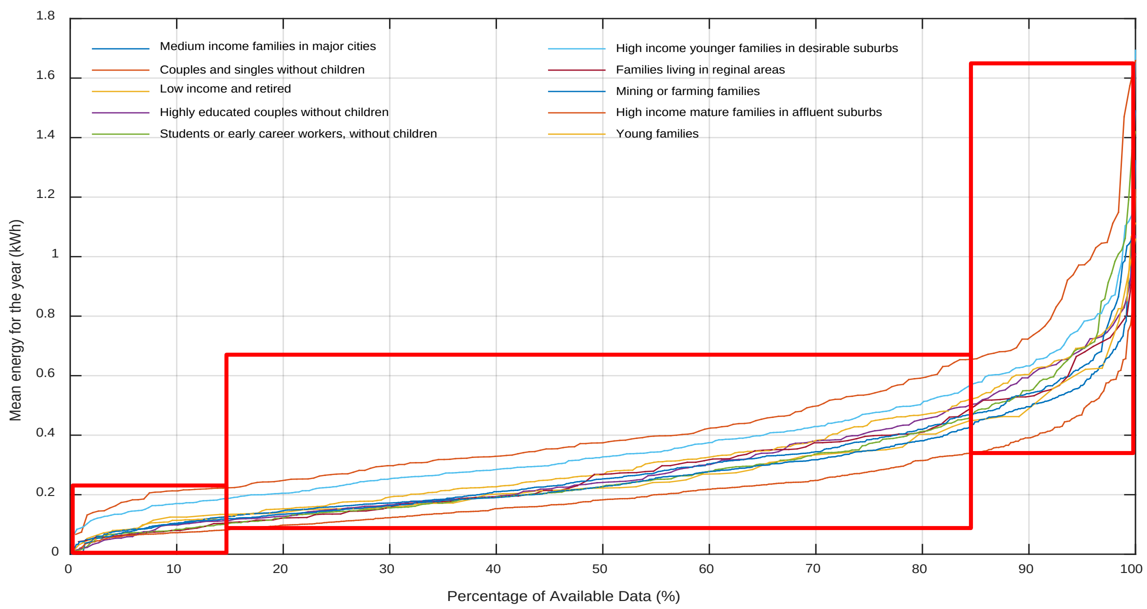


Figure 4.8: Clustered Mosaic dataset demand profiles with three subsets of user types identified.

Advantages of the approach are that it allows Mosaic geo-demographic data to be used for electricity demand simulations. It captures extreme user behaviour and unoccupied residences while reducing model training times. This method also simplifies the trend complexity and improves the demand simulation accuracy. Forecasting processes are then provided with a simulation vector to represent the household and precinct residents. The demand model predicts the precinct demand as the output data, as depicted in Figure 4.9.

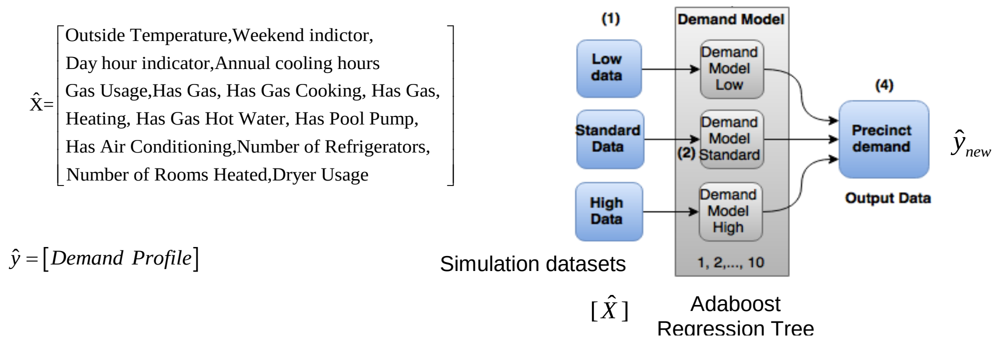


Figure 4.9: Input data types and process for deriving precinct output demand profiles.

4.5 Model Evaluation

Following on from the model training and estimation process, an assessment of the model output accuracy demonstrates that the model simulates a demand that matches very well with the measured demand. The following figure shows measured and simulated demand profiles for selected evaluation locations. Figure 4.10 shows the peak demand period for 2013 for three case study precincts containing 150 homes. These homes were extracted from the SGSC dataset before model training; the demand model was used to simulate the demand. The measured demand from the SGSC dataset was compared to the simulated demand.

The red line shows the measured smart meter demand for the precinct and the green line shows the simulated demand. It can be seen in all precincts that the peak demand has been simulated very accurately; the performance improvement is due to the AdaBoost CART algorithm focusing on hard to predict instances, such as the peak events. The blue line shows the demand from the grid when each home in the precinct has an optimised solar and battery system, which is operated to minimise the cost of energy paid by the consumer and meet a grid reliance percentage of 50%. The inclusion of the solar and battery system causes a reduction in peak demand due to the controller shifting solar energy to the evenings to avoid peak pricing.

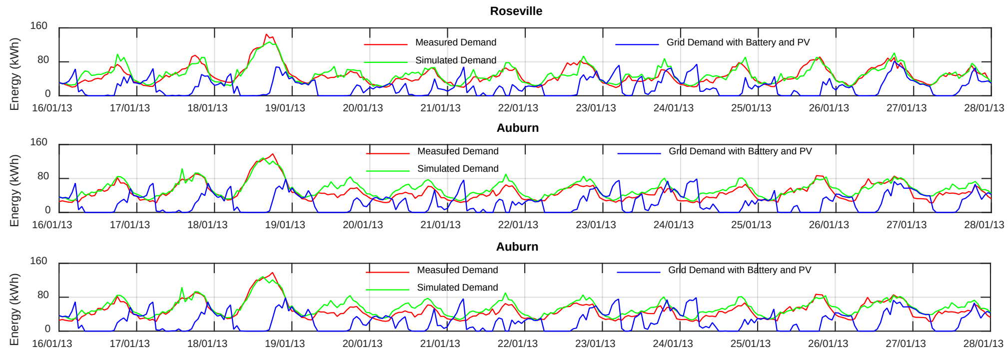


Figure 4.10: Measured and simulated demand profiles for selected evaluation locations.

Table 4.2 shows the evaluation metrics used for these case study Precincts. Table 4.2 shows the high coefficient of determination (R^2) values found for each precinct, indicating that the variance in the observed data is captured by the model. These results also shows that the model can describe yearly peak events and that the effect of changing seasons on evening peaks is captured by the model.

	R2	RMSE	Yearly Peak Meas. (kWh)	Yearly Peak Sim. (kWh)	Time of Summer Peak Measured	Time of Summer Peak Simulated	Time of Winter Peak Measured	Time of Winter Peak Simulated
Auburn, AdaBoost HML Data Division	0.85	6.55	143.96	137.02	19:10	19:18	19:57	20:06
Roseville, AdaBoost HML Data Division	0.76	7.36	129.77	123.05	19:29	19:33	19:59	20:08
New Lampton, AdaBoost HML Data Division	0.76	8.82	135.94	129.70	19:19	19:30	19:56	20:08

Table 4.2: Evaluation metrics for three case study precincts.

The precinct electricity demand verification process involved the application of the model to 51 metered households in Lochiel Park. A sample of this demand is shown in Figure 4.11, achieving an R^2 value of 0.79 for this precinct. This value represents a relatively high simulation accuracy. This comparison of measured and simulated demand profiles in Figure 4.11 demonstrates that the simulated demand closely matches the measured demand, capturing demand peaks well. This is an example of how the electricity demand model can be used to simulate the demand of a precinct when only a small set of data inputs are known. This process could be used by developers to estimate the network connection requirements for a new development and investigate the grid infrastructure savings that can be reduced through the installation of solar and battery systems.

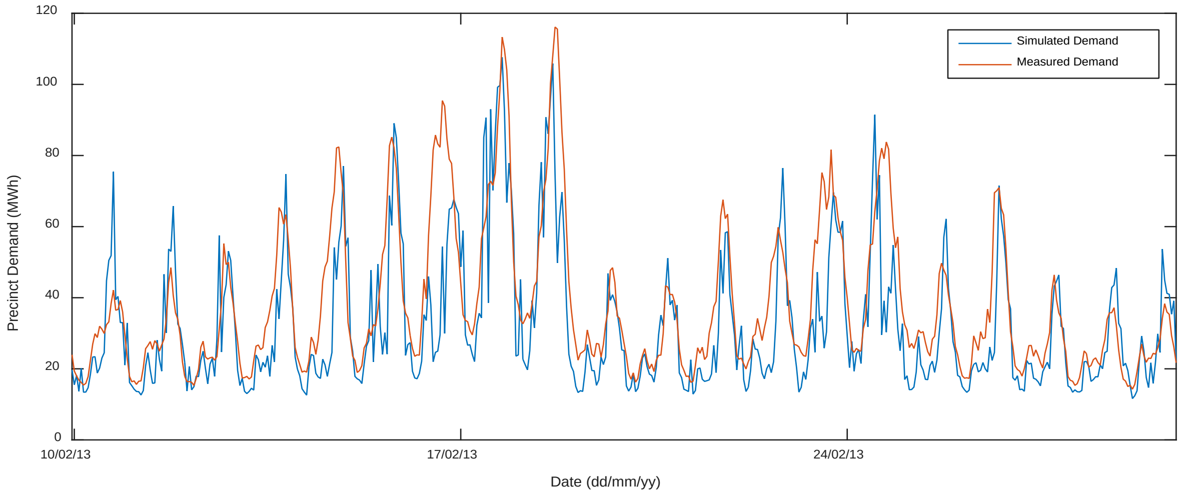


Figure 4.11: Measured and simulated demand profiles for the Lochiel Park precinct.

4.6 Battery and Solar Microgrid Modelling

Extending the ability of the energy demand model, estimations for residential battery systems and solar microgrids can assist in enhancing interactions with other forecasting domains and ultimately precinct planning processes. The motivation for battery systems in residential homes includes the ability for battery systems to allow for more energy to be used in the household, to reduce emissions and to reduce peak energy usage. Due to their nature of energy supply, battery systems also reduce transmission losses and can reduce energy bills if controlled correctly. Also, battery costs have reduced significantly in the past two years as indicated in Figure 4.12.

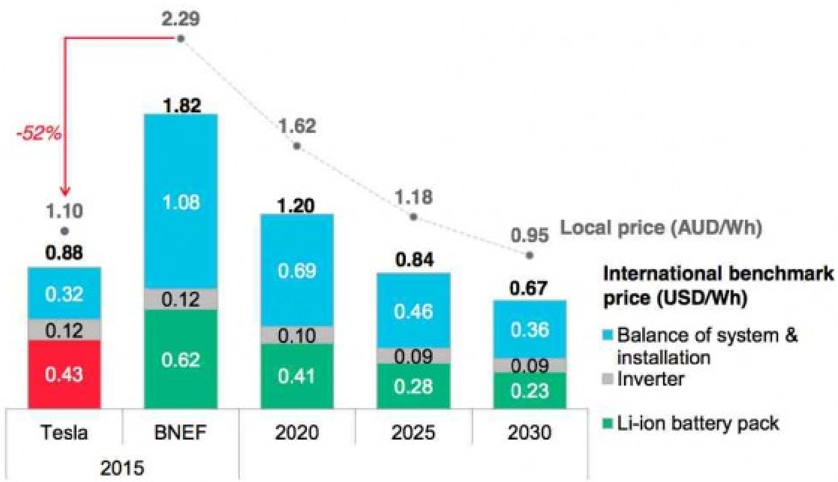


Figure 4.12: Forecast battery storage system prices. (Source: http://reneweconomy.com.au/2015/tesla-already-forcing-down-battery-storage-prices-in-australia-57681)

Battery-solar optimisation routines (Percy et al. 2016) utilise inputs relating to solar irradiance, emissions constraints and system costs. It combines with the demand model for evaluations as was illustrated in Figure 4.4.

4.7 Solar and Battery Model

The Microgrid model is a mixed integer linear programming optimisation model that considers household demand, technology and cost attributes. It provides an optimal solar and battery configuration with household energy costs and related energy impacts as illustrated in Figure 4.13.

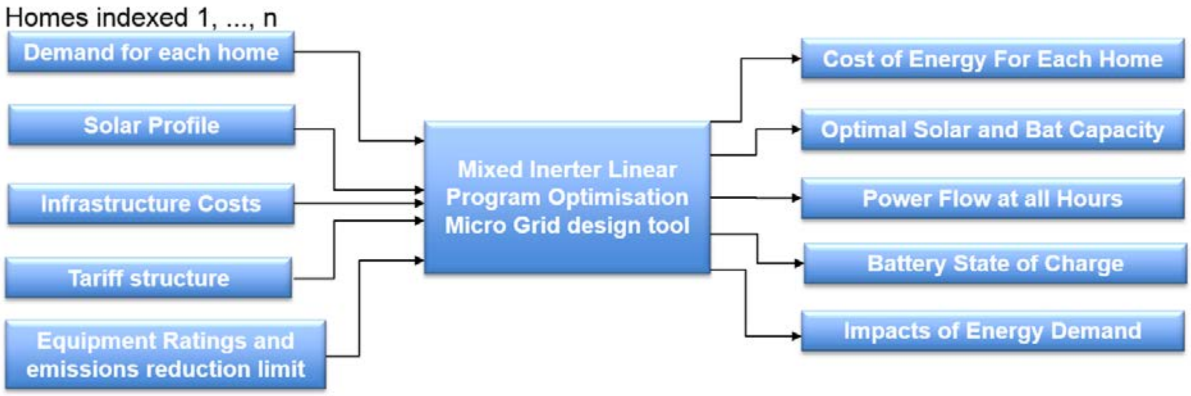


Figure 4.13: Microgrid design tool with inputs and outputs.

The mixed integer linear programming optimisation considers the hourly demand for all homes in the precinct and designs the battery system or microgrid system to minimise costs of energy. The optimal control strategy implemented by the model provides an estimation of the demand impacts due to microgrids or solar and battery systems.

The following equations, ie. (Equation 4.2) to (Equation 4.14) describe the formulation of the solar and battery model, where h is the hour of the year, 1-8760. (Equation 4.2) defines the objective function which minimises the total cost of solar infrastructure, C^{PV} , battery infrastructure, C^{Bat} , grid imported energy, C^{I} , and grid exported energy, C^{E} (Equation 4.3) defines the multi-period constraint that describes the link between battery storage level at hour h, B_h^{Lev} , and the energy in the battery in the previous hour, B_{h-1}^{Lev} . This considers the energy flow into the battery G_h^{Bat} and the battery energy used to supply demand, D_h^{Bat} . Where the battery storage efficiency is defined by η (92%), (Tesla Motors, 2015). (Equation 4.4) is the energy balance constraint that ensures solar generation, G_h^{Sol} , grid import G_h^{Imp} and battery generation equals demand, D_h^{Home} and battery recharge for every hour of the year. (Equation 4.5) and limit the charging and discharging of the battery to 0.25 times battery capacity (Panasonic, 2015). (Equation 4.7) defines the solar generation based on the solar profile parameter $S(h)$. For simplicity, we assume that all panels are unshaded, have the same efficiency, identical azimuth and angle. (Equation 4.8) and (Equation 4.9) ensure that energy from the grid is not exported, G_h^{Exp} and imported at the same time. M, which is the network capacity used to ensure that the binary variable α_h is one if importing power from the grid and zero otherwise. (Equation 4.10) ensures that the total energy from the grid does not exceed the grid reliance constraint L. (Equation 4.11) and (Equation 4.12) defines the investment cost of the solar system based on the investment cost per kWh, I, and the capacity, S^{Cap} and B^{Cap} . (Equation 4.13) and (Equation 4.14) define the energy grid import and export costs, where T^{h} is the import tariff for every hour of the year and e is the energy export rate.

Minimise:

$$C^{PV} + C^{Bat} + C^{I} - C^{E} \qquad \text{(Equation 4.2)}$$

Subject to ∀ h ∈ {1,2, ..., 8760}:

$$B_h^{Lev} = B_{h-1}^{Lev} - G_h^{Bat} + \eta \cdot D_h^{Bat} \qquad \text{(Equation 4.3)}$$

$$D_h^{Home} + D_h^{Bat} + D_h^{Exp} = G_h^{Sol} + G_h^{Bat} + G_h^{\mathrm{Imp}} \qquad \text{(Equation 4.4)}$$

$$G_h^{Bat} \le 0.25 \cdot B^{Cap} \qquad \text{(Equation 4.5)}$$

$$D_h^{Bat} \le 0.25 \cdot B^{Cap} \qquad \text{(Equation 4.6)}$$

$$G_h^{Sol} = S_h \cdot S^{Cap} \qquad \text{(Equation 4.7)}$$

$$G_h^{\mathrm{Imp}} \le M \cdot \alpha_h \qquad \text{(Equation 4.8)}$$

$$G_h^{Exp} \le M \cdot (1 - \alpha_h) \qquad \text{(Equation 4.9)}$$

$$L = \frac{\sum_{h=1}^{n} G_h^{\mathrm{Imp}}}{\sum_{h=1}^{n} D_h^{Home}} \quad \text{(Equation 4.10)}$$

$$C^{PV} = \mathrm{I}^{PV} \cdot \mathrm{S}^{Cap} \quad \text{(Equation 4.11)}$$

$$C^{Bat} = \mathrm{I}^{Bat} \cdot B^{Cap} \quad \text{(Equation 4.12)}$$

$$C^{\mathrm{Imp}} = \mathrm{R} \cdot \sum_{h=1}^{n} G_h^{\mathrm{Imp}} \cdot T_h + 365 \cdot R \cdot I^{Con} \quad \text{(Equation 4.13)}$$

$$C^{Exp} = R \cdot \sum_{h=1}^{n} D_h^{Exp} \cdot e \quad \text{(Equation 4.14)}$$

The following equation defines the discount rate multiplier, R, used to define the net present value of energy costs based on the discount rate, r. The value of 25 is used to simulate a 25 year solar system lifetime.

$$R = \sum_{y=1}^{25} \frac{1}{(1-r)^y} \quad \text{(Equation 4.15)}$$

4.8 Evaluation of Cost, Capacity and Degradation in Australian Residential Battery Systems

The battery model has been used to investigate the cost trade-offs between battery capacities, energy purchased and battery degradation using a linear programing model of residential battery systems (RBS). The model is used to simulate different commercially available battery capacities, at 1.2kWh steps. All costs are presented, and an upper limit on battery cost is calculated. For each battery capacity, a one-year charge profile is analysed using rain flow counting, and the impact of cycling on battery degradation is discussed. For full details of this work please see Percy et al. (2016).

Table 4.3 shows the cost comparison for the seven capacity levels and the three different households (see also Figure 4.14). It was observed that grid import costs reduced as battery capacity increased. For Home B, there was a $3920 NPV saving between having no storage and including a 7kWh battery. This was due to the growing amount of onsite solar generation stored in the battery and later used for self-supply. Storage of solar energy also caused the solar export profit to reduce, as expected. For Home B, there was a $1003 NPV increase between having no storage and including a 7kWh battery. Due to the higher tariff during the evening, the stored solar energy had an increased value. Thus the installation of an RBS caused an import cost reduction (energy savings).

The energy costs increased for the higher demand home (Home C), this was a difference of $4725 between Home A and Home C for no battery and a difference of $1397 between Home A and Home C for a 7kWh battery. Home C gains a larger cost saving by installing a battery system compared to Homes A and B due to the higher evening peaks, and usage during non-solar generation times. This indicated, while battery costs are high, higher demand homes should be targeted for uptake of these systems. It also can be noticed that a lower grid reliance percentage is achievable for the low demand home (Home A).

	Battery Capacity (kWh)	0	1.2	2.4	3.6	4.8	6	7
Low Demand	Grid Import ($)	8425	7206	6808	6703	6658	6633	6620
	Solar Export ($)	7094	6779	6661	6630	6616	6609	6605
	Grid Difference ($)	1331	427	147	73	42	24	15
	Grid Reliance (%)	56	21	8	4	3	2	1
Med Demand	Grid Import ($)	11083	9639	8637	7995	7569	7310	7163
	Solar Export ($)	6720	6379	6119	5947	5831	5759	5717
	Grid Difference ($)	4363	3260	2518	2048	1738	1551	1446
	Grid Reliance (%)	61	43	30	21	15	11	9
High Demand	Grid Import ($)	13150	11585	10300	9306	8646	8241	8017
	Solar Export ($)	6097	5750	5431	5172	4996	4887	4825
	Grid Difference ($)	7053	5835	4869	4134	3650	3354	3192
	Grid Reliance (%)	55	44	34	25	20	16	14

Table 4.3: Energy cost and (25 years NPV), 5kW solar selected in the optimisation for all homes.

For the uptake of RBS to be high, the installation of the RBS must be economically beneficial for the home owner. That is, the total cost of installing batteries should meet the lowest cost energy supply option, in this case this was the grid and a

5 kW solar system. This can be represented as an upper limit on battery cost per kWh. For each scenario, the upper limit on NPV battery infrastructure costs is given in Table 4.3. Due to the non-linear change in total energy cost for all homes, as shown in Figure 4.14, the most achievable upper limit is always for the 1.2kWh capacity battery. Depending on the demand characteristics this gives an upper limit, NPV cost to run a battery system over 25 years, of between $753 to $1015/kWh (see Table 4.4).

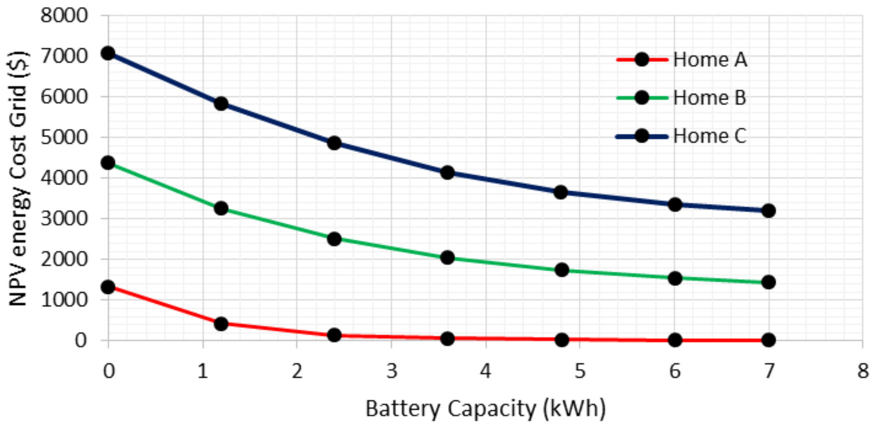


Figure 4.14: 25-year NPV energy cost minus export profit.

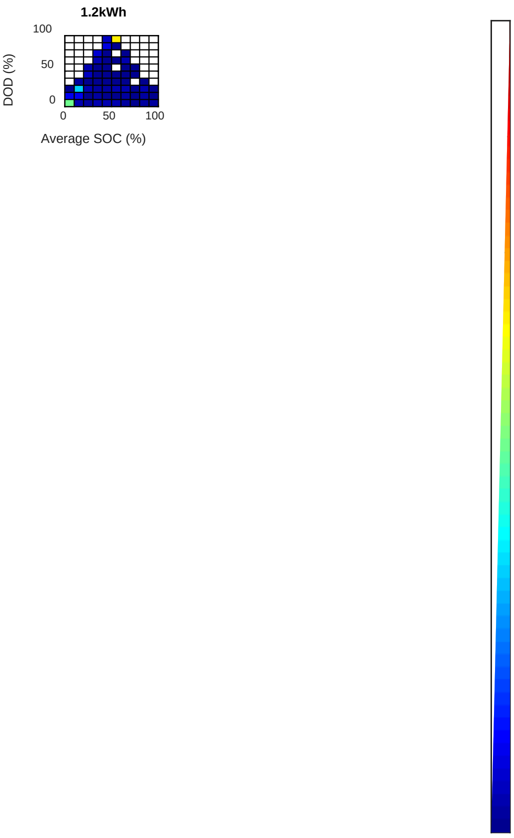
If there is a zero export requirement, such as that implemented by Ergon and Energex, the value proposition for battery systems would be improved. The upper limit cost for the three case study homes, for a 1.2 kWh system, would be between $847 to $1266 /kWh. Table 4.4 summarises the upper limit costs for the two scenarios for all battery capacities.

The model assumed a fixed tariff over the 25 years solar system lifetime, although many price forecasts show this is not always the case. The Australian Energy Market Commission expects a yearly 2.4 % increase in residential energy tariffs over the next three years (AEMC, 2014). Additionally, the Future Grid Form 2015 Report (Energy Networks Australia, 2015), forecasts a three year reduction in energy tariff and a long-term increase to 2050. These uncertainties, and the unknowns about network scenarios were the reason this was not considered in the model. Increasing energy tariffs would provide an additional value proposition for RBS.

	Battery Capacity	1.2	2.4	3.6	4.8	6	7	
$0.06 Solar Export Rate	Low Demand	753	493	349	269	218	188	$/kWh
	Med Demand	919	769	643	547	469	417	$/kWh
	High Demand	1015	910	811	709	617	552	$/kWh
Zero Solar Export Rate	Low Demand	847	555	394	302	245	212	$/kWh
	Med Demand	1140	1047	951	840	733	658	$/kWh
	High Demand	1266	1139	1017	890	774	693	$/kWh

Table 4.4: Upper limit on NPV Battery Cost

Besides the time-of-use tariff, there exists no additional incentive for the home owner to control the time of the day that energy is exported to the grid. If a new incentive is provided by the network operator, with the goal to alleviate network pressures, as discussed in Wang, Gu and Li, (2015), a further value proposition for distributed storage could be achieved, as a result further increasing the upper limit on battery costs, In_{Bat}^{NPV} .



(a) Home A (b) Home B (c) Home C

Figure 4.15: Discharge Cycling Characteristics for the three homes in Brisbane

Results in Figure 4.15 show the cycling counts for the different mean state of charge (SOC) and depth of discharge using the rain flow counting technique. The columns represent each case study demand profile, and the rows indicate the different battery capacity steps. It can be seen that the small capacity batteries, i.e. 1.2 and 2.4kWh, are cycled harder than large batteries to gain a maximum economic benefit for the home. For example for Home A: 1.2kWh: 220, 95% cycles, compared to, 7kWh: 48, 95% cycles. The result of this is faster battery degradation of small batteries, meaning the batteries have to be replaced more regularly, increasing the In_{Bat}^{NPV} value if not covered by the manufactures warranty. This result is further emphasised for Home B in Table 4.5 where the 1.2kWh battery experiences 320, 90-95% depth of demand (DOD) cycles compared to only 62 with the seven kWh battery. It can also be seen that for the low demand profile, the battery usage is less intense; also increasing battery lifetime.

The outcome of this is that there was an observed trade-off between DOD, cycling and battery utilisation. Results presented in this paper provide insight; for example, the 7kWh battery has a longer lifespan but is not utilised as much. Thus the payback is not as high compared to the initial investment. The 1.2kWh battery is highly utilised, with a low initial investment is likely to degrade more quickly, based on a 95% DOD. Examining the Figure 4.15 histograms for a small home (Home A), it is clear that batteries above 4.8kWh are not well utilised, indicated by a large number of white cells. However, examining Figure 4.15 for a large home (Home C), it is clear that battery installs of 2.4kWh and below have a large number of deep discharges, indicated by the red cells; this degrades the battery life. The results in Figure 4.16 show that RBS sizing is directly related to load demand, as expected. For a small home, the 2.4kWh size is highly utilised and does not experience deep discharges. The corollary is true for the medium sized house in the 3.6 to 6kWh histograms, and for battery sizes above 4.8kWh in large houses. Thus, battery selection should aim to; fully utilise the battery based on load demand and minimise deep discharge events.

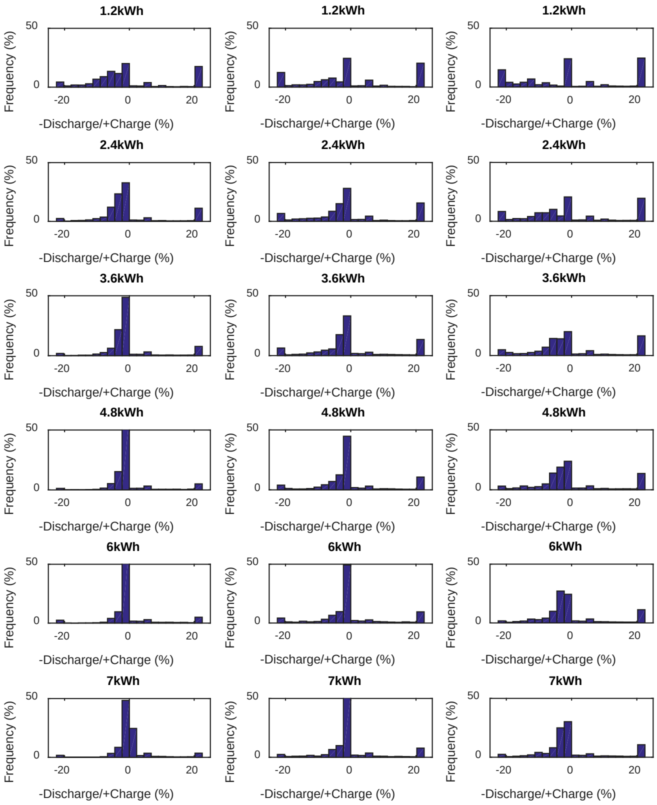
DOD	1.2kWh	2.4kWh	3.6kWh	4.8kWh	6kWh	7kWh
0-10%	349	294	261	262	222	265
10-20%	154	93	70	64	75	55
20-30%	212	120	144	108	142	112
30-40%	32	16	30	48	46	47
40-50%	31	27	50	62	51	54
50-60%	7	26	40	23	29	38
60-70%	23	33	43	43	40	33
70-80%	14	35	35	41	33	30
80-90%	19	34	35	26	24	14
90-95% a	320	220	149	96	90	62
Total	1161	898	857	773	752	710

a. A limit cycle depth of 95% was applied to the model.

Table 4.5: Home B, Total number of cycles in 365 days

The Enphase RBS system gives a warranty for 7300 cycles, and rate the DOD to 95%. Assuming that the top four DOD groups in Table 4.5 degrade the battery most, for Customer B, operating the 1.2kWh battery gives 747 cycles, and for the 7kWh battery there are 479 cycles; giving an expected cycle life of 9.8 years and 15.2 years respectively. This result indicates the warranty is aligned with the intended use of batteries larger than 1.2kWh for a moderate demand customer. It should be noted that this quick calculation does not consider the impacts of temperature and discharge rate on battery degradation. But does underline that battery warranties are likely to be dependent on household demand.

Figure 4.16 shows the number of different percentage charges and discharges of the battery over one hour for the three homes. It can be seen that for all homes the low capacity batteries endure more high percentage charge and discharge hours, than the larger capacity batteries. This is due to the maximum discharge rate being a function of battery capacity, and 5kW of solar is installed in all scenarios. Since battery degradation is a function of charge current, the smaller capacity batteries will degrade faster due to the increased frequency of high discharge usage.



(a) Home A (b) Home B (c) Home C

Figure 4.16: Charge/discharge percentage over 1 hour for the 3 homes in Brisbane.

An upper limit to battery infrastructure cost was shown to be higher for high demand homes, indicating more economic benefit can be gained from RBS in high demand homes. A trade-off was observed between: DOD, cycling, battery utilisation and battery life. Results indicated battery utilisation and degradation across the three homes in this study is related to installed capacity and load demand.

4.9 Combining Solar and Battery Models

To capture the complete impact of solar PV and battery systems on residential demand, a two stage model has been implemented. This model combines the residential demand model and microgrid model, as shown in Figure 4.17. When simulating a new or existing precinct, this model first simulates the demand hourly demand profiles for each home using a description of the Mosaic demographic and appliance ownership information. Next these household demand profiles are provided to the microgrid model, along with local hourly solar generation and cost data. The output of this stage of the model provides infrastructure requirements, final demand profiles and how energy flows in the microgrid system. The two-stage model can be used to evaluate the complete carbon impact, network connection requirements for new precincts, and determine how network connection capacities can be reduced using microgrid technologies. Additionally, this model can be used to evaluate the cost trade-offs from installing solar and battery microgrid technologies in residential precincts.

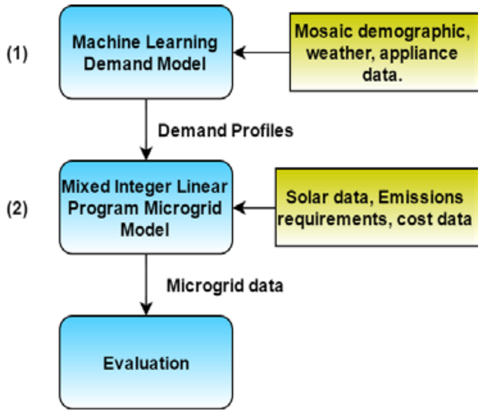


Figure 4.17: Flowchart for the combined solar and battery optimisation model.

5 Transport Domain Forecasting

Travel in Australian metropolitan areas is typically dominated by journeys made in private cars. The car provides a convenient, flexible, comfortable and relatively cheap mode of transport, well suited to urban regions with relatively low population densities. Public transport alternatives including bus, rail, tram, taxi and ferries provide travellers with alternatives to the car however overall mode shares for these options are greatly reduced when compared to private vehicles. The active modes of walking and cycling typically occur over shorter distances with increased travel times, limiting their suitability for many trip purposes. Freight modes are also present in metropolitan regions, transporting goods at large and smaller operational scales and for numerous goods types.

Historic and forecast traffic volumes for Australian capital cities expressed as passenger-car-unit equivalents has been determined by the Australian Bureau of Infrastructure, Transport and Regional Economics (BITRE) and represented between 1990 and 2030 in the following figure.

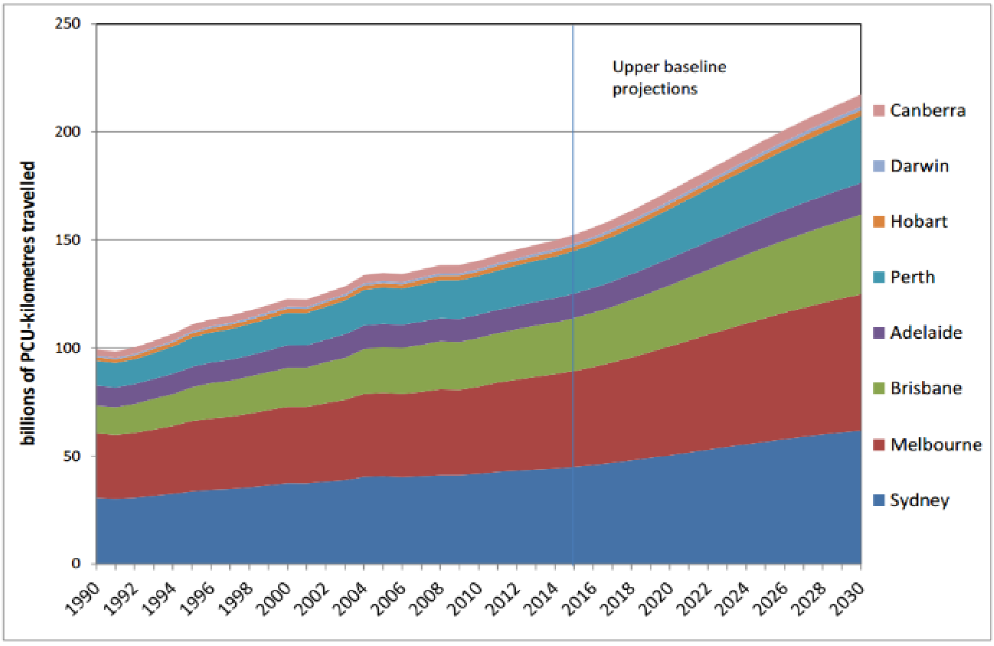


Figure 5.1: Total projected traffic for Australian capital cities to 2030, upper baseline scenario (source: BITRE 2015).

The previous figure shows that total travel in Australian cities more than doubles in the 40 year period, with private road vehicles currently accounting for 87 per cent of the aggregate urban passenger task, approximately half of which occurs in Melbourne and Sydney. Under current expected patterns of metropolitan population growth, an overall (generally linear) trend increases aggregate urban traffic, with total vehicle-kilometres travelled (VKT) forecast to increase around two per cent per annum to 2030. These traffic delay increases have BITRE base case projections of the costs of metropolitan congestion rising to around $30 billion by 2030.

Across an average weekday, the spread of urban vehicle demand is typified with a morning and an evening peak heavily influenced by traffic volumes resulting from current standard commuting patterns, as represented in Figure 5.2.

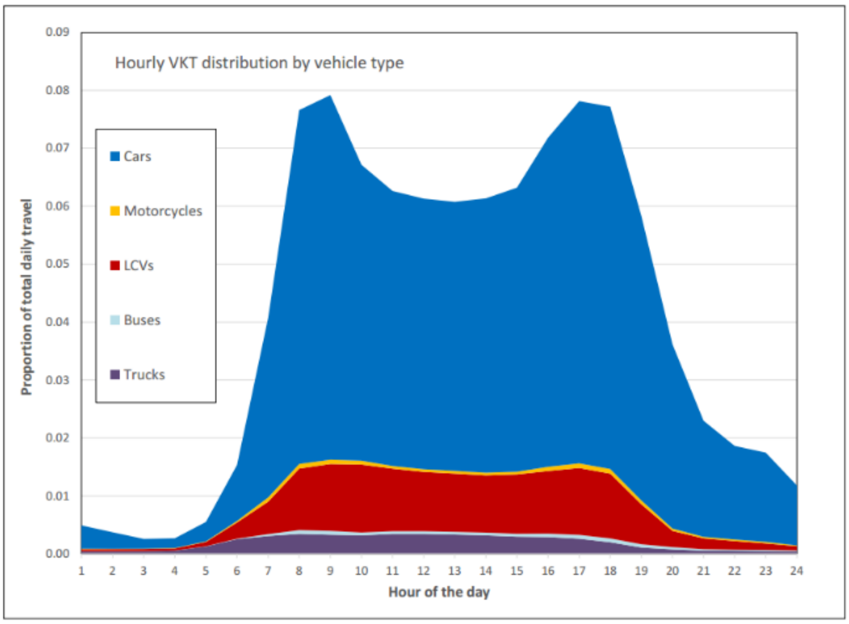


Figure 5.2: Representative daily profile of urban vehicle use, across an average weekday (source: BITRE 2015).

Figure 5.2 shows that travel demand is typically highest during the peak periods in the morning and afternoon causing some transport networks and in particular road networks to approach capacity and introduce delays due to congestion effects. Congested, inefficient travel occurs which results in lower travel speeds, longer travel times introduces negative environmental impacts as private vehicle emissions increase from stop-start travel and slower running speeds. Accurate forecasting for travel demand therefore needs to account for these congestion effects and other influences of the transport networks such as travel times, transport network capacities and also the nature of the demands placed upon them, including mode, trip purposes and time of day of travel.

A direct relationship exists between the total kilometres of travel in motorised modes (particularly inefficient, congested travel) and the emissions generated by the transport sector expressed as a carbon impact. The transport contribution to Australian CO2-e is illustrated by Figure 5.3.

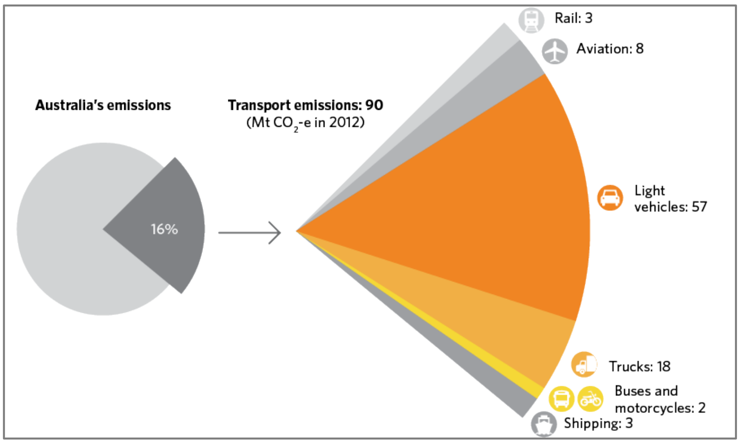


Figure 5.3: Australia's transport emissions by mode, 2012 (source: CCA 2016).

Greenhouse gas emissions from the transport sector come primarily from fossil fuels (petrol, diesel) combusted in vehicles. The domestic transport sector contributed 90 Mt CO2-e, or 16 per cent of Australia's greenhouse gas emissions in 2012. Transport emissions increased by 50 per cent between 1990 and 2012 with 52 Mt CO2-e attributable to light vehicles or predominantly the privately owned car. It is therefore important for the forecasting to accurately represent demands and present a sound and precise connection from travel demand to emissions.

Travel patterns associated with a precinct will demonstrate similar characteristics to that of the surrounding city region unless influenced by policy or technology interventions associated with the precinct design and resulting travel demands. Forecasting processes need the ability to assess the nature of motorised transport modes and how this relates to demand for other modes. This includes assessing mode alternatives, network inclusions, initiatives such as pedestrianisation and vehicle sharing and recognition of new mode possibilities in the future. Resultant travel patterns will then provide the ability to assess emissions and the carbon impact of the precinct.

Forecasting the patterns of urban transport demand is driven by the need to plan for and provide the community with future transport systems and to develop policy strategies to help manage them (Holyoak, 2001). This is certainly not a new concept with the first popular approaches developed in 1950's with the assistance of mainframe computers and many early applications based in the USA and in Europe (Weiner, 1992). Today, Strategic Transport Models (STMs) contain well researched, highly refined and widely applied routines, supported by detailed and informative survey data (household travel surveys, journey-to-work surveys). Multimodal models account for private and public transport demand, non-motorised modes and freight modes and can operate at a range of scales including micro-scale models for detailed operations with dynamic simulations and macro scale models for entire metropolitan regions with static output types (Holyoak and Stazic, 2009). Strategic urban transport forecasting processes are supported by a range of ever increasingly sophisticated software platforms, including Cube (Citilabs, 2013) and TransCAD (Caliper, 2002). Estimates of transport behaviour patterns are based largely on socio-demographic and land use data and assigned to a representative network for transport provision.

State Government Departments of Transport are commonly the biggest stakeholders in the development of STM's with outputs influencing decisions made in relation to future year transport infrastructure requirements, e.g. new roads or bridges. Forecasts results can also be used to help assess the impact policy strategies, eg. minimising environmental impact and maximising transport efficiency. Ortuzar and Willumsen (2011) and Holyoak (2001) detail general strategic modelling approaches with Australian state-based examples of application detailed in SKM (2009), Holyoak (2009) and NSW BTS (2011). The following figure shows a typical forecast estimation process associated with a macro-scale STM with input data (orange) and intermediate outputs (yellow).

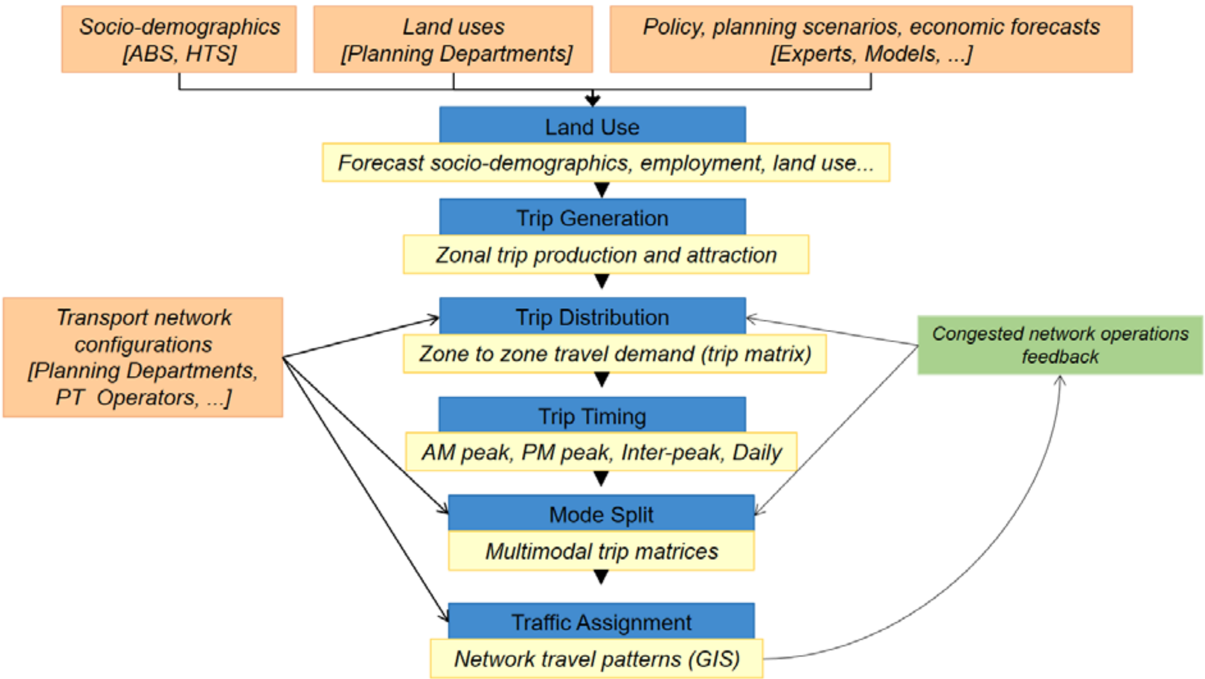


Figure 5.4: Typical strategic-level, macro scale forecasting employing the 5-stage model approach.

Key inputs to the forecasting process include population estimates (sourced from the ABS, government planning departments, other forecast models), household attributes (including location, residents, working/non working status, car ownership and income) and employment and education data (including employees in industry types, and education enrolments). Transport system operations are also a vital part of the input data for forecasting, providing detail on private and public vehicle networks, operational characteristics, travel times, costs, and so on. In general terms, output data reports on the transport system performance comprise network travel patterns and volumes of passenger and vehicle traffic by time period, and can extend to further statistics relating to economic and environmental performance.

In all Australian capital cities, transport planning processes are supported by STM's (Taplin et al, 2014) which provide a valuable resource in terms of a detailed, accurate and validated multimodal transport forecasting process to provide transport behaviour data. These tools are therefore viewed as a valuable resource for the transport domain forecasting process and in the estimation of travel demand and subsequent emission estimations. The challenge is therefore representing the precinct in STM, tapping into routines and utilising relevant information from these models.

5.1 Modelling and Representing Precinct-level Travel Demand

Carbon emission performance is a key consideration in precinct analysis. Indeed, reduction of such emissions is a key objective of the CRC. Quantitative estimation of carbon performance at the precinct level is required so that full knowledge of this is available to developers, planners, designers, infrastructure systems managers and service providers. Thus the demand forecasting tools need to be capable of use in estimating carbon emissions at the precinct level and to relate these to the demand for infrastructure and services use by precinct residents and occupants. In the case of travel demand, the precinct has to be viewed as a source of carbon emissions, although (e.g. for precinct-based travel that takes place outside the precinct) the location of the emissions will be outside the precinct. All such emissions need to be accounted for. The standard representations of travel demand and resulting loads on transport networks have the capability to provide suitable representations of precinct travel demands, but some re-adjustment of the ways to present the demands is required.

5.2 Regional Travel Demand Forecasting

The transport demand forecasting paper (Holyoak, 2013) produced for the ETWW project describes the general methods used to estimate travel demand and transport network performance at the regional level, including the travel demand of a specified precinct.

In terms of the standard representation of a study region in the travel demand models, i.e. through the use of small scale traffic activity zones (TAZ)[1] to represent the distribution of land uses and population across the region, the precinct may be considered as an individual TAZ. This is a first step in representing precinct travel demand, as it means that the demand is explicitly included and is identifiable in the outputs from the regional travel demand model. One issue here is that the given precinct may be part of an existing TAZ in the regional model, depending on its physical size or its population. In this case, and in general to meet the requirements of precinct level planning and design, the precinct should be treated as a TAZ in its own right in the regional model. This could therefore require partition of an existing TAZ in to two separate TAZs, one for the precinct and one for the remainder of the original TAZ. For purposes of the following discussion the precinct is considered to be a TAZ and given the set i =1, ..., n of TAZ in the region, the precinct is designated as the TAZ with $i = \psi$.

The designation of the precinct as a TAZ may be seen in Figure 5.5, which is a schematic representation of the precinct and the (urban) region in which it is situated.

[1] A TAZ is defined in principle as a small geographic area of homogeneous land use, compatible with administrative boundaries and conventionally separate from the major transport networks (i.e. network links may form part of the spatial boundary of the TAZ but would not puncture it). The size of the TAZ generally depends on the basic level of aggregation of available socio-economic and demographic data. Thus, for example, the TAZ could be no smaller than an ABS statistical area SA1 (or its equivalent). Historically, due to computational and computer memory and storage constraints, TAZ would have been composed of 2-4 contiguous SA1s, but the advances in computer technology now mean that a TAZ can often and reasonably be taken as an individual 'SA1'.

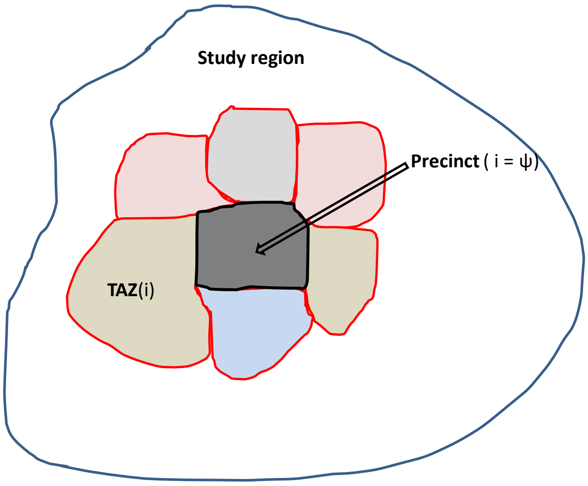


Figure 5.5: The precinct as TAZ ψ in the study region.

On the basis of treating the precinct as a TAZ, a full travel demand forecasting analysis can be undertaken for the region. This will include the generation of travel, trip distribution, mode choice, time of day analysis and traffic assignment to yield traffic volumes, passenger movements and freight flows on the strategic transport network of the region, which will be in balance (equilibrium) with the final modelled travel costs (including travel times, and hence congestion levels) on the network. This is the conventional output from a regional travel demand model. Given that there will be good data for a given precinct, the issue of the precinct being smaller than an existing TAZ (which contains the precinct) will be resolved simply: all necessary information for use in the regional travel demand model will be available as part of the precinct design data, including data for alternative design scenarios.

For precinct-based analysis we need to be able to focus on, identify and utilise the transport demand associated with the precinct. This can be done by examining the origin-destination (O-D) trip matrices available from the regional analysis. There will be a family of these matrices, indicating travel by trip purpose (*k*), mode (*m*) and time of day (*t*) in the region. Specifically, each matrix may be written as

$$\mathbf{T}^{kmt} = \begin{bmatrix} T_{11}^{kmt} & \cdots & \cdots & T_{1n}^{kmt} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & T_{ij}^{kmt} & \cdots \\ T_{n1}^{kmt} & \cdots & \cdots & T_{nn}^{kmt} \end{bmatrix} \quad \text{(Equation 5.1)}$$

in which T_{ij}^{kmt} is the number of trips between origin i and destination j for trip purpose k made by transport mode m and starting in time interval t. For simplicity of notation in the following model definitions, let us just consider a generic O-D matrix T defined as

$$\mathbf{T} = \begin{bmatrix} T_{11} & \dots & \dots & T_{1n} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & T_{ij} & \dots \\ T_{n1} & \dots & \dots & T_{nn} \end{bmatrix} \quad \text{(Equation 5.2)}$$

while remembering that this is one of a family of such matrices. Accompanying the O-D matrix is a similar matrix **C** containing the travel costs between zone pairs, i.e.

$$\mathbf{C} = \begin{bmatrix} c_{11} & \dots & \dots & c_{1n} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & c_{ij} & \dots \\ c_{n1} & \dots & \dots & c_{nn} \end{bmatrix} \quad \text{(Equation 5.3)}$$

which also forms part of the output of the regional travel demand model (cij is the travel cost between origin i and destination j). There will be a family of these matrices, by mode and time of day (if not also trip purpose). In addition, there may be alternative definitions of travel cost, including distance, travel time, or generalised cost. Distance will be determined by network topology but travel time and generalised cost will also depend on levels of congestion on the network.

The region-wide travel demand of the precinct is in two parts, both of which are held in matrix T:

1. trips originating from the precinct, given by the row vector $\mathbf{r}_{\psi}$

$$\mathbf{r}_{\psi} = \begin{bmatrix} T_{\psi 1} & \dots & T_{\psi n} \end{bmatrix} \quad \text{(Equation 5.4)}$$

and

2. trips finishing in the precinct, given by the column vector $\mathbf{s}_{\psi}$

$$\mathbf{s}_{\psi} = \begin{bmatrix} T_{1\psi} \\ \dots \\ T_{n\psi} \end{bmatrix} \quad \text{(Equation 5.5)}$$

These two vectors are the row and the column for ψ in the O-D matrix of Equation 5.2. While these two vectors describe all travel demand with a trip end in the precinct, they cannot be used directly to model that demand due to double counting of the intra-precinct demand $T_{\psi\psi}$. To remove the double counting, define two new vectors of trips: (1) extra-precinct travel demand with origins in the precinct (u_{ψ}) and (2) extra-precinct travel demand with destinations in the precinct (v_{ψ}). These two vectors are:

$$\mathbf{u}_{\psi} = [u_1 \quad \ldots \quad u_n]$$ (Equation 5.6)

in which $u_j = T_{\psi j}$ for j ≠ ψ and $u_j = 0$ for j = ψ; and

$$\mathbf{v}_{\psi} = [v_1 \quad \ldots \quad v_n]$$ (Equation 5.7)

in which $v_i = T_{i\psi}$ for i ≠ ψ and $v_i = 0$ for i = ψ. The intra-precinct travel demand Tψψ is then treated as a separate quantity (which, for example, is not assigned to the regional transport network because it does not leave the precinct). The total travel demand generated by the precinct is given by the trip sum N(ψ), which is

$$N(\psi) = \sum_{j=1}^{n} u_j + \sum_{i=1}^{n} v_i + T_{\psi\psi}$$ (Equation 5.8)

noting that N(ψ) may not always be a fixed number (e.g. in an analysis including elastic travel demands as would be the case in the study of travel behaviour change). The total travel cost Z(ψ) of precinct-generated travel is

$$Z(\psi) = \sum_{j=1}^{n} c_{\psi j} u_j + \sum_{i=1}^{n} c_{i\psi} v_i + c_{\psi\psi} T_{\psi\psi}$$ (Equation 5.9)

Knowledge of precinct trip interchanges and travel costs may be used to estimate energy consumption, air quality emissions, greenhouse gas emissions, and carbon performance of precinct-related travel, given additional information or assumptions about the proportions of different vehicle/fuel types used for that travel. Previous research has seen the development of a family of suitable models for this purpose, from simple fixed rate per unit distance models to models reflecting variable congestion levels across a network (Taylor (1996), Taylor and Young (1996), Taylor et al 2010).

5.3 Estimation of Energy and Carbon for Precinct Travel

Equation 5.3 indicates that travel costs associated with travel out of the precinct, into the precinct, and inside the precinct can be identified separately. A convenient representation of precinct-related travel and its costs is as a trip length frequency distribution (e.g. Figure 5.6), which can be derived from the available trip numbers and travel costs (see equations (5.3) – (5.7). The frequency distribution may also be used to estimate energy, general emissions and carbon performance of the precinct at the regional scale. Separate trip length frequency distributions for out-bound precinct travel and in-bound precinct travel can be generated. In addition, distributions for travel by time of day, for a given mode, or for a given trip purpose can also be computed given the individual trip frequency distributions.

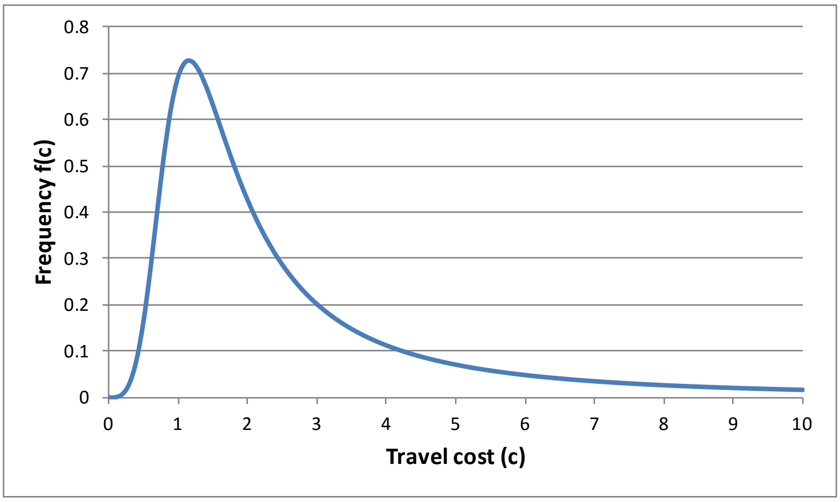


Figure 5.6: Example trip length frequency distribution for a precinct.

We have previously established methods for estimating energy consumption and pollutant emissions from the outputs of regional travel demand models. These methods are also suitable for estimation of carbon performance of precinct-based travel. A generic model for energy and emissions estimation is formulated for use at the network link level but may also be applied at more aggregate levels such as that of the trip length frequency distribution. These methods are also suitable for estimation of carbon performance of precinct-based travel.

If more detailed information on network travel conditions and congestion levels is required (i.e. a link-level analysis identifying when, where and by whom energy is consumed or emissions are generated) then this can be obtained through further modelling and analysis, initially using a multi-class traffic assignment and when necessary a path-flow estimator such as that described by Bar-Gera, Boyce and Nie (2012).

5.4 Intra-Precinct Travel Demand Analysis

Given the energy/carbon focus of Low Carbon Precincts research, further consideration must also be given to intra-precinct travel, as low carbon options may seek to maximise this, e.g. through mixed land use development. This also gives direction as to the appropriate form of the travel demand estimation models at the precinct level. On this point, note that behaviour change is an important consideration in the general research activities of the CRC, and so model forms that can accommodate behaviour change are also important.

The precinct design methods under consideration will also mean that the precinct is defined in some detail and that a comprehensive data description of the precinct should be available, through the *Precinct Information Model* (PIM). A discussion of the concepts of PIM and its formulation is available in Newton et al (2013). Usefully, this report also provides a working definition of a precinct:

> *'a precinct can be represented an urban area of variable size that is considered holistically as a single entity for specific analyses or planning purposes, as well as in a contextual sense to represent the interactions that occur with elements of the surrounding urban area. It typically comprises land parcels occupied by constructed facilities (generally buildings), including open space, and often clustered in to urban zones that share some common characteristics (uses) and supported by physical infrastructure services to manage energy, water, waste, communication and transport as well as a range of social infrastructures related to health care, education, safety, retailing and entertainment' (Newton et al 2013, p.6).*

The precinct may thus be taken to consist of a small geographic area including building and facilities, serviced and connected by infrastructure networks. The networks will include streets and pathways of varying capacity for physical movement, so that the precinct contains its own transport network configuration. It can be considered as a set of micro-zones, which represent the buildings, facilities and other activity zones within in, all connected by an internal network, and represented in a PIM. Figure 5.7 provides a schematic representation of a precinct suitable for the purposes of travel demand estimation.

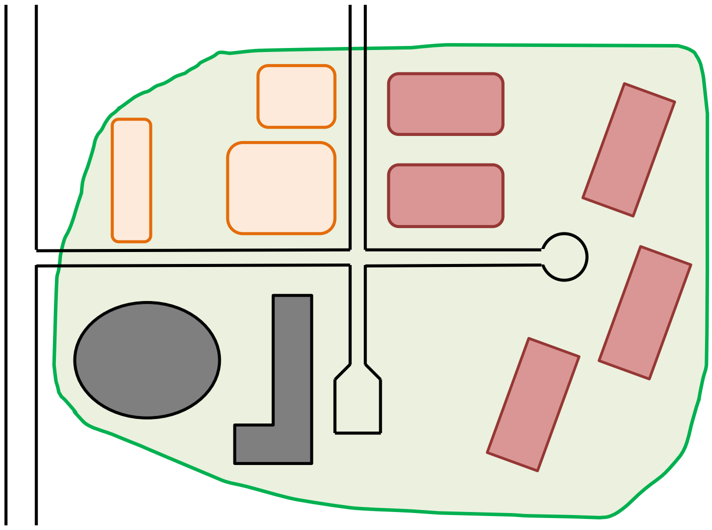


Figure 5.7: Representation of a precinct as a connected set of buildings and facilities (which can be represented as 'micro-zones').

The buildings and facilities are occupied and/or used by residents, enterprises, businesses, service providers, workers, customers and service users. The micro-zones may be considered as a study region in microcosm. The intra-precinct travel demand (defined by $T_{\psi\psi}$ in the previous discussion on regional travel) represents the total amount of travel movement within the precinct, which of itself has origins (h) and destination (d) between the micro-zones. Thus there is an internal O-D matrix $\boldsymbol{\tau}^{\Psi}$ for the precinct,

$$\boldsymbol{\tau}^{\Psi} = \left[\tau_{hd}^{\psi}\right] \qquad \text{(Equation 5.10)}$$

with

$$T_{\psi\psi} = \sum_{hd} \tau_{hd} \qquad \text{(Equation 5.11)}$$

Precinct-level travel demand analysis requires knowledge of both ex-precinct travel $\mathbf{u}^{\Psi}$ and $\mathbf{v}^{\Psi}$, together with $\boldsymbol{\tau}^{\Psi}$. In future research this may require study of trip chains, in which a traveller makes multiple stops in a tour anchored at a particular site, such as the individual's home. Given the interest in travel behaviour change in low carbon transport, this may be a necessary consideration. Given that the conventional regional travel demand models are not designed for trip chaining analysis, it may be necessary to move to an activity-based modelling approach (which is available in the commercial software packages such as *CUBE*). It may also be useful to consider LUTI (land use-transport interaction) models in this regard.

The basic unit for analysis of intra-precinct travel needs to be cast at a finer grain than the TAZ. The most likely units of analysis is the household for home-based travel and the enterprise (office, shop, etc) for non-home-based travel. This is best represented by utility-maximising discrete choice models for transport choices at the following steps: vehicle ownership and access, trip generation, trip distribution, modal choice and time of day, as these models can be estimated at the household level and can capture the individual differences between households. Their results may be used in the macro-level models for regional analysis – i.e. the focus of study is always on the precinct, which is examined in detail whereas more aggregated (TAZ-level) analysis is used for all other zones. The precinct models will produce the basic O-D and travel cost matrices, which would then be refined by the use of a regional network traffic assignment model (for ex-precinct travel) and perhaps a multi-modal microsimulation model for intra-precinct travel. Given that we have access to suitable models in this regard (e.g. *Aimsun* and (especially) *Infraworks 360*) this is quite feasible.

A key to considering low carbon transport options (or indeed alternatives to transport) may be found in the concept of transport accessibility planning, for which accessibility is defined , for example, as 'the ease for people to participate in activities from specific locations to a destination using a mode of transport at a specific time' (Primerano and Taylor, 2005). Transport accessibility is concerned with the ability of people to access services and facilities within close proximity, and the ability of service providers to cater for the needs of a local community. Accessibility analysis may be used to locate services in and around a precinct and to identify opportunities provided through telecommunication and on-line services as substitutes for physical movement.

5.5 Precinct Scale Data Considerations

Defining precinct-based data inputs for the STM will vary according to the specific data requirements and nuances of the particular STM at hand, however in general terms there will need to be some consideration given to the data classes and items summarised in the following table.

Data Class	Specific Data Item
TAZ configuration	Precinct zones and sub-zones representing land-use parcels.
	TAZ centroid location.
Transport networks	Road links with attributes including speed or free-flow travel time, and capacity.
	Public transport links recognising transport mode, service attributes, and stop locations.
	Walking and cycling network configurations.
	Centroid connector locations.
Resident population descriptors	Total households and population.
	Residents, per household identifying workers.
	Household income.
	Vehicles per household and by type, including bicycles.
Non-residential land use information	Total employment for the TAZ recognising industry sectors such as service, manufacturing, technical/trade, transport, retail, education and other fields.
	Enrolments in primary, secondary and tertiary education institutions.

Table 5.1: Data requirements for STM forecasting.

For each precinct, the spatial configuration of the TAZ transport networks and activity centres such shopping centres and schools influence the overall nature of the land use data with special consideration given to residential land use data. The precinct will also connect to the wider metropolitan region through transport networks and services and through origin-destination pairs, for it does not operate in isolation. The STM can then estimate for the precinct the following output data descriptors:

- Origin to destination (OD) travel demand for within and beyond the precinct, disaggregated by
    - Travel purpose,
    - Time of the day
    - Travel modes that the OD trips will take,
- Assigned routes for motorised travel,
- Multimodal travel distances and congested network travel times,
- Travel on different road types (freeway, arterial, local).

Select output data configurations will also provide source information for more detailed representations in micro and nano scale modelling simulations, such as those achieved in *AIMSUN* or *Infraworks360* software packages. Data outputs from the STM allow the user to identify the travel demand that 'belongs' to the precinct, both in terms of daily household travel and the other land uses that attract people to the precinct.

Integrating the STM forecasting processes with the ETWW framework involves the development of precinct, network and scenario descriptors, data links to STM packages, to other model domains and with carbon estimation routines, as illustrated in Figure 5.8.

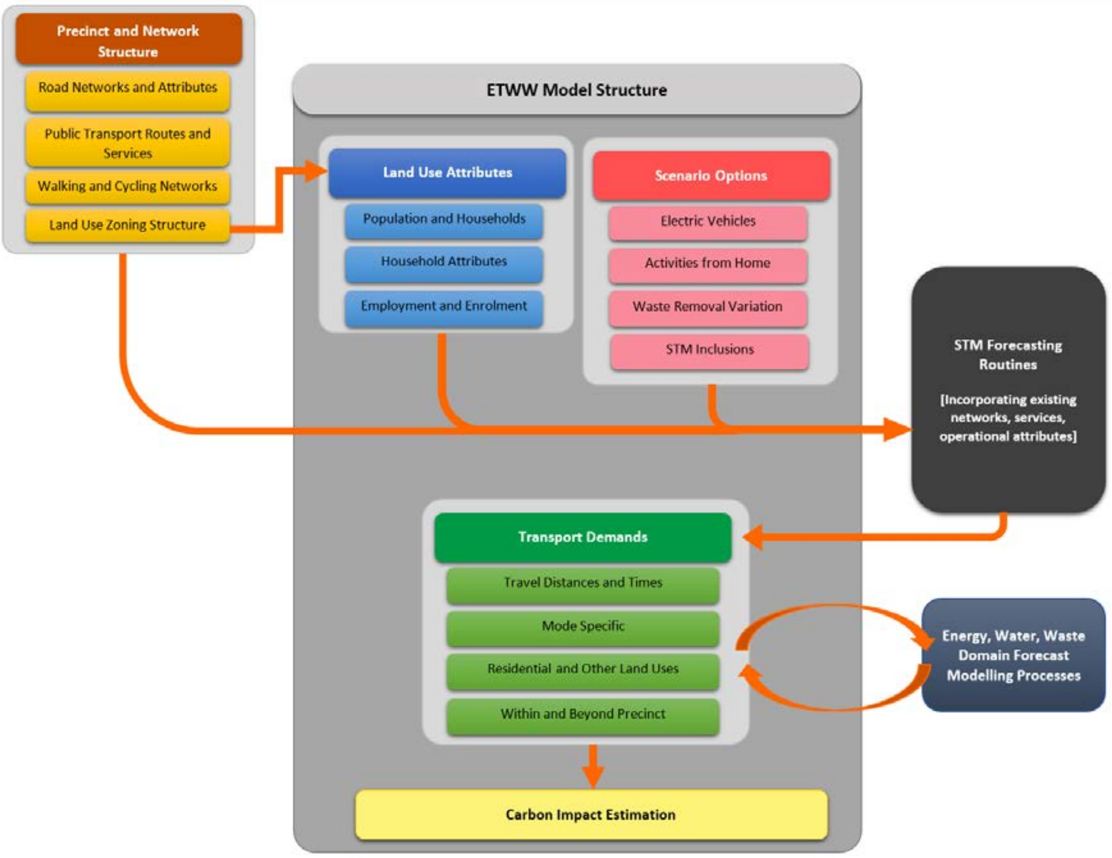


Figure 5.8: Transport forecasting processes connecting with the ETWW structure.

Definition of the precinct and network structure primarily involves zoning allocation and the road network configuration with associated attributes. Network connections to an existing STM model network will require attributes such as road link capacity and speed, distance, also intersections and other features such as one-way links and class restrictions. Public transport routes and services include on-road and non-road (i.e. rail and ferry) based networks, with routes including frequency of service, stop locations, service operation times, vehicle capacity, connections to other modes and facilities such as park and ride, interchanges, as well as fare structures, tolls and parking charges, etc. Walking and cycling networks are often more detailed (i.e. contain more links) than road networks, and will recognise appropriate speeds and connections to public transport networks.

For each defined TAZ, a land use allocation is required with respective descriptors required. Activity centres and resident populations should be adequately described for an accurate modelling function.

Possible scenario options involved in the ETWW forecast and relevant to the transport domain include:

- Electric Vehicle ownership and Use: *define EV type, trip purpose and percentage travel expected by EV*,
- Activities from home: *define one or more of work, shopping or education,*
- Waste removal variation: *define the disposal vehicle and travel distance by waste type.*

Utilising routines and operations incorporated in the STM forecasting structure, the transport domain has the ability to estimate the demand and resulting carbon impacts from changes to:

- Public transport services including fares, networks and frequency,
- Walking and cycling networks,
- Precinct accessibility and connectivity to surrounding areas,
- Car sharing and ridesharing activities,
- Multimodal transport network configurations including mode interchanges, capacity and accessibility,
- And more.

Resulting transport domain outputs that relate to the precinct are largely presented as travel distances (i.e. total kilometres travelled) and travel times (i.e. total hours spent travelling) between origin and destination pairs and ultimately associated with the precinct. Travel is disaggregated by all motorised and non-motorised modes however reporting can vary depending on mode. Private car travel is reported per vehicle and vehicle type, whereas public transport travel relates to the travel per passenger. Cycling and walking demand is reported as travel per person. The STM generates forecast travel demand for both residential and all other land uses and so there is no need for additional estimation routines beyond what is generated in the STM.

As all origin and destination pairs are recognised in the estimation process it is possible to identify travel that occurs entirely within the precinct and travel that extends beyond the precinct boundary to the wider metro area. This is of particular interest when considering pedestrian and cycling activity within the precinct as well as cohorts of travellers making similar travel, who may suit car sharing modes. Travel between origin and destination can be further disaggregated by road link types used during the journey, ranging from local roads to arterial and freeway road links, an important distinction when determining emissions generated from travel demands.

5.6 Transport Emissions Estimation

In Australia today, light vehicle greenhouse gas emissions are significant contributor to the total annual emissions load from all sectors including stationary energy generation and industrial processes as depicted in Figure 5.9 and Figure 5.10 with historical and forecast emissions by sector. This is a challenging issue for government authorities as they seek to manage emission production into the future.

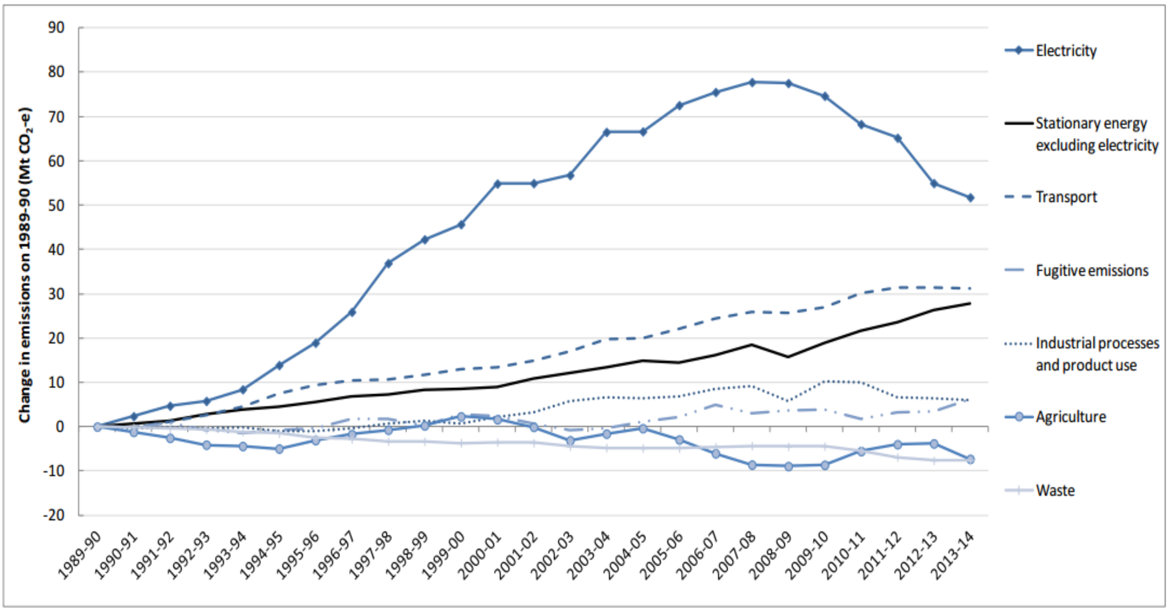


Figure 5.9: Historical trends for greenhouse gas emissions in Australian sectors (Department of Environment and Energy, 2016).

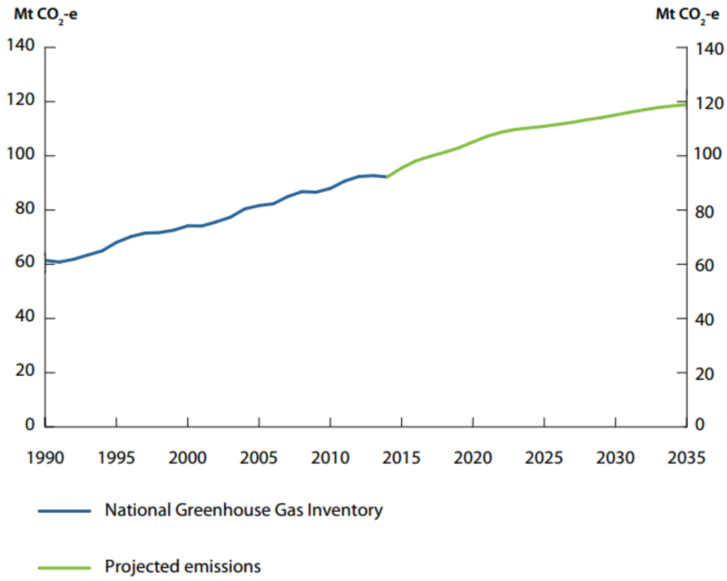


Figure 5.10: Australian national greenhouse gas inventory and projected emissions for CO2e (Department of Environment and Energy, 2016).

Forecast targets for greenhouse gas emissions have been established at the Paris climate conference (COP21) in 2015, with 195 countries adopting a legally binding global climate deal. This agreement established a global action plan to limiting global warming to well below 2°C. The assessment of policy strategies employed to achieve this goal therefore requires the application of accurate and reliable forecast tools, essential for managing the transition to sustainable communities.

5.7 Transport Emission Forecasting Approaches

The research dedicated to this issue as part of the ETWW project seeks to develop confidence intervals for GHG emission rates for light vehicle traffic on Australian roads, as reported by Iankov (2016) and Iankov, Taylor and Scrafton (2017). Current practice largely employs three methodologies for forecasting road transport greenhouse emissions.

The tier 1 estimation methodology employs fuel specific emission rates (*EF*) for consumed quantities of fuel according to the following equation:

$$Emission = \sum_{a} [Fuel_a \cdot EF_a] \qquad \text{(Equation 5.12)}$$

In a similar manner, the tier 2 estimation methodology employs: emission rates applicable to fuel types, and to vehicle classes and emission controlled technologies (a, b, c) as:

$$Emission = \sum_{a,b,c} [Fuel_{a,b,c} \cdot EF_{a,b,c}] \qquad \text{(Equation 5.13)}$$

Tier 3 estimation is more detailed in nature as emission rates applicable to fuel types, vehicle classes, emission controlled technologies are applied over different operating conditions:

$$Emission = \sum_{a,b,c,d} [Distance_{a,b,c,d} \cdot EF_{a,b,c,d}] + \sum_{a,b,c,d} C_{a,b,c,d} \qquad \text{(Equation 5.14)}$$

The approach developed as part of this research estimates total emissions based on emission rates for traffic that satisfy requirements for vehicle age, size and traffic condition (s, y, f) as per the following equation:

$$\boldsymbol{Emissions} = \sum_{s,y,f} [\boldsymbol{Traffic_{s,y,f}} \cdot \boldsymbol{EF_{s,y,f}}] \qquad \text{(Equation 5.15)}$$

Traffic flow totals are estimated by transport demand modelling present in STMs and reported by the transport demand domain of the ETWW model structure. The emission estimation routine enables sensitivity analyses that are important for local authorities, and are user-friendly.

5.8 Emission Forecasting Tasks

The estimation of emission rates (and the confidence intervals around them), a critical component in emission estimation has required the application of a number of data sources relating to vehicles belonging to the existing vehicle fleet as:

- Unique database integrating several large datasets from external and internal sources,
- Australian Green Vehicle Guide,
- Survey of Motor Vehicle Use,
- Motor Vehicle Census,
- National In-Service Study 2 (NISE2),
- Log book data.

Forecasting for the future emissions has required the development of emission rates for traffic consisting of vehicles that will be manufactured in future. This estimation has required:

- Unique database integrating data from multiple external sources
    - *US EPA and NHTSA final rulemaking for CAFÉ 2025*
    - *BTIRE, CSIRO*
    - *German Environmental Agency (UBA), UK committee on Climate change*
    - *AEA Ricardo, JAMA, KAMA*
    - *ATO*
    - *International Energy Agency, AEMO*

5.9 Estimating Market Shares

The methodology for estimating market shares allows for the development of emission rates for vehicles to be manufactured in the future. This method employs a simulation procedure that requires input data relating to technology costs, running costs and buyer willingness to pay. It also incorporates uncertainty and variance of alternatives with determination of buyers choice which in turn is a key factor in determining the composition of the future vehicle fleet, and hence traffic emissions. Figure 5.11 illustrates an operational flowchart for forecasting fleet emission procedures.

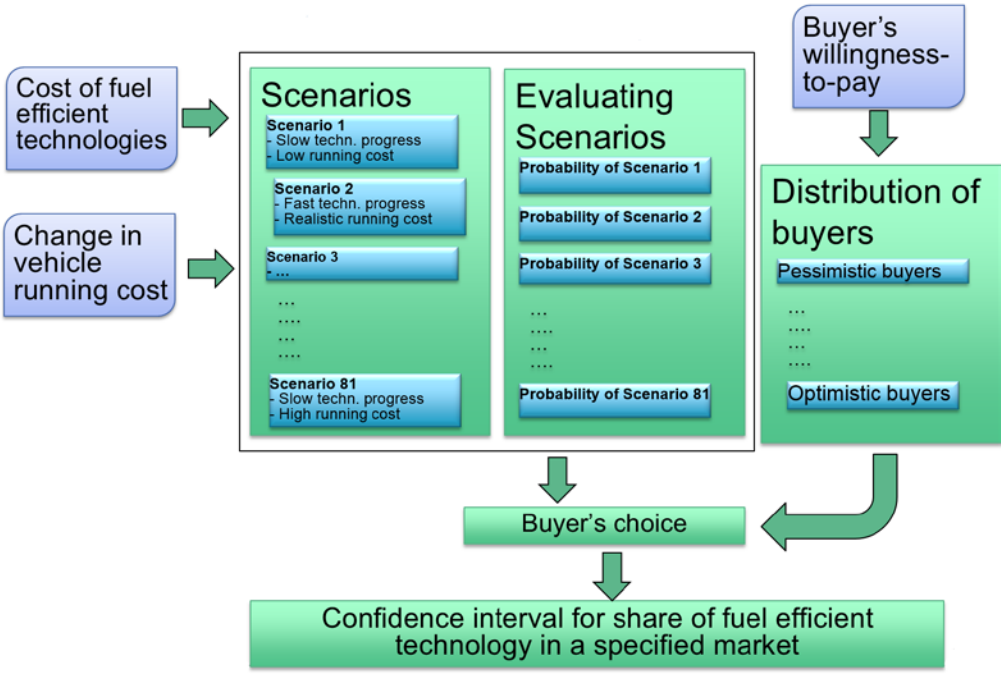


Figure 5.11: Operational flowchart for forecasting fleet emission procedures.

The employed buyer's willingness to pay, or utility is illustrated in the following figure for a number of electric vehicle (EV) and internal combustion engine (ICE) types relating average capital and annual running costs for each class of vehicle.

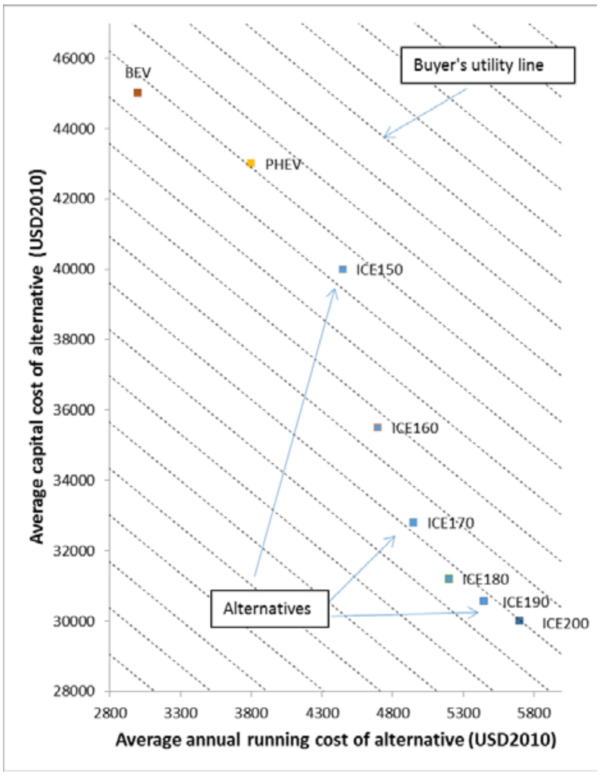


Figure 5.12: Determination of buyers choice.

The assumptions employed here are that the buyer always selects the most attractive alternative in a highly competitive non-regulated market. Vehicles that belong to a specified vehicle class are assumed to have similar annual vehicle mileages.

5.10 Car Buyer Choice

Based on a review of a range of sources, the car buyer choice reveals a wide variation in the estimates of willingness-to-pay for energy efficiency. Data sources also reveal that consumer responses are more complex than economic assumptions suggest with loss aversion due to uncertainty about future fuel prices and the fuel economy. Manufacturers assume that buyers will pay only for 2-4 years of fuel savings as they consider additional manufacturing costs required to achieve lower emission rates (Figure 5.13). It is assumed that this behaviour is not likely to change dramatically in the future. The distribution of car buyers by acceptable repayment period for energy efficiency is provided in the figure.

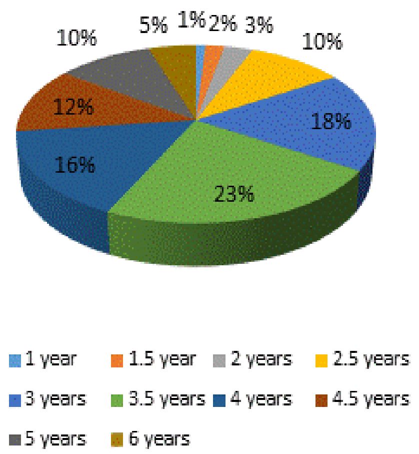


Figure 5.13: The distribution of car buyers by acceptable repayment period for energy efficiency.

The relationship between additional manufacturing costs and lower vehicle emission rates is demonstrated in Figure 5.14 for a range of vehicle classes.

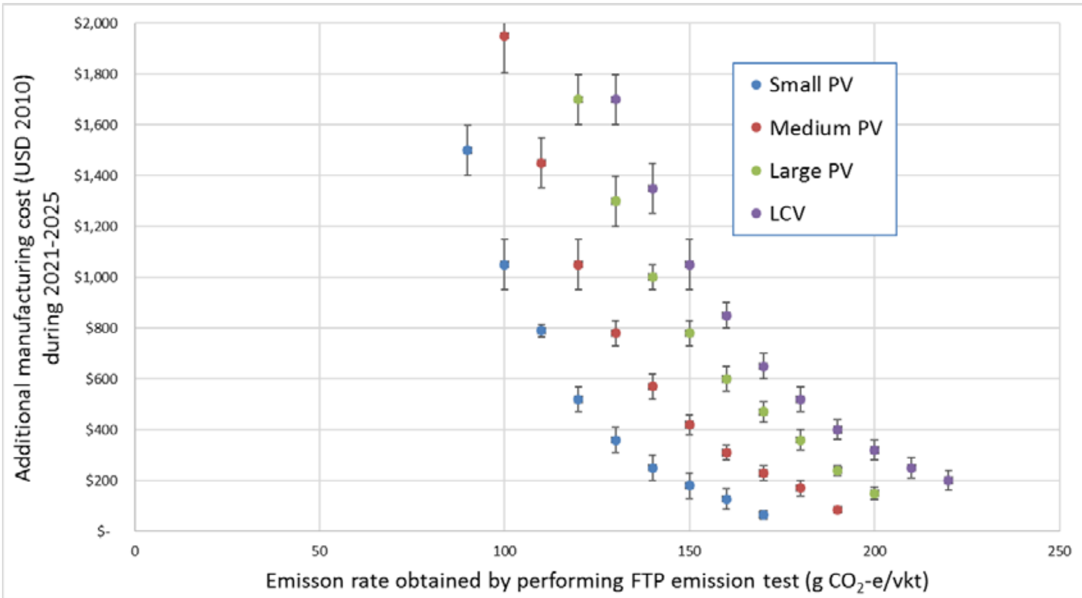


Figure 5.14: Relationship between cost and vehicle emission rate.

This figure also suggests that for each vehicle class an exponential relationship exists between additional manufacturing costs and reductions to emission rate, with all classes demonstrating a similar relationship. For electric vehicles, the provision of a battery is also an additional manufacturing cost, dependant on the battery type and vehicle class, as shown in Figure 5.15.

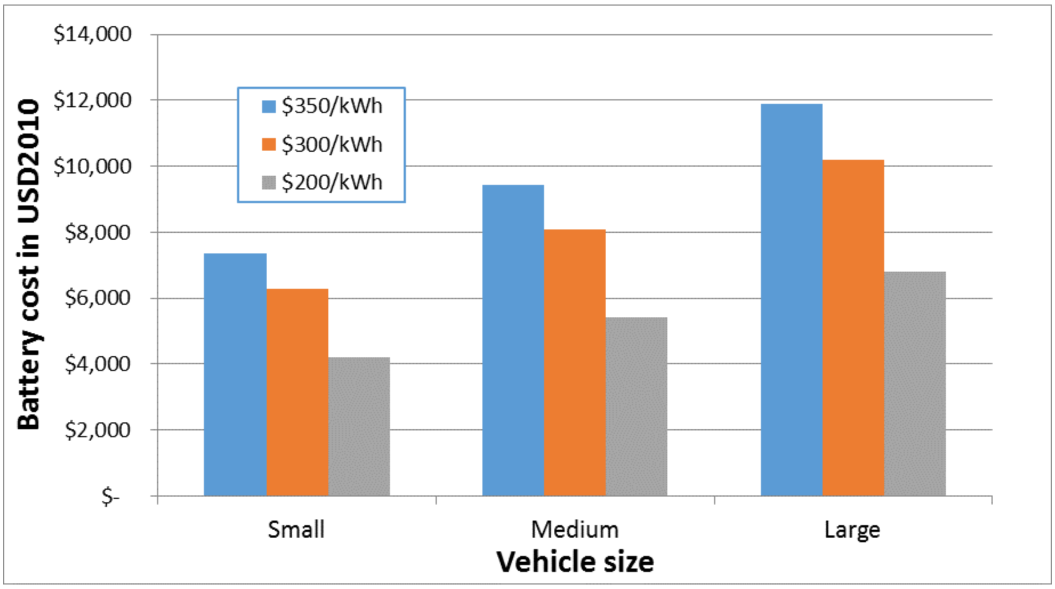


Figure 5.15: Relationship between cost and vehicle size for a range of battery types.

The relationship between cost and vehicle size for a range of battery types as an additional cost shows that battery capacity and cost remain critical factors for the uptake of BEVs and PHEVs. Estimates are made based on the small, medium and large battery capacities here as 24, 27, 31 kWh batteries and a 160 km driving range. Electric vehicle battery performance is driven by initiatives such as the US Advanced Battery Consortium, with objectives including the continued development of high-power battery technologies to meet 2020 performance and cost goals (USABC, 2016)

5.11 Vehicle Running Cost

Considerations associated with the running cost associated of privately owned light vehicles includes the energy price and consumption rate (for both fossil fuelled and electric vehicles), utility factor (PHEV only) and annual travel distance. Figure 5.16 illustrates the relationships between vehicle running cost and technologies for various time periods and for a range of light vehicle classes.

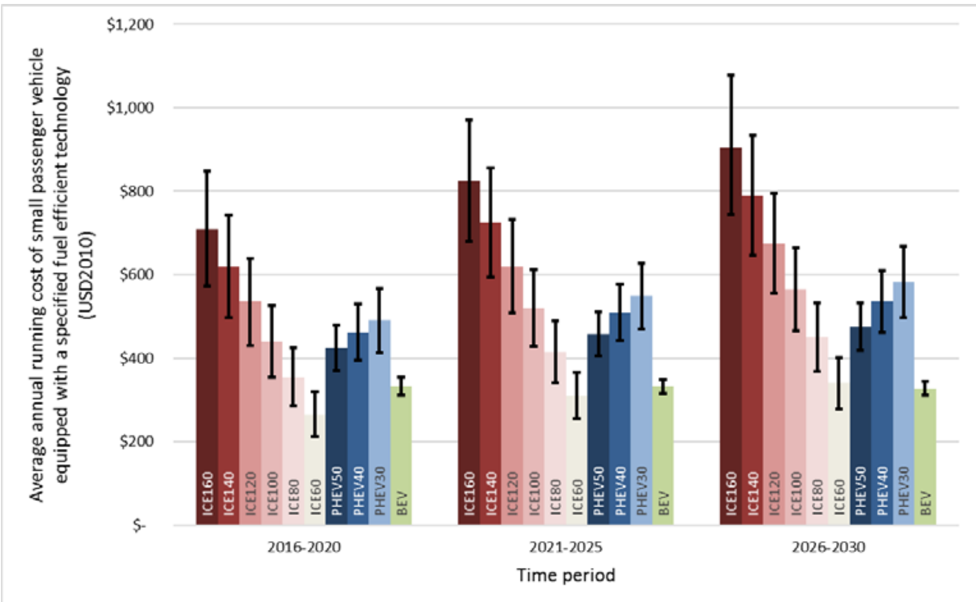


Figure 5.16: Relationship between vehicle running cost and technologies for various time periods.

ICE vehicle running costs should increase over 2016-2030, as will PHEV running costs, but at lower rate. The running costs of BEVs are expected to be stable over the period and running costs of BEVs are comparable to costs of ICEVs equipped with advanced fuel efficient technologies.

5.12 Market Shares

Simulated market shares results for the period 2016 to 2030 for various vehicle classes are provided in Figure 5.17 below with expected values and 95% confidence intervals as shown in Figure 5.16, which allows for assessments of variations to market shares.

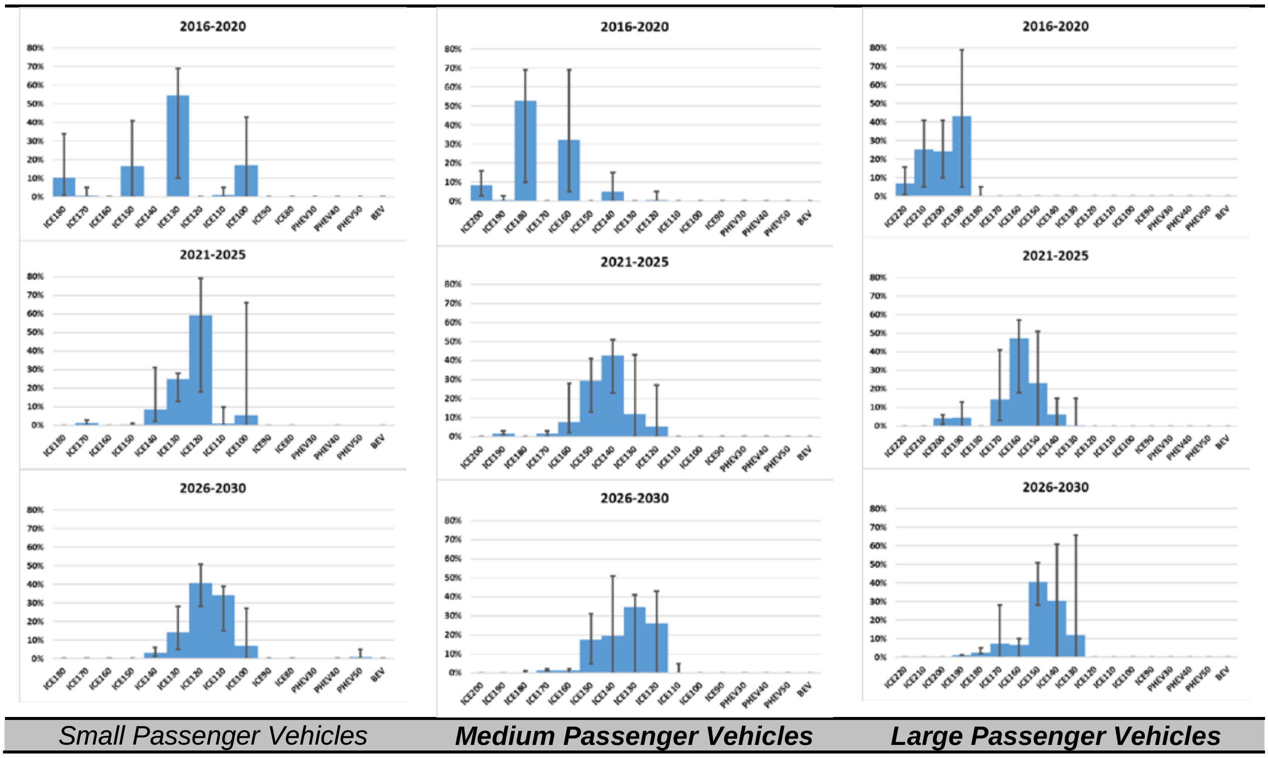


Figure 5.17: Simulated market shares results for the period 2016 to 2030 for various vehicle classes.

The forecast market shares illustrate that conventional vehicles are the predominant buyer's choice for purchase until 2025 when there are emerging shares for plug in hybrids and electric vehicles until 2030. This emergence is most pronounced in the small passenger vehicle class.

5.13 Emission Rates

Emission rate estimates are based on the modelled market shares achieved in Figure 5.17 previously. Estimated emission rates are provided as tank to wheel rates for various vehicle classes and for various periods. The final results illustrate greenhouse gas emission rates with 95% confidence interval and it is possible to distinguish the effect of vehicle size and manufacture year. Figure 5.18 illustrates these results.

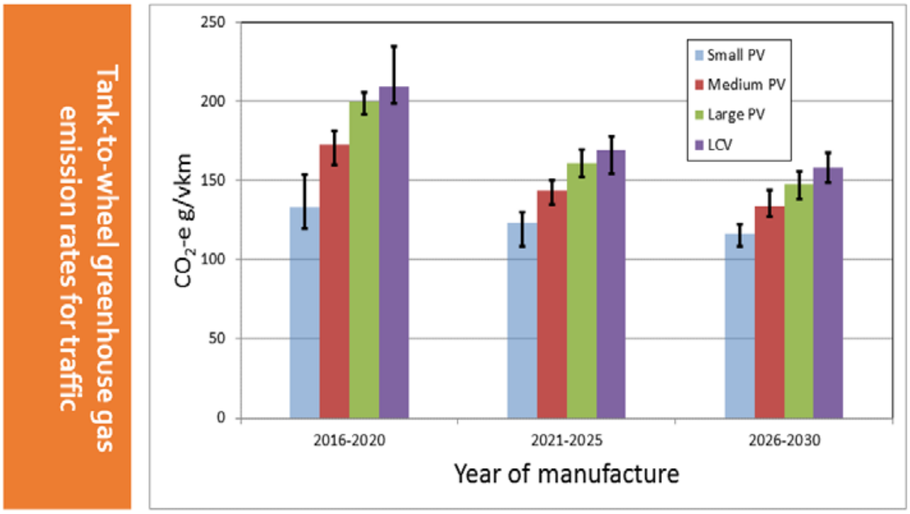


Figure 5.18: Tank-to-wheel greenhouse gas emission rates for traffic.

Results demonstrate a relative level of certainty with overall confidence between 20 and 25 g CO2e/vkt or about 10-15% of the magnitudes of the emission rates, with no interaction effect. A moderate improvement of fuel efficiency is achieved over the entire period as Figure 5.18 illustrates the influence of vehicle size and year of manufacture on emission rate.

Earlier knowledge about emission rates is refined and extended by providing alternative emission rates that allow forecasts of transport greenhouse gas emissions and provide for comprehensive analysis of scenarios in more efficient ways than current practice. Confidence intervals with practical widths are achieved even though it was necessary to utilise estimates with inherent high uncertainty. The emission rates are user friendly and allow important sensitivity analysis for transport planners who assist local authorities. Market competition can lead to moderate improvement of fuel efficiency of the light vehicle fleet. Significant government support by incentives and policies will be necessary as market forces are likely to be insufficient to promote BEVs and PHEVs on the Australian market over the next 15 years.

6 Waste Domain Forecasting

Wastes can be defined as “materials that are not products produced for market, for which the initial user has no further use in terms of his/her own purposes of production, transformation or consumption, and of which he/she wants to dispose. Wastes may be generated during the extraction of raw materials, the processing of raw materials into intermediate and final products, the consumption of final products, and other human activities” (OECD 2013). With growing global populations, waste production is becoming an ever increasing concern to urban and non-urban communities with treatment and disposal an issue threatening the sustainable development of society (Benítez et al. 2008). The discharge of urban waste has negative impacts on all scales from locally to global biogeochemical cycles and climate. As humanity today is experiencing a dramatic shift to urban living, cities and precincts are becoming even more concentrated locations of production, consumption, and waste disposal that are driving a host of global environmental problems (Grimm et al 2008). Besides the increasing amount and complexity of waste generation and treatment, the growth of waste generation leads to a multitude of environmental hazards such as environmental degradation, water and soil pollution, and greenhouse gas emissions (Pakpour et al. 2014).

Australia ranks in the top five per-capita waste producing nations worldwide (Living Smart Program, 2011). Economic growth, population increase, and urbanisation compound this management issue when looking to the future and so waste generation regulations such as the National Waste Policy established by the Australian Government’s Department of the Environment and Energy (2009) seek to control the national waste generation. The Environment Protection Regulations (EPA, 2017) also seek to guide the minimisation of waste generation and increase the recycling of resources. At a household level, psychological factors all play a significant role in the prediction of waste management behaviour, with research such as reported by (Barr, 2007) investigating attitudes and behaviours related to waste generation at a household level.

6.1 Waste Estimation Methodologies: Operational ETWW Forecasting Routines

The methodology described in Section 6.1 outlines a simplified waste production estimation approach employed to draw upon the resources developed for the waste domain and allows for residential and non-residential waste forecasting for a range of waste types. This forecasting process accounts for both the production of wastes, their disposal process and the carbon impacts associated with this. The bulk of the outcomes from the ongoing PhD-based research as part of this project are not in a sufficient state of refinement to allow for reliable estimation processes in a practical sense. Outcomes of the PhD research in the waste domain *to date* are summarised in their current condition in Section 6.2, with potential for future incorporation and application to the larger ETWW precinct forecasting environment.

6.1.1 Residential Waste Estimation Routine

Estimation of household waste, that is waste totals generated by the precinct residents and subsequently collected for either treatment or disposal, are classified into three defined types, each requiring separate collection, re-use and/or treatment processes:

- Landfill waste: household ‘garbage’ that requires transportation to landfill site, dumping and compaction,
- Recycling: mixed materials requiring removal and individual recycling processes for paper, plastics, metals and glass waste types,
- Organic: ‘green’ materials that require bio-degradation in the form of composting processes of to turn waste into compost, mulch and fertilisers.

Precinct residential waste forecasting therefore require estimations for each of these three waste types. Volume and mass estimation processes for each waste type are similar in nature and are based largely on survey data and literature on the waste type composition, collection methods and treatment outcomes.

The waste production survey data collected at Lochiel Park is augmented with data reported by Zero Waste SA (2013) to define waste production at a household level. The bin types used in Lochiel Park are typical of most current Australian household bins collected by waste removal trucks and are used to define individual bin capacity in the estimation process. These bin volumes are reported in Table 6.1. The ETWW model allows the user to define how full the bins are at collection time, within the modelling application using average values of between 40% to 50% (as reported from Lochiel Park) for all waste types applied as a default.

Uncompacted waste densities defined by the Victorian EPA (2016) are also reported in Table 6.1 with compaction ratios applied to achieve a compaction densities of:

- Landfill/garbage: 228 kg/m3
- Organic: 194 kg/m3
- Recycling: 198 kg/m3

Waste compaction occurs within the collection vehicle and a range of compaction densities are often possible depending on the vehicle settings. Compaction ratios vary according to waste types with the highest applying to the landfill waste types as these do not undergo any treatment process and higher compaction suits the ultimate transport and disposal processes. The lowest compaction ratio applies to organic waste as this waste is assumed to be of a higher density when disposed of at the household. Recycling material requires sorting and processing at the depot location and therefore cannot be compacted to higher densities. Research conducted by Zero Waste SA (2013) has also guided the compaction ratio selection as displayed in Table 6.1.

	Waste Type		
Item	**Landfill**	**Organic**	**Recycling**
Household bin volume (m3)	0.14	0.24	0.24
Uncompacted density (kg /m3)	76	97	76
Compaction Ratio	3:1	2:1	2.6:1

Table 6.1: Household waste production characteristics.

If the ETWW model now assumes the waste household characteristics identified in the previous table, the process for the estimation of all three waste types at the precinct level is firstly, to estimate the volume of waste deposited in the bins and the uncompacted mass, each week. Compacted volume and mass is consequently summed for all households for each waste type within the precinct and across one complete week to provide the weekly total. Total precinct masses of each waste type are used to determine the carbon impact, accounting for decomposition, composting processes and recycling processes as appropriate

For landfill waste, dumping into landfill locations results in the production of a number of gas types over time, which can ultimately be represented by a carbon-dioxide equivalent (CO2-e) production. Australian national greenhouse accounts factors (DoE, 2014) stipulate that the average municipal solid waste generates a total of 1.4 kg of CO2-e per kg of landfill waste.

Organic waste treatment involves the composting, or more specifically the aerobic decomposition of the material to a state that suits re-use as mulch or compost. This composting process also generates carbon-dioxide equivalent at a rate of 1.35 kg of CO2-e per kg of waste on average (DoE, 2014).

Waste to be recycled requires an estimation of the energy involved in this process and subsequently the carbon produced from generating the required energy. Firstly the proportion of each recycling material contained within the waste, (Department of Sustainability, Environment, Water, Population and Communities, 2013) is determined along with their respective energy intensities for recycling processes (Cooper and Gutowski, 2015 and Morris, 1996). The resulting energy intensity for household municipal recycling waste is 5.426 kilowatt hours of energy to recycle 1 kg of material.

6.1.2 Non-Residential Waste Estimation Routine

Waste production estimates for each non-residential land-uses are made according to a range of waste generation factors, relating to various land use types. Once again, the three waste type productions for landfill, recycling and organic are made in accordance with the degree of activity (as reported number of full-time equivalent employees (EFTE). Table 6.2 details these waste generation rates in terms of volume and mass of waste types generated per day.

	Waste Type					
	Landfill		Organic		Recycling	
Land Use	(kg/EFTE)	(m3/EFTE)	(kg/EFTE)	(m3/EFTE)	(kg/EFTE)	(m3/EFTE)
Commercial	0.16986	0.00134	0.02740	0.00014	0.24658	0.00176
Education	0.68493	0.00452	0.00000	0.00000	0.21918	0.00176
High Value Industry	0.54795	0.00401	0.00000	0.00000	0.21918	0.00157
Open Space Park	n/a	n/a	0.00525	0.00003	n/a	n/a
Open Space Trees	n/a	n/a	0.00225	0.00001	n/a	n/a
Open Space Shrubs	n/a	n/a	0.00300	0.00002	n/a	n/a
Open Space Roadside	n/a	n/a	0.00450	0.00002	n/a	n/a
Retail and Mixed Use	4.54795	0.02820	0.27397	0.00137	3.72603	0.02666

Table 6.2: Daily waste production factors for non-residential land-uses (Source: derived from Department of Sustainability, Environment, Water, Population and Communities, 2013).

Estimates of CO2-e production and energy intensities associated with the landfill, organic and recycling waste from non-residential land uses are made in from a similar approach to the residential wastes. Table 6.3 defines the carbon and energy intensity factors applied to the various land use waste productions. Variations in these values are due to the differing composition of the waste generated for the land uses.

		Waste Type		
		Landfill	Organic	Recycling
Land Use	**Waste Production Classification**	**kgCO2e/kg**	**kgCO2e/kg**	**kWhr/kg**
Commercial	Administrative and Support Services	1.9065	1.3500	5.5556
Education	Education and Training	1.2720	1.3500	6.5972
High Value Industry	Professional, Scientific and Technical Services	1.8800	1.3500	5.5556
Open space	Estimated	1.6000	1.2700	
Retail and Mixed Use	Retail	1.3813	1.3500	5.6637
Ret_2	Food Retail	1.2922	1.3500	5.6637

Table 6.3: Energy and carbon intensity factors for non-residential land-use wastes.

6.1.3 Emissions From Waste Transport

Transport of waste from the precinct households and other land uses is commonly performed by waste removal/compaction trucks, similar to that depicted in Figure 6.1.

Figure 6.1: Image of a typical suburban waste removal vehicle.

These vehicles are most often diesel powered and when assigned to the waste collection task perform travel from/to their depot or 'home' location to the precinct, within the precinct and also to/from the landfill or treatment location. During this travel task, emissions are generated by the truck with are largely dependent on operational information relating to characteristics of the collection truck and of the dump/treatment site location. The ETWW model estimation assumes that trucks required once a week for landfill waste and once every two weeks for the collection of organic and recycling waste. Table 6.4 displays this and other operational characteristics of the waste collection vehicles.

	Truck Attributes		
Attribute	**Landfill**	**Organic**	**Recycling**
Capacity (m3)	17	13.6	13.6
Fuel type	Diesel	Diesel	Diesel
Fuel use - Empty Load (litres/km)	1.26	1.26	1.26
Fuel use - Full Load (litres/km)	1.58	1.58	1.58
Truck fuel emission (kgCO2e/litre)	2.68	2.68	2.68
Truck 'home' location to precinct site distance (km)	9.50	9.50	9.50
Dump/recycling treatment location: one-way travel distance (km)	26.30	73.37	19.60
On-site precinct route distance (km)	3	3	3
Collection repeat (days)	7	14	14

Table 6.4: Waste removal truck operational characteristics.

All vehicles will travel from the 'home' location to the precinct, and then repeat the '*On-site precinct route distance' plus* travel to/from the '*Dump/recycling treatment location*' until the entire precinct waste volume is removed. The number of repeating cycles is determined by the total compacted volume to be removed (as estimated previously) and the truck capacity. Once complete the truck will return to the 'home' location.

A distinction is made between the fuel consumption of the vehicle when it is travelling full and when it is empty. Total estimates for organic and recycling are for two-weeks and so are halved to obtain a weekly estimate to match landfill. Total precinct emission estimates (for each waste type) of CO2-e are then allocated to each house or land-use in the proportion of the waste volume generated by that precinct component.

The ETWW model structure allows for the user-intervention of any listed parameter, allowing for the assessment of the carbon impact of scenarios such as:

- Variations to the truck capacity with changes to truck size or compaction ratios
- Introducing waste trucks with better 'traditional' fuel consumption efficiencies

- Introducing waste trucks that use alternative fuel types, including biodiesel and electric vehicle possibilities
- Changes to recycling energy intensity, which will influence the energy required for treatments,
- Changes to dumping/treatment locations and hence the travel distances required
- On-site waste treatment, eliminating the need for, or reducing the frequency of, waste collection trucks for particular waste types

6.2 Residential Waste Estimation Methodologies: Outcomes of Ongoing Research

This section provides a background discussion on the procedures that are part of ongoing PhD research associated with the ETWW model development for estimation of household waste generation for precinct analysis. The bulk of the procedures and outcomes discussed are not in a sufficient state of refinement to allow for reliable estimation processes in a practical sense. Outcomes of the PhD research in the waste domain *to date* are summarised in this current condition in this Section of the report, with potential for future incorporation and application to the larger ETWW forecasting environment.

This topic is a relatively new one for research, and as such, there is a lack of substantial data on it. This project has made a start on the assembly and collection of household-based waste generation, but this area requires significant further research beyond the scope of the present research project before there can be a proper understanding of waste generation behaviour at the household (then precinct) level. This report section first considers the general situation regarding waste generation in Australia as revealed by published data. It then considers the modelling approaches used to estimate waste generation by sector and type, which use economic input-output models and are therefore directed at regional analysis. Finally the section and associated appendices report on work undertaken in this project to consider waste generation at the household and precinct levels. A series of policies for waste management have been published that include the following:

- National Waste Policy agreed in November 2009 (Department of the Environment 2014).
- Environment Protection Regulations 2009 published on 1 July 2010 (Environment Protection Authority 2015).
- Waste levy regulations for Australian states, with waste levy fees increasing annually.

In order to achieve desired sustainable municipal waste management (WM) systems in Australia, there is a need an accurate and reliable analysis of the amount of waste generation and treatment. This is a difficult process due to the absence of substantial data to feed such an analysis in Australia. ABS (2016) indicated that in the period between 1996 and 2014, the index of waste generation far outstripped those for energy consumption, GHG production and water use, with populations generating increasing amounts of waste per capita (Figure 6.2).

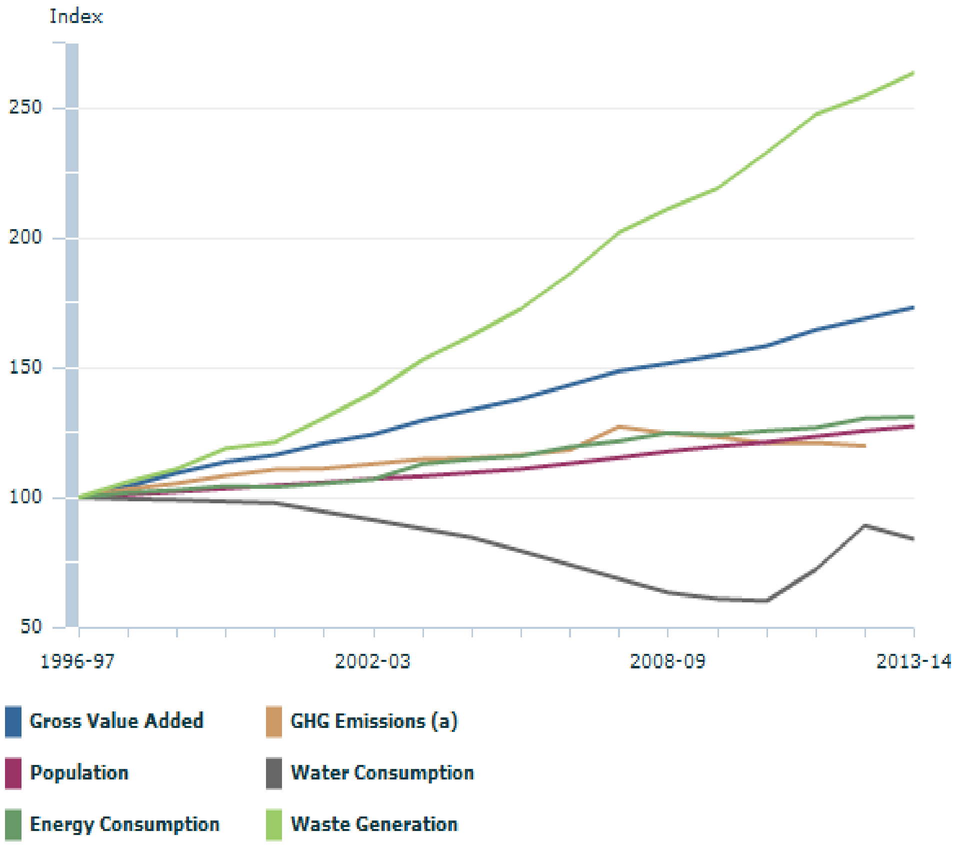


Figure 6.2: Socio-economic and environmental measures, Australia, 1996–97 to 2013–14 (source: ABS, 2016).

Other estimates, from ABS (2013), indicated that of the 53.7 million tonnes of waste generated annually in Australia, households were responsible for 12.4 million tonnes (Figure 6.3). Approximately half of this total waste volume was disposed of in landfill sites while the remainder was mostly recovered through recycling activity and a small proportion exported (Figure 6.3).

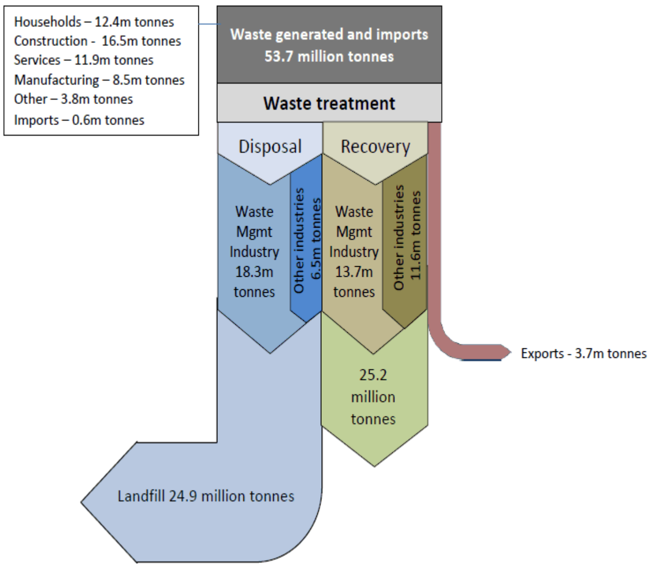


Figure 6.3: Waste generation and management (source: ABS, 2013).

More information is needed about the waste generation and sources to provide a better understanding of the disposal and recovery processes. This information is required at a number of levels of disaggregation, from the national scale to the precinct scale.

The research therefore needs to address which factors affect waste generation, how waste policies affect waste generation and waste sources and treatment. Figure 6.4 provides a systematic structure of the waste management process with important components under each heading noted. In this illustration:

- Regional scale – defines the spatial boundary, from national level to precinct level
- Waste stream – which waste types are assessed
- Variables – which factors affect waste generation
- Models – forecasting approaches for waste generation assessment.

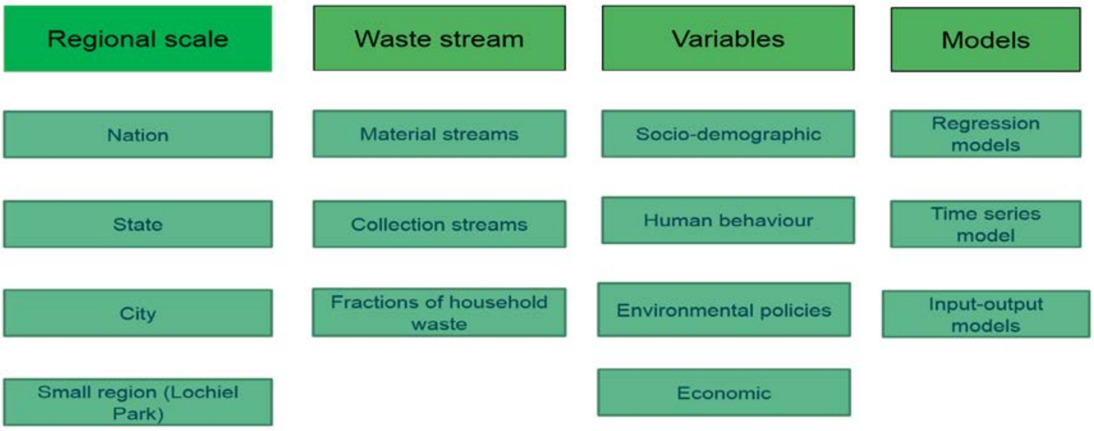


Figure 6.4: A systematic structure of waste management, showing regional scales.

There are two main schools of thought on waste data analysis and forecasting methodology (He He, 2017). The first approach is a 'top-down' method, where waste generation is assumed to be proportional to production in each industry sector, and analysed as part of the material flows. The second approach is a 'bottom-up' forecasting method, where a waste generation rate is established by small physical boundary (such as household), and is then expanded to different regional scales and ultimately to the whole economy. These approaches are described in the following sections .

6.2.1 The 'Top-Down' Method

The top-down approach in this research requires the application of input-output models and regression models at national scale. Methods can analyse how socio-demographic, environmental policies, and economic variables affect waste generation and treatment. Figure 6.5 indicates the designated components of waste management analysis using the top-down method.

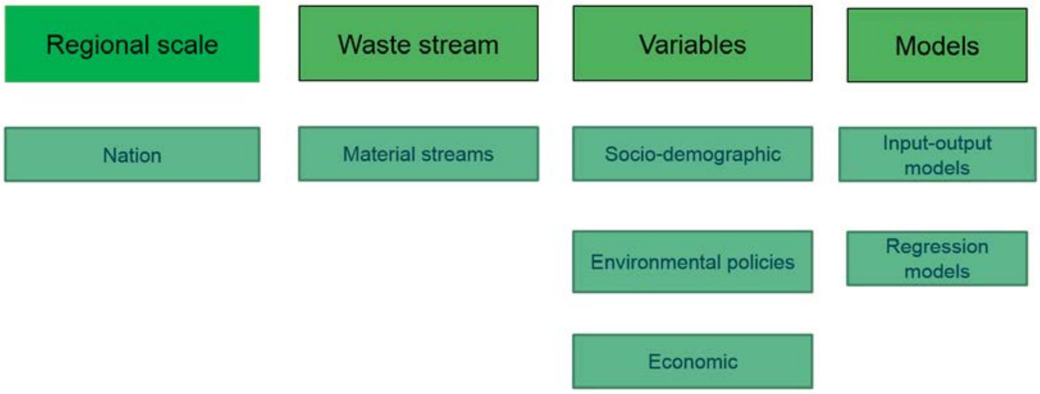


Figure 6.5: Waste Designated components of waste management for top-down method.

For the top-down approach, a larger scale is adopted allowing for more variables to be considered as input-output models and regression models are applied to the forecasting. There are five main research questions when considering the top-down method for forecasting waste generation as indicated in Figure 6.6. Note that there is a two-way interplay between the research questions and the postulated solutions.

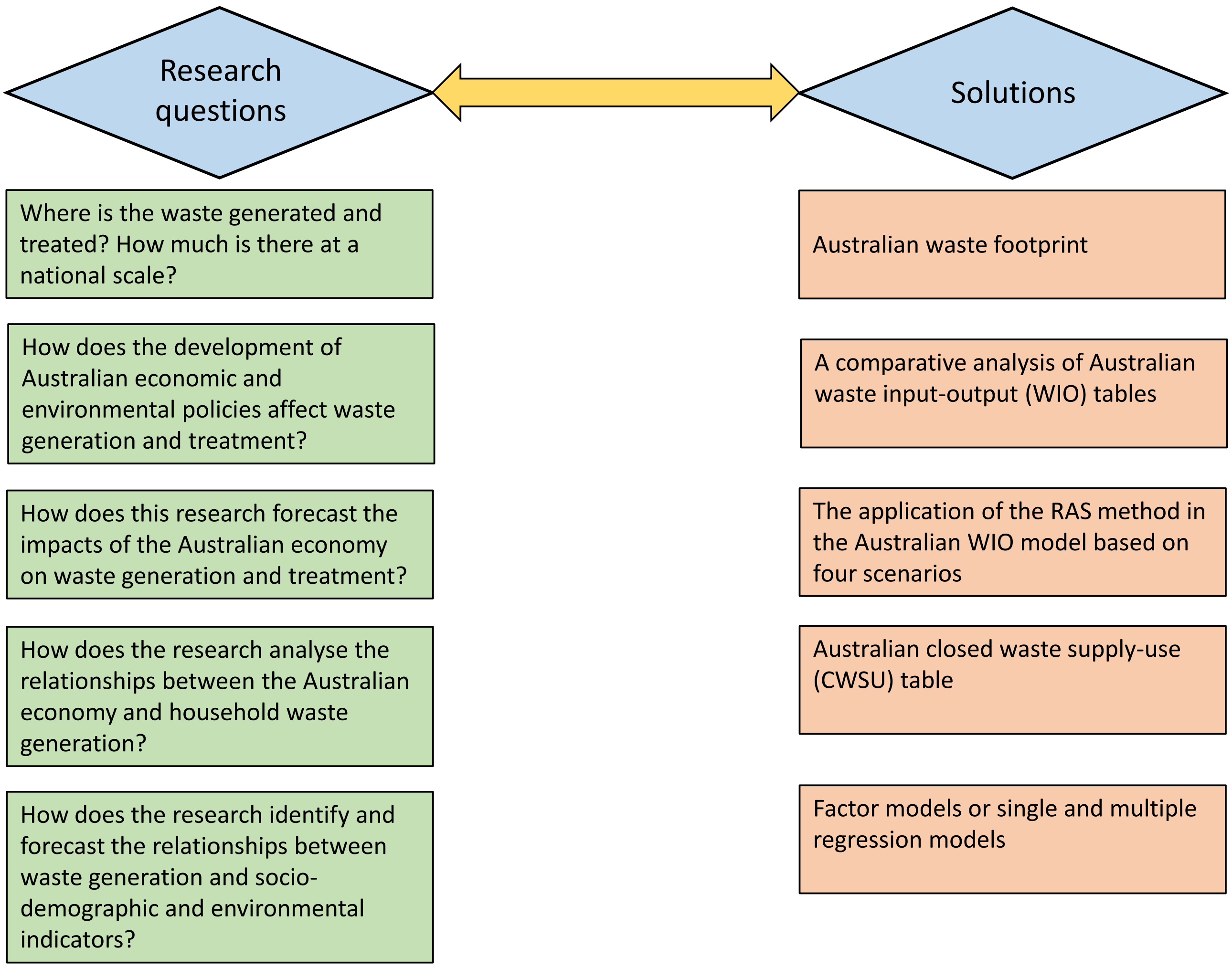


Figure 6.6: Research questions and solutions in the research

Research questions relate to household waste generation at a national scale, considering environmental policies, economic impacts and socio-demographic factors (which include household type and size). Proposed solutions involve the application of waste input-output, closed waste supply-use and other data tables with factor models and regression models developed as required. A range of waste sources or sectors is an important classification process for the analysis and abbreviations for the terms in Table 6.5 apply to the following figures and tables in this section.

Waste source sector	Sector Abbreviation
Agriculture, forestry, and fishing	Ag
Mining	Mi
Manufacturing	Ma
Electricity, gas, and water	EGW
Waste management services	WMS
Construction	Co
Public administration	Pa
All other industry	AOI,
Paper and cardboard	Pap & C
Glass	Gl
Plastics	Pl
Metals	Me
Organics	Org
Masonry	Mas
Electrical and electronic waste	EE
Solid hazardous waste	SH
Leather and textiles	L & T
Tyres and other rubber	T & OR
Timber and wood products	T & Wood
Inseparable/unknown waste	I/U

Table 6.5: Waste source sectors and abbreviations.

The impact of the proposed solutions on research questions was studied by He He (2017). He developed a summary of the Australian waste footprint based on the Australian waste accounts published by ABS and the waste input-output model formulated in his PhD research (as summarised below). The relationships are shown in Figure 6.7 for the Australian waste footprint in 2009-10.

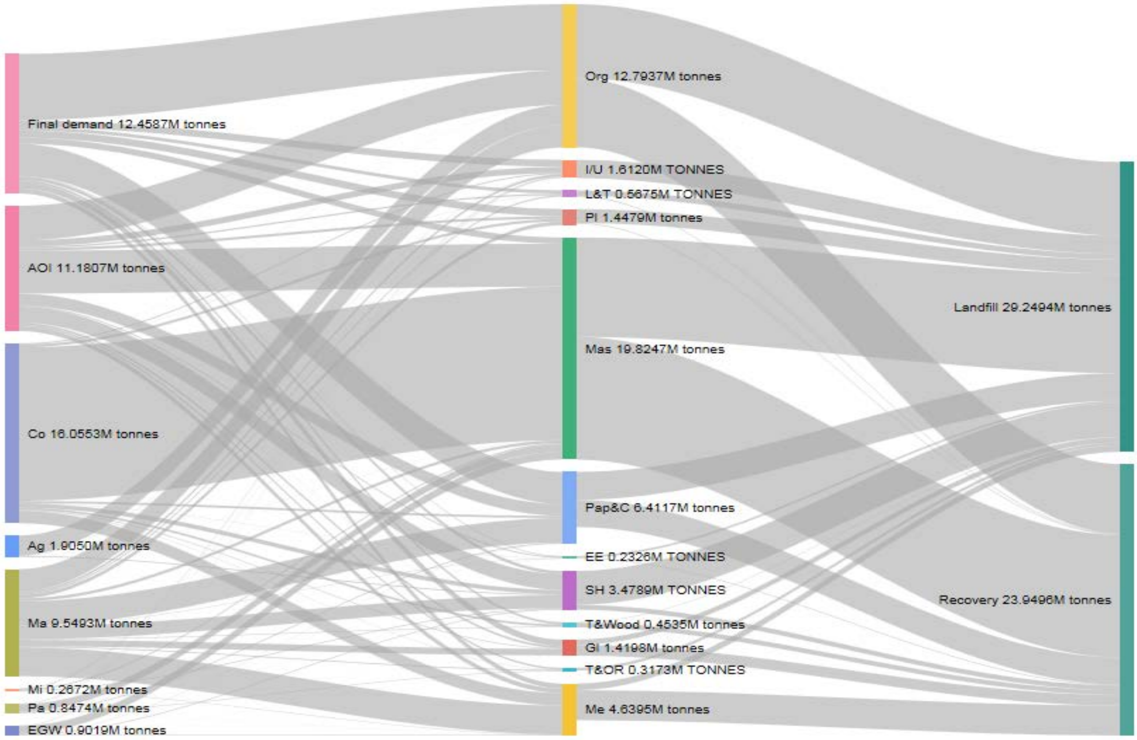


Figure 6.7: Australian waste footprint 2009-2010 (He He 2017)

Figure 6.7 shows waste generation flows from source into the waste types and treatment sector. The majority of waste in terms of weight is recovered masonry. This figure and the data sources to support it (ABS 2016) can tell us about the main contributors to landfill and recovered waste types. A comparative waste footprint for the following year 2010-11 was also developed by He He (2017), and is provided in Figure 6.8.

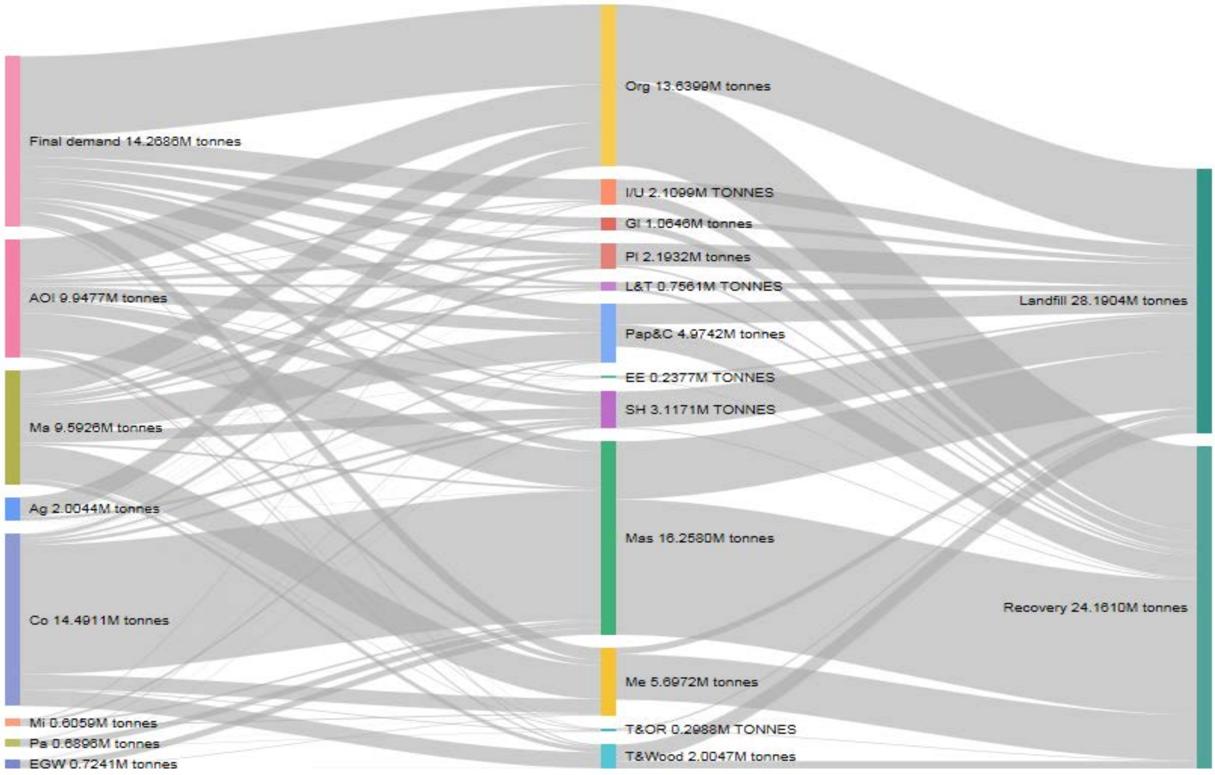


Figure 6.8: Australian waste footprint 2010-2011 (He He 2017)

The waste flow footprint in the 2010-11 year shows a similar illustration of the data for waste flows and types to the previous figure with similar proportions for waste sources, types and treatment methods. A major influences for changes between the two years are the series of environmental policies relating to waste management published in Australia between 2009 and 2011 (Department of Environment 2014, Environment Protection Authority 2015, see also ABS 2016).

In order to assess the impacts of these policies and the development of Australian economy on waste generation and treatment, a comparative analysis of waste input-output (WIO) was conducted at the national level. Table 6.6 provides a structure for this comparison.

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="7">Intermediate sectors</th><th colspan="2">Treatment sectors</th><th>Final demand</th><th rowspan="2">Total output</th></tr>
<tr><th>Ag</th><th>Mi</th><th>Ma</th><th>EGW</th><th>Co</th><th>Pa</th><th>AOI</th><th>Landfill</th><th>Recovery</th><th>Households</th></tr>
<tr><th rowspan="7">Intermediate sectors</th><th>Agriculture, forestry & fishing (Ag)</th><td colspan="7" rowspan="7">$K_{I,I}$</td><td colspan="2" rowspan="7">$K_{I,II}$</td><td rowspan="7">$X_{I,F}$</td><td rowspan="7">X_I</td></tr>
<tr><th>Mining (Mi)</th></tr>
<tr><th>Manufacturing (Ma)</th></tr>
<tr><th>Electricity, gas, and water EGW)</th></tr>
<tr><th>Construction (Co)</th></tr>
<tr><th>Public administration (Pa)</th></tr>
<tr><th>All other industry (AOI)</th></tr>
<tr><th rowspan="2">Treatment sectors</th><th>Landfill</th><td colspan="7" rowspan="2">$SG_{\cdot,I}$</td><td colspan="2" rowspan="2">$SG_{\cdot,II}$</td><td rowspan="2">$SW_{\cdot,F}$</td><td rowspan="2">X_{II}</td></tr>
<tr><th>Recovery</th></tr>
</table>

Table 6.6: Waste Input-Output (WIO) table structure.

In the WIO the intermediate sectors relate to the monetary flow and the treatment sectors relates to the physical flow relating to waste. The analysis uses the notation described in Nakamura and Kondo (2002). The WIO model in balanced form is written as:

$$\begin{pmatrix} K_{I,I} & K_{I,II} \\ SG_{\cdot,I} & SG_{\cdot,II} \end{pmatrix} + \begin{pmatrix} X_{I,F} \\ SW_{\cdot,F} \end{pmatrix} = \begin{pmatrix} x_{I} \\ x_{II} \end{pmatrix} \qquad \text{(Equation 6.1)}$$

where $K_{I,I} \in R^{N^{I} \times N^{I}}$ represents intermediate sectors' matrix for N^{I} goods and service-producing sectors, the components of $K_{I,II} \in R^{N^{I} \times N^{II}}$ means the monetary inputs from per intermediate industry into N^{II} waste treatment sectors, S is an $N^{II} \times N^{w}$ nonnegative matrix for N^{w} waste types, and the s_{ij} in the matrix represent the proportion of waste j treated by waste treatment method i, $G_{\cdot,I}$ is defined as an $N^{w} \times N^{I}$matrix for the category of waste generated by intermediate sector, $G_{\cdot,II}$ represents an $N^{w} \times N^{II}$matrix that the waste is generated by N^{II} waste treatment sectors. A final demand matrix for N^{I} goods and service-producing sectors is defined as $X_{I,F}$ for N^{F}sectors, and $W_{\cdot,F}$ is the waste generated by final demand. $x_{I} \in R^{N^{I} \times 1}$ refers to a gross output vector for N^{I} goods and service-producing sectors, and $x_{II} \in R^{N^{II} \times 1}$ presents the total amount of waste to be treated by N^{II} waste treatment sectors. The coefficient matrix of WIO model can be expressed as:

$$\begin{pmatrix} A_{I,I} & A_{I,II} \\ B_{I,I} & B_{II,II} \end{pmatrix} \begin{pmatrix} x_{I} \\ X_{II} \end{pmatrix} + \begin{pmatrix} X_{I,F} \\ SW_{\cdot,F} \end{pmatrix} = \begin{pmatrix} x_{I} \\ x_{II} \end{pmatrix} \qquad \text{(Equation 6.2)}$$

Where we define input coefficients matrices $A_{I,I} = K_{I,I}\,\widehat{x_{I}}^{-1}$(million \$AUD / million \$AUD), $A_{I,II} = K_{I,II}\,\widehat{x_{II}}^{-1}$(million \$AUD /t), $B_{I,I} = SG_{\cdot,I}\,\widehat{x_{I}}^{-1}$(million \$AUD /\$), and $B_{II,II} = SG_{\cdot,II}\,\widehat{x_{II}}^{-1}$ (t/t), where the "hat" over a vector x denotes a diagonal matrix with the elements of the vector along the main diagonal. For instance, if

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \text{ then } \widehat{X} = \begin{matrix} x_1 & 0 & 0 \\ 0 & x_2 & 0 \\ 0 & 0 & x_3 \end{matrix}. \qquad \text{(Equation 6.3)}$$

The solution for the model described by equations 6.1-6.3, i.e. the total output of the Australian economic and waste data, is given by:

$$\begin{pmatrix} x_{\mathrm{I}} \\ x_{\mathrm{II}} \end{pmatrix} = \left(I - \begin{pmatrix} A_{\mathrm{I},\mathrm{I}} & A_{\mathrm{I},\mathrm{II}} \\ B_{\mathrm{I},\mathrm{I}} & B_{\mathrm{II},\mathrm{II}} \end{pmatrix} \right)^{-1} \begin{pmatrix} X_{\mathrm{I},F} \\ SW_{\cdot,F} \end{pmatrix} \qquad \text{(Equation 6.4)}$$

The direct, total, and the change of direct and total effects of intermediate sectors on waste treatment method for Landfill are then shown in Table 6.7.

Landfill						
Sector	**Direct effects**		**Differences of direct effects**	**Total effects**		**Differences of total effects**
	2009–2010	2010–2011		2009–2010	2010–2011	
Ag	0.0226	0.0253	0.0027	0.0608	0.0628	0.0020
Mi	0.0023	0.0047	0.0024	0.0681	0.0677	-0.0004
Ma	0.0116	0.0118	0.0002	0.0442	0.0421	-0.0021
EGW	0.0087	0.0053	-0.0034	0.0641	0.0461	-0.018
Co	0.0686	0.0527	-0.0159	0.3383	0.3025	-0.0358
Pa	0.0291	0.0185	-0.0106	0.2957	0.2388	-0.0569
AOI	0.0058	0.0048	-0.0010	0.0295	0.0252	-0.0043

Note: units are 1000 tonnes per million $AUD of output for intermediate sectors

Table 6.7: Direct, total, and the change of direct and total effects of intermediate sectors on waste treatment method: Landfill

Table 6.7 indicates that between 2009-10 and 2010- waste production decreased in all sectors apart from the Agricultural (Ag) sector. This shows that policies are achieving their overall aims.

Direct, total, and the change of direct and total effects of intermediate sectors on waste treatment method for Recovery are shown in Table 6.8. The direct effect of an intermediate sector means that the total output of the sector directly causes the effect on other intermediate sectors. Total effects are direct effects plus the secondary (indirect and induced) effects (Miller and Blair 2009).

Recovery						
Sector	**Direct effects**		**Differences of direct effects**	**Total effects**		**Differences of total effects**
	2009–2010	2010–2011		2009–2010	2010–2011	
Ag	0.0144	0.013	-0.0014	0.0463	0.0454	-0.0009
Mi	0.0011	0.0029	0.0018	0.0598	0.0656	0.0058
Ma	0.0122	0.0117	-0.0005	0.0406	0.0397	-0.0009
EGW	0.007	0.0061	-0.0009	0.0567	0.0476	-0.0091
Co	0.0657	0.0599	-0.0058	0.3125	0.3183	0.0058
Pa	0.0227	0.0211	-0.0016	0.2599	0.2421	-0.0178
AOI	0.0037	0.0034	-0.0003	0.0242	0.0231	-0.0011

Note: units are 1000 tonnes per million $AUD of output for intermediate sectors.

Table 6.8: Direct, total, and the change of direct and total effects of intermediate sectors on waste treatment method: Recovery

6.2.1.1 Forecasting of WIO

Forecasting of WIO is achieved through the application of the RAS method (e.g. Bacharah 1965), a 'biproportional' matrix balancing technique,

$$Q = \hat{r} A \hat{s} \qquad \text{(Equation 6.5)}$$

Here, ***r*** refers to a diagonal matrix of elements modifying rows, the ***A*** to the coefficient matrix being modified, and ***S*** to a diagonal matrix of column modifiers. The RAS method (e.g. see Bacharach 1965 and Miller and Blair 2009) is used to forecast a new coefficient matrix of a target-year according to a coefficient matrix of the base-year in the Input-Output (IO) model and three pieces of information including total gross output, total inter-industry sales, and total inter-industry purchase (Miller and Blair 2009). Figures D.8 and D.9 depict the application of the RAS method to the WIO datasets available.

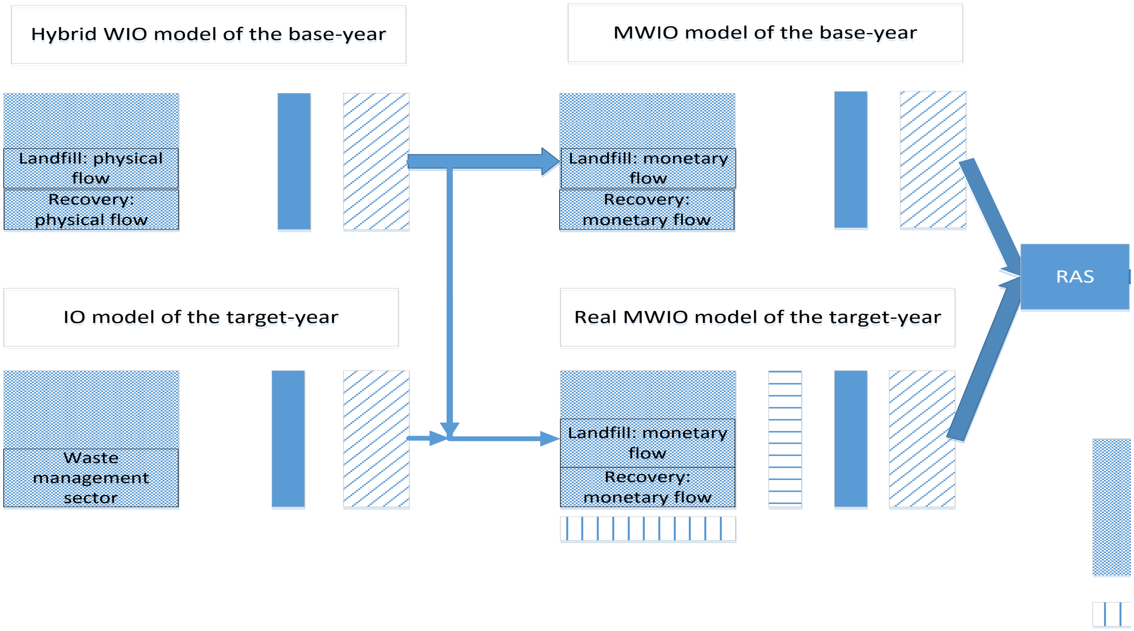


Figure 6.9: Process of the forecasting experiment: Hybrid and Real Input-Output models.

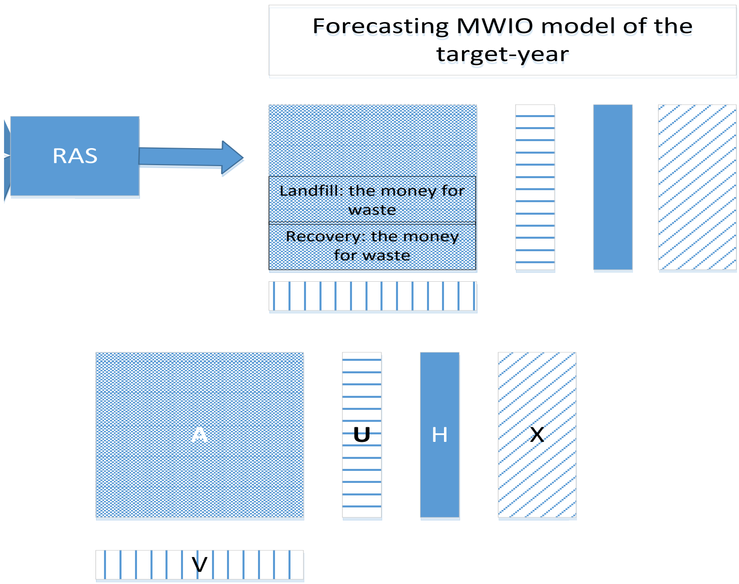


Figure 6.10: Process of the forecasting experiment: Forecasting Input-Output models.

In Figure 6.9 and Figure 6.10 u, v and X are the total inter-industry sales, the total inter-industry purchase, and the total gross output of the target-year, respectively. The input coefficient matrix of the base-year is not only considered as the '*A*' in the RAS procedure, but also used for the calculation of u, v, and X of the target-year. Recall that the same unit in the matrix is essential for the calculation of the RAS method. However, the WIO table developed by Nakamura and Kondo (2002) is a hybrid model with monetary flows of intermediate sectors and physical flows of waste treatment methods (i.e. the WIO table not only includes economic data but also waste data, and thus is designated as an hybrid WIO table). Therefore, it is necessary to transfer the hybrid WIO table into the MWIO table of the base-year. In order to obtain the u,

v, and X of the target-year, the input-output table (IOT) of the target-year is transferred into the table with two waste treatment methods according to the information of the base-year.

In the process of forecasting, individual panels in Figure 6.10 display the households demand (H), the total inter-industry sales (U), total inter-industry purchase (V), the input coefficient matrix (A) and the total output (X) in a schematic form, as labelled in the bottom right of Figure 6.10. In Figure 6.10, the study first obtains the MWIO table of the base-year by splitting the monetary flow of the waste management services sector into two waste treatment method sectors according to the weight of physical flow of waste disposed by two waste treatment methods. The base-year input coefficient matrix A is derived from the MWIO table, as indicated in Figure 6.9. Second, the weight of physical flow of waste is used to transfer the IO model of the target-year into the real MWIO model of the target year. As a result of this step, the values of u, v, and X of the target-year are calculated from the real MWIO model of the target year. Finally, the base-year input coefficient matrix A as well as the u, v, and X of the target-year are put into the RAS method to forecast the MWIO model of the target-year.

The definition of four scenarios is to assess the effects of input coefficient matrix and the weight of physical flows for the Landfill sector and recovery sector in different years on the forecasting accuracy. The forecasting experiment is applied to four scenarios in this research:

1) Scenario I is that the input coefficient matrix of base-year is 2009–10 and the real MWIO of 2012–10 is calculated based on the weight of physical flows for the Landfill sector and recovery sector in 2009–10.
2) Scenario II is that the input coefficient matrix of base-year is 2010–11 and the real MWIO of 2012–10 is calculated based on the weight of physical flows for the Landfill sector and recovery sector in 2010–11.
3) Scenario III is that the input coefficient matrix of base-year is 2009–10 and the real MWIO of 2012–10 is calculated based on the weight of physical flows for the Landfill sector and recovery sector in 2010–11.
4) Scenario III is that the input coefficient matrix of base-year is 2010–11 and the real MWIO of 2012–10 is calculated based on the weight of physical flows for the Landfill sector and recovery sector in 2009–10.

The projections of input coefficient matrix of MWIO in 2012-13 are compared with the real MWIO coefficient matrix[2] in 2012-13 by the Mean Absolute Difference (*MAD*) method introduced by Miller and Blair (2009):

(1) *MAD* measures the average amount by which an estimated coefficient differs from the target-year coefficient as:

$$MAD = (1/n^2) \sum_{i=1}^{n} \sum_{j=1}^{n} \left| q_{ij} - b_{ij} \right| \qquad \text{(Equation 6.6)}$$

The *MAD* values for the four scenarios are shown in Table 6.9. All values of *MAD* are smaller than 30%, and imply that the RAS method can be used in the WIO model because the accepted forecasting accuracy in the field of waste generation is ‘‘±30 % accuracy’’ (Reynolds, Geschke et al. 2015). The largest value of *MAD* of the four scenarios is from Scenario III (15.4%), followed by Scenario I (14.8%), Scenario II (10.9%), and Scenario IV (10.0%). This reveals that when the input coefficient matrix of the base-year is closer to that of the target-year, the forecasting accuracy of WIO model will be higher.

[2] The real MWIO matrix was derived from the ABS database, see He He (2017).

Scenario	MAD (%)
I	14.78
II	10.85
III	15.35
IV	9.95

Table 6.9: The values of *MAD* for the four scenarios.

6.2.1.2 Australian closed waste supply-use model

A novel extension of Lenzen and Reynolds's waste supply-use tables (WSUT) framework (Lenzen & Reynolds 2014) was proposed by He He (2017). This involved moving the column of the Household sector from the Final demand and adding the row of the Income into the Intermediate sectors to illustrate the direct, indirect, and total impacts of the Household sector as an intermediate sector in the economic and waste system (Miller and Blair 2009). This allows for the explicit inclusion of households in the input-output analysis and thus provides a first step for consideration of domestic (household) waste generation in the equations. An aggregate estimation of household waste generation is then possible, which opens the door to the estimation of household waste (by waste type) at the precinct level. This new model is called the closed waste supply-use (CWSU) model, while the CWSUT is the set of tables resulting from the model. He He (2017) describes in full the development of the new model and tables.

The CWSU model can identify the relationships between the national economic account and the amount and composition of household waste (HW) generation and treatment provided that the household is an endogenous component of waste generation in the CWSU framework. This can be accomplished by assuming (1) that the state of the national economy is important in determining national levels of household income, (2) that this in turn will be spent to a large extent in the domestic economy therefore influencing the level of national consumption, and (3) that this will then influence the amount of HW generation. The CWSU model and the CWSUT provide this analysis by incorporating the column of the household and the row of the household income to the WSUT model. In addition, the Import sector and the Export sector are considered as a column and a row treating the waste to balance the waste account in the IO table, respectively.

This innovative model shows how waste generation and treatment are affected by industry sectors and household consumption with inclusions as identified in Table 6.10.

		Intermediate demand sectors		**Waste treatment sectors**		**Waste types**	**Final demand**	**Gross output**
		1…..N_1	Households	1…..N_2	Import	1…..N_3	1…..N_F	
Intermediate supply sectors	1…..N_1	T_{11} ($)	T_{12} ($)	T_{13} ($)			f ($)	x_1 ($)
	Income 1	T_{21} ($)		T_{23} ($)				x_2 ($)
Waste treatment sectors	1…..N_2					W_{35} (kt)		x_3 (kt)
	Export 1					W_{45} (kt)		x_4 (kt)
Waste types	1…..N_3	W_{51} (kt)	W_{52} (kt)	W_{53} (kt)	W_{54} (kt)		W_f (kt)	x_5 (kt)

Table 6.10: Australian closed waste supply-use, including explicit identification of households as waste generators

Using this approach, the Australian aggregated CWSU transaction estimates for the households in two years (2009-10 and 2010-11) were calculated (He He 2017), and are provided in Table 6.11.

Year		Intermediate sectors (units: million $AUD)											
		Ag	Mi	Ma	EGW	Co	Pa	AOI					
2009–2010	**Households**	**6424.46**	**2079.76**	**113657.15**	**16635.05**	**14.56**	**1942.39**	**501193.09**					
2010–2011	**Households**	**6881.90**	**2237.29**	**114475.48**	**18530.26**	**17.60**	**1997.32**	**513171.18**					
Year		**Waste types (units: kilotonnes)**											
		Pap & C	Gl	Pl	Me	Org	Mas	EE	SH	L & T	T & OR	T & Wood	I/U
2009–2010	**Households**	**2871.72**	**586.07**	**648.81**	**439.55**	**5904.62**	**556.76**	**70.88**	**278.26**	**292.91**	**0**	**190.39**	**618.68**
2010–2011	**Households**	**1357.63**	**798.95**	**967.8**	**1049.55**	**6740.98**	**844.65**	**72.42**	**293.34**	**299.24**	**28.01**	**113.5**	**1702.57**

Table 6.11: Aggregated CWSU transaction estimates for Australian households: intermediate sectors and waste types

The previous tables (Table 6.10 and Table 6.11) translate to Australian aggregated input coefficient matrix estimates of the CWSU for households in the two financial years 2009-10 and 2010-11, as given in Table 6.12.

Year		Intermediate sectors (units: million $AUD per million $AUD of output for the households)											
		Ag	Mi	Ma	EGW	Co	Pa	AOI					
2009–2010	**Households**	**0.0117**	**0.0038**	**0.2073**	**0.0303**	**0.0000**	**0.0035**	**0.9143**					
2010–2011	**Households**	**0.0119**	**0.0039**	**0.1980**	**0.0321**	**0.0000**	**0.0035**	**0.8877**					
Year		**Waste types (units: tonnes per million $AUD of output for the households)**											
		Pap & C	Gl	Pl	Me	Org	Mas	EE	SH	L & T	T & OR	T & Wood	I/U
2009–2010	**Households**	**5.2387**	**1.0691**	**1.1836**	**0.8018**	**10.7714**	**1.0157**	**0.1293**	**0.5076**	**0.5343**	**0.0000**	**0.3473**	**1.1286**
2010–2011	**Households**	**2.3485**	**1.3821**	**1.6741**	**1.8155**	**11.6608**	**1.4611**	**0.1253**	**0.5074**	**0.5176**	**0.0484**	**0.1963**	**2.9452**

Table 6.12: Aggregated CWSU input coefficient estimates for Australian households: intermediate sectors and waste types

The Australian aggregated total waste generation multiplier estimates of the CWSU for the households in the two financial years are estimated as shown in Table 6.13, including waste treatment methods.

Year	Intermediate sectors (units: million $AUD per million $AUD of output for the household)								Waste treatment methods (units: tonnes per million $AUD of output for the household)			
	Agri-culture	Mining	Manufac-turing	Electricty, Gas & Water	Const-ruction	Public Admin-istration	All Other Industry	Income	Landfill	Recovery	Export	
2009-2010	0.2374	0.2978	2.0716	0.3083	0.5554	0.0848	6.5621	3.5461	**134.00**	123.62	18.54	
2010-2011	0.2114	0.2772	1.8611	0.3051	0.5189	0.0795	6.0519	3.3806	**103.17**	123.90	16.41	
	Waste types (units: tonnes per million $AUD of output for the household)											
Year	Paper & Cardboard	Glass	Plastics	Metals	Organic	Masonry	Electrical & Electronic waste	Solid Hazardous waste	Leather & Textiles	Tyres & Other Rubber	Timber & Wood Products	Inseparabl e/ Unknown wastes
2009-2010	**35.11**	7.60	8.00	24.28	**70.49**	**96.14**	1.26	17.11	3.22	1.59	2.50	8.85
2010-2011	**22.91**	5.77	10.80	27.21	**67.96**	**69.71**	1.15	13.07	3.71	1.32	8.39	11.48

Table 6.13: Aggregated total waste generation multipliers for Australian households: intermediate sectors and waste types, highlighting the main waste treatment method and the main waste types

From Table 6.13 we can note a resultant reduction in the total household waste volumes directed to landfill sites, largely the result of reductions in paper, organic and masonry type wastes.

6.2.1.3 Regression models for waste management

Regression models for forecasting of household waste generation at the national level were estimated based on a number of explanatory variables. The available explanatory variables included socio-demographic indicators and environmental indicators. The socio-demographic indicators that were considered included:

- Gross Value Added GVA (million $AUD)
- Household income per week ($AUD)
- Number of employed persons
- Total number of persons in the household.

Previous research has suggested that a number of socio-demographic factors can play important roles in waste generation (Beigl et al 2004, Benitez et al 2008). The following environmental indicators were thus included in the regression analysis were:

- Greenhouse gas (GT)
- Water consumption (GL)
- Energy consumption (PJ)
- Kilometres for all vehicles
- Environmental taxes paid by industry and households.

The regression analysis suggested that socio-demographic variables were the most useful in estimating household waste generation, and the specific variables of most importance were found to be weekly household income and gross value added. Figure 6.11 shows the relationship between household income and waste generation. The multiple regression equation based household income and gross value added is given as equation 6.7.

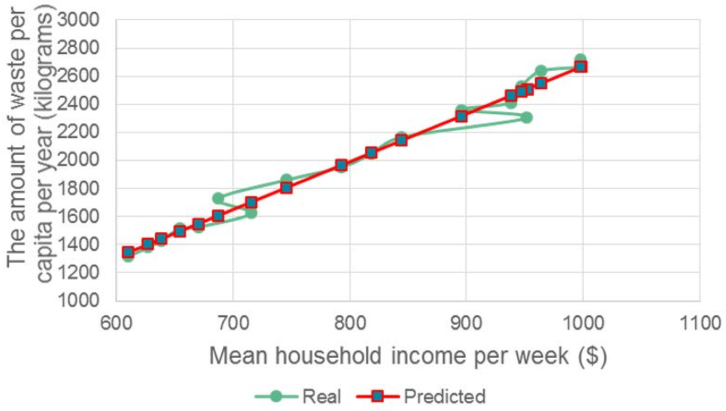


Figure 6.11: Single regression model outcomes – weekly household income and per capita waste generation

The resulting multiple regression equation based on the socio-demographic indicators gross value added and household income is as follows:

$$Y = -832.6180 + 0.0021 * x_1 + 0.9214 * x_2 \qquad \text{(Equation 6.7)}$$

where Y represents the estimated amount of annual waste per capita, x_1 is the gross value added and x_2 is the mean household income per week.

When considering environmental indicators, greenhouse gas emissions and energy consumption relationships are illustrated in Figure 6.12. These plots indicate that these two environmental indicators are correlated to household waste generation, but the relationships are less useful than those of the socio-demographic indicators.

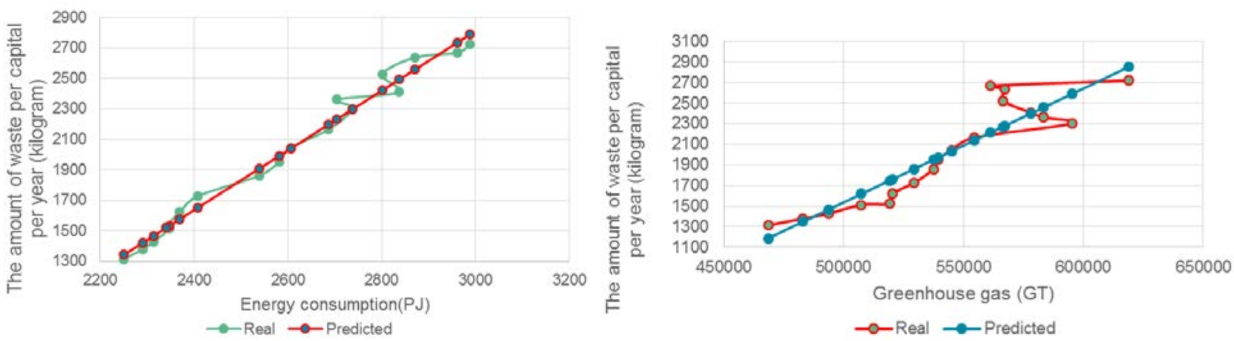


Figure 6.12: Single regression model outcomes - environmental indicators of energy consumption and greenhouse gas.

6.2.2 The 'Bottom-Up' Method

The 'bottom-up' method aims at exploring how human behaviour and socio-demographic variables affect household waste (HW) generation and the seasonal variation of HW over the months of a year. This approach is best suited to small area (precinct level) analysis. A bottom-up approach is adopted here for estimation purposes with components of this research suggested in Figure 6.13.

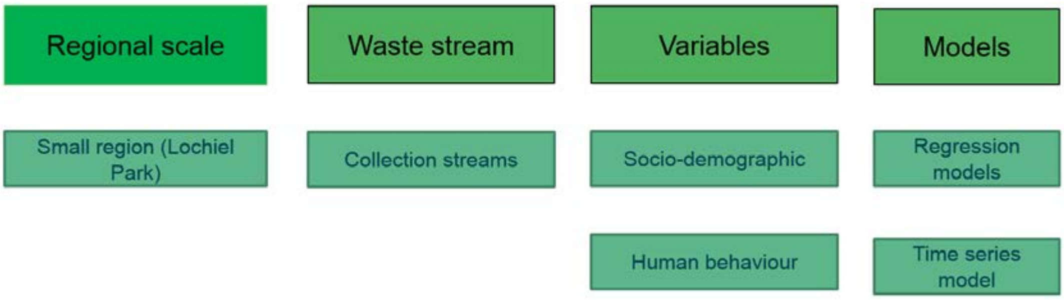


Figure 6.13: Designated components of waste management for bottom-up method.

In this research project, the development of the waste domain research approach considered Adelaide's Lochiel Park precinct, an urban residential development located approximately 7km north east of Adelaide's CBD, containing approximately 106 households (Land Management Corporation, South Australian Government 2008) and depicted in Figure 6.14.

Figure 6.14: Lochiel Park Green Village in South Australia (looking north)

The precinct contains households of various sizes, with varying population types representing a range of waste production levels. Lochiel Park is also an operational 'living laboratory' for the Low Carbon Living CRC (Berry and Davidson, 2015) from which demand and other survey datasets are compiled. The Adelaide Living Laboratory venture is an action based research project drawing evidence from three key Adelaide development sites at Tonsley, Lochiel Park and Bowden. Each of these sites has been established to meet specific government policy objects, is physically created by the local building and construction industry and includes detailed household monitoring processes. The Living Laboratory project utilises the expertise and skills of community, industry and university participants to undertake site-specific research to build a stronger evidence base supporting government policy and planning, and industry delivery.

Lochiel Park is one of the two case study sites used in the full project, and this application of the integrated model is described in Section 9. The modelling and analysis of waste generation for the precinct included behavioural and socio-demographic variables, and the project also sought to make a comparison with a conventional suburban area[3]. Regression and time series models were applied. This process involved research and model development using the following steps:

1. Analysis of impacts of human behaviours on sustainable waste management (Reuse, Recycling, Reduce, and Avoid)
2. Exploration of the effects of human behaviours and socio-demographic indicators on household waste generation (regression models)
3. Examination of seasonal variations in household waste in Lochiel Park (Time series models).

The survey in Lochiel Park had two parts:

1. A questionnaire survey distributed to all 106 households in the precinct. The questionnaire form is reproduced as Appendix C: Waste Behaviour and Attitudes Questionnaire. Usable responses were obtained from 28 households
2. Of the responding households, eight agreed to have their rubbish bins weighed each week for a period of 14 weeks (December 2015 – March 2016). The three bin Kerbside Waste Collection service at Lochiel Park indicates the functions of the different bins: the blue bin for general waste, the yellow bin for recyclables, and the green bin for green organics (Campbelltown City Council 2017a).

The questionnaire included information on the socio-demographic characteristics of the households, their waste generation and waste management behaviour, and their attitudes to environmental issues. Consideration of the Mosaic data for Lochiel Park indicated that the precinct contained only three Mosaic household types (D16, C13 and B05) and was dominated by Mosaic type D16 households (60 of 106) – see Table 3.1 for descriptions of these household types. The survey responses correspond with this household type breakdown.

In terms of behaviour for waste management (reduce, reuse, recycle), the following questions from the questionnaire (Appendix C: Waste Behaviour and Attitudes Questionnaire.) were of primary importance:

1. For *reduction*, Q21 – how often do you:
    a. Buy products with minimum packaging
    b. Use own shopping bag rather than one provided by the shop
    c. Seek packaging capable of easy reuse or recycling
    d. Buy fruit and vegetables without packaging
    e. Buy products with minimum packaging
2. For *reuse*, Q22 – how often do you:
    a. Try repairing items before purchasing new ones
    b. Reuse paper
    c. Reuse glass bottles and jars
    d. Wash and reuse dishcloths rather than purchase new
    e. Reuse old plastic containers (e.g. margarine tubs)
3. For recycling, Q23 – how often do you recycle the following:
    a. Glass
    b. Paper/magazines/newspapers
    c. Plastic goods
    d. Textiles
    e. Foil
    f. Metal goods
    g. Books/DVDs/CDs.

The survey results for these questions are shown in Figure 6.15. Figure 6.15(a) indicates the responses for waste reduction behaviour, Figure 6.15(b) indicates the responses for reuse, and Figure 6.15(c) indicates the responses for recycling.

The results suggest that Lochiel Park residents are strongly committed to waste reduction, reuse and recycling behaviours. For instance, Figure 6.15(c) indicates that at least 60 per cent of respondents ‘always’ or ‘often’ recycled all of the listed items, while the only items with any ‘never’ responses were foil (21 per cent ‘never’) and books/DVDs/CDs (14 per cent ‘never’ – which could perhaps imply that these items were retained). In terms of reuse (Figure 6.15(b)), more than 80 per cent of respondents ‘always’, ‘often’ or ‘sometimes’ reused all of the listed items. Indeed 68 per cent or more of the

[3] The original plan for the PhD research on waste management in the research project was to conduct surveys of waste disposal behaviour and attitudes in Lochiel Park and in another suburban area, for purposes of comparison. The survey in Lochiel Park was conducted successfully, and results of that survey are presented here. A pilot survey was also conducted in the City of Marion, a municipality in the southern suburbs of Adelaide. For reasons beyond the control of the research project team and especially the PhD candidate, it proved impossible to undertake a full survey in that area and thus a comparison was not possible. As can be seen from the results obtained in Lochiel Park, the residents of that precinct were strongly aware of and concerned about environmental issues, and were strongly committed to waste reduction, reuse and recycling and to waste avoidance. How representative they were of the rest of the community outside their precinct (e.g. in metropolitan Adelaide, the state of South Australia and Australia in general) is still to be determined, and should be the subject of future research.

respondents ‘always’ or ‘often’ reused the items (with the exception of old plastic containers, where 43 per cent of respondents ‘always’ or ‘often’ reused these, and 39 per cent ‘sometimes’ did so).

Reduction behaviour was also markedly strong, see Figure 6.15(a). At least 78 per cent of respondents ‘always’, ‘often’ or ‘sometimes’ sought to reduce consumption of all of the listed items, and all respondents ‘always’ or ‘often’ bought fruit and vegetables without packaging, and used their own shopping bags. In the latter case, the fact that South Australia brought in legislation banning the use of lightweight shopping bags in 2009 probably has a major bearing on this observed behaviour (it is an expected result). The only reduction item that yielded any ‘never’ responses was that of seeking packaging capable of easy reuse or recycling, with seven per cent of respondents. Sixty per cent of respondents ‘always’ or ‘often’ sought to buy products with minimum packaging, 36 per cent did so ‘sometimes’, and the remaining four per cent did so ‘rarely’. The choice of reusable products over disposable ones was made ‘always’ or ‘often’ by 75 per cent of respondents – the remainder did so ‘sometimes’.

These behaviours are indicative of a precinct community striving to manage its waste in ways that assist sustainability. Lochiel Park has to be seen as a different community, with its built environment constructed on the principles of energy efficiency and environmental sustainability. The dominant Mosaic resident household type, D16, is basically reasonably affluent retired couples. Thus the survey results are perhaps in line with expectations. This point is further reinforced by the responses to attitudinal questions in the Lochiel Park household survey.

Question 25 (see Appendix C) sought opinions on different methods for avoiding the creation of household waste, and put forward the following methods:

a) Avoid buying items that you would never use
b) Sell/rent/borrow items that are rarely used
c) Donate rarely or never used items to relatives or other people
d) Manage or store food properly
e) Share and redistribute used products through collaborative consumption.

Respondents were asked if they ‘strongly agreed’, ‘agreed’, were ‘neutral’, ‘disagreed’ or ‘strongly disagreed’ with each of these methods. The results are shown in Figure 6.16, and are striking. Three of the five methods ((a), (c) and (d) above) received unanimous agreement, with ‘strongly agree’ representing more than 50 per cent of respondents. Only method (e) received any negative response, with four per cent (one household) responding ‘disagree’ to this method.

Attitudes on more general environmental issues were tested by Question 15 (see Section 15), which asked respondents to indicate how seriously they regarded the following:

a) Global warming
b) Ozone layer depletion
c) Desertification
d) Water pollution
e) Pollution from general waste.

Figure 6.17 indicates the expressed attitudes on these issues. The large majority of responses (over 90 per cent for each issue) indicated that respondents were concerned about the issues, and all other responses were ‘neutral’. There were no responses citing the issues as unimportant.

These attitudinal responses confirm the strong pro-environment focus of the residents of Lochiel Park.

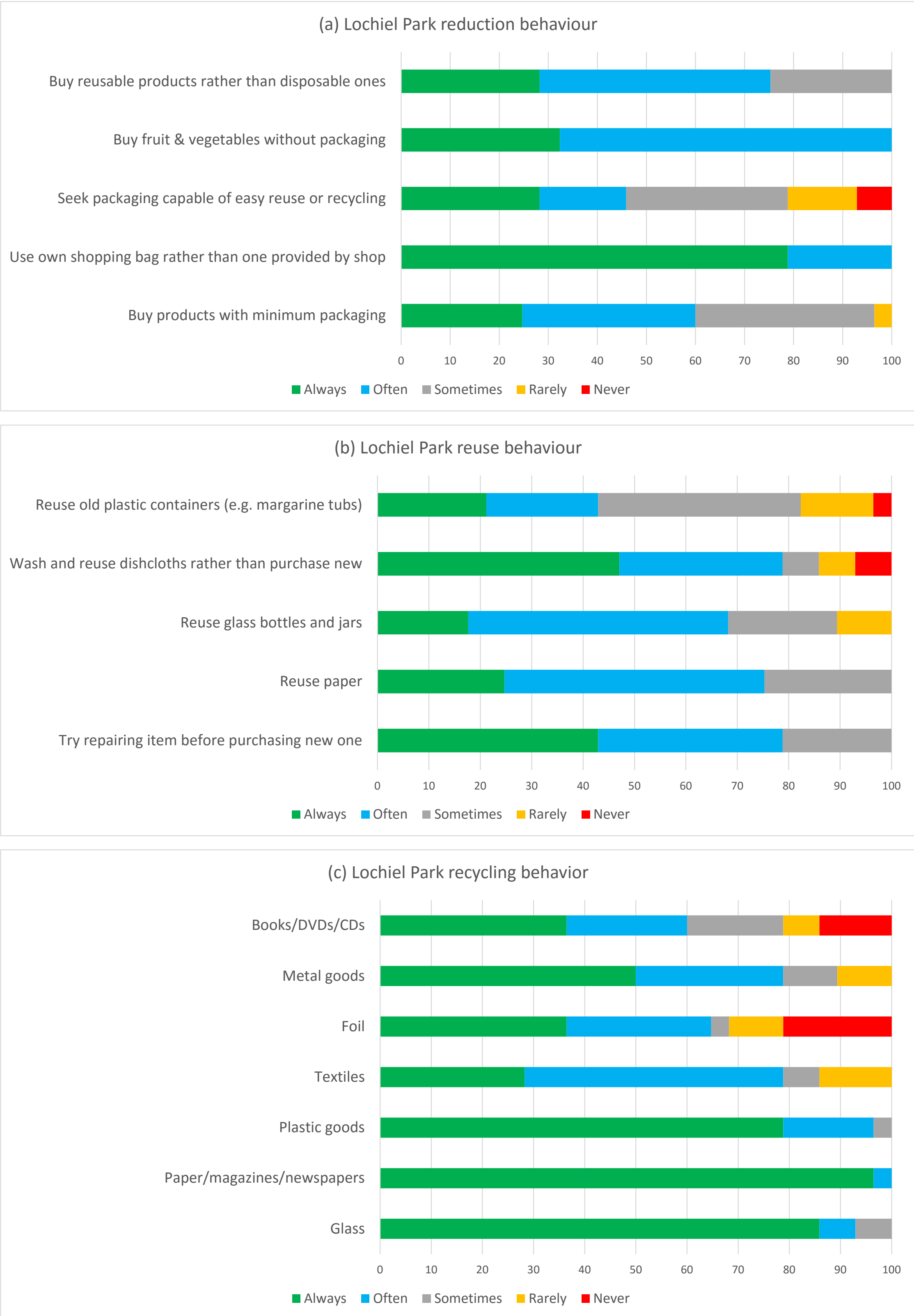


Figure 6.15: Lochiel Park reported waste management behaviour for (a) reduction, (b) reuse, and (c) recycling, using Lochiel Park survey data collected for the ETWW project

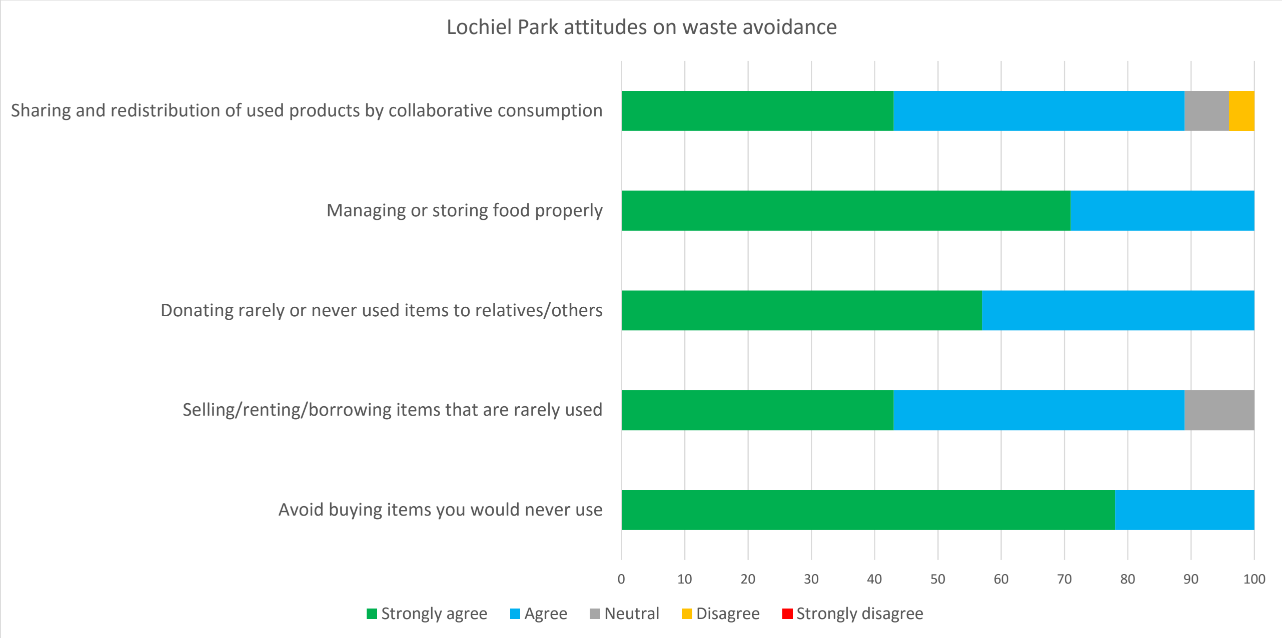


Figure 6.16: Reported waste management attitudes for avoidance of household waste generation, Question 25 from Lochiel Park survey

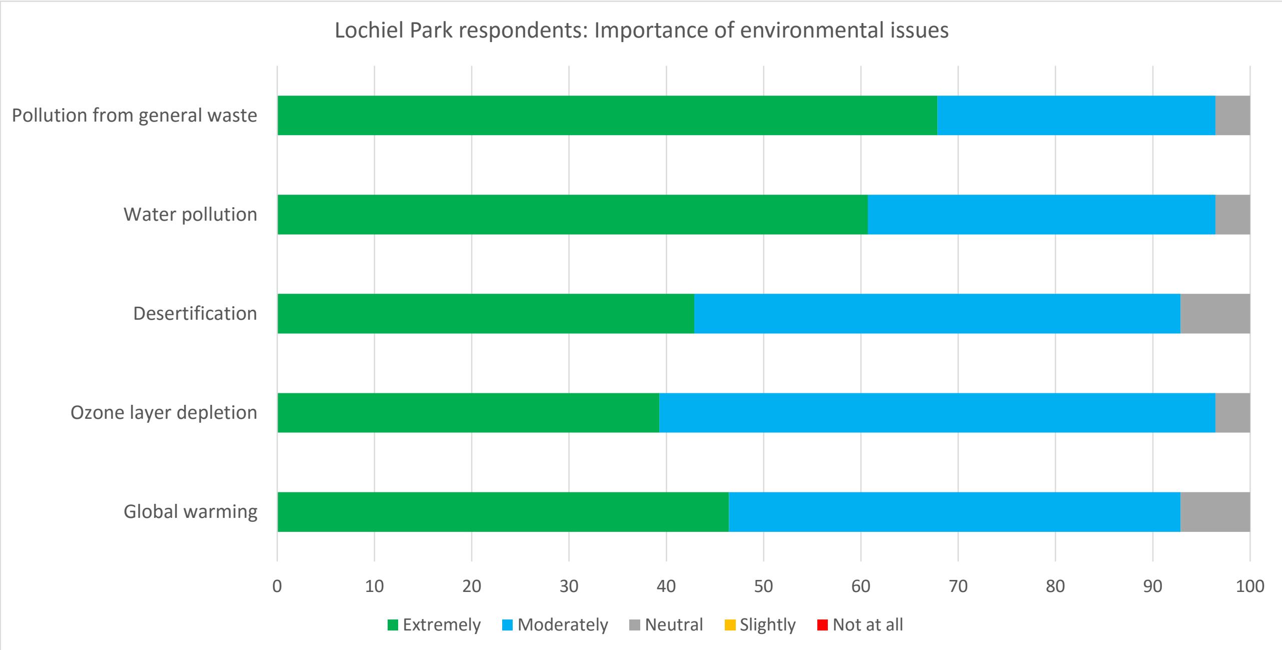


Figure 6.17: Attitudes of Lochiel Park residents to broad environmental issues, Question 15 from Lochiel Park survey

The second part of the Lochiel Park waste study involved the weighing of the waste bins of the eight households who had agreed to this. The weighing was conducted for 14 consecutive weeks, in the period December 2015 to March 2016. Summary results from this experiment are shown in Table 6.14. The table shows the average weekly waste generation for general (landfill) waste and recyclable wastes for each of the participating households, and the total waste generated, for each household and per capita.

Hhld	Mosiac code	Persons /hhld	Weight of general waste (kg/week/ hhld)	Per capita general waste (kg/week pc)	Weight of recyclable waste (kg/week/ hhld)	Per capita recyclable waste (kg/week pc)	Total waste (kg/week/ hhld)	Per capita total waste (kg/week pc)	Net floor area of dwelling (m^2)
1	B05	2	3.83	1.92	7.85	3.93	11.68	5.84	232
2	D16	2	2.97	1.49	7.63	3.82	10.60	5.30	220
3	D16	2	9.04	4.52	5.43	2.72	14.47	7.24	220
4	D16	2	6.06	3.03	18.39	9.20	24.45	12.23	204
5	D16	2	2.74	1.37	5.14	2.57	7.88	3.94	200
6	D16	2	5.92	2.96	8.54	4.27	14.46	7.23	340
7	D16	4	4.82	1.21	7.12	1.78	11.94	2.99	210
8	D16	2	8.01	4.01	7.71	3.86	15.72	7.86	320
		Average	***5.42***	***2.56***	***8.48***	***4.02***	***13.90***	***6.58***	
		Average of D16 hhlds	***5.65***	***2.65***	***8.57***	***4.03***	***14.22***	***6.68***	

Table 6.14: Average weekly weights of waste generated by surveyed households in Lochiel Park, December 2015 – March 2016 (from He He 2017)

These results are summarised in Figure 6.18, which provides a visual comparison of household and per capita waste generation by the individual households. Recyclable wastes (by weight) tend to exceed general waste both for households and per person. The recyclables include recyclable products and packages, and garden waste. These are collected on alternate weeks. Garden waste is by nature likely to be of higher mass density than other wastes. Six of the eight households generated more recyclable waste than general waste, and one household generated 2.5 times more recyclable waste than all of the others. There was no statistically significant difference between the sole B05 type household and the seven D16 households. Per capita waste generation showed the same pattern, but given that seven of the eight households had the same number (two) of members, this is expected – household no 7 had four members (two adults and two children), and in terms of its per capita waste generation it was ranked lowest of the eight, while it was the fourth lowest in terms of total waste generation, and thus ‘within range’ compared to its neighbours.

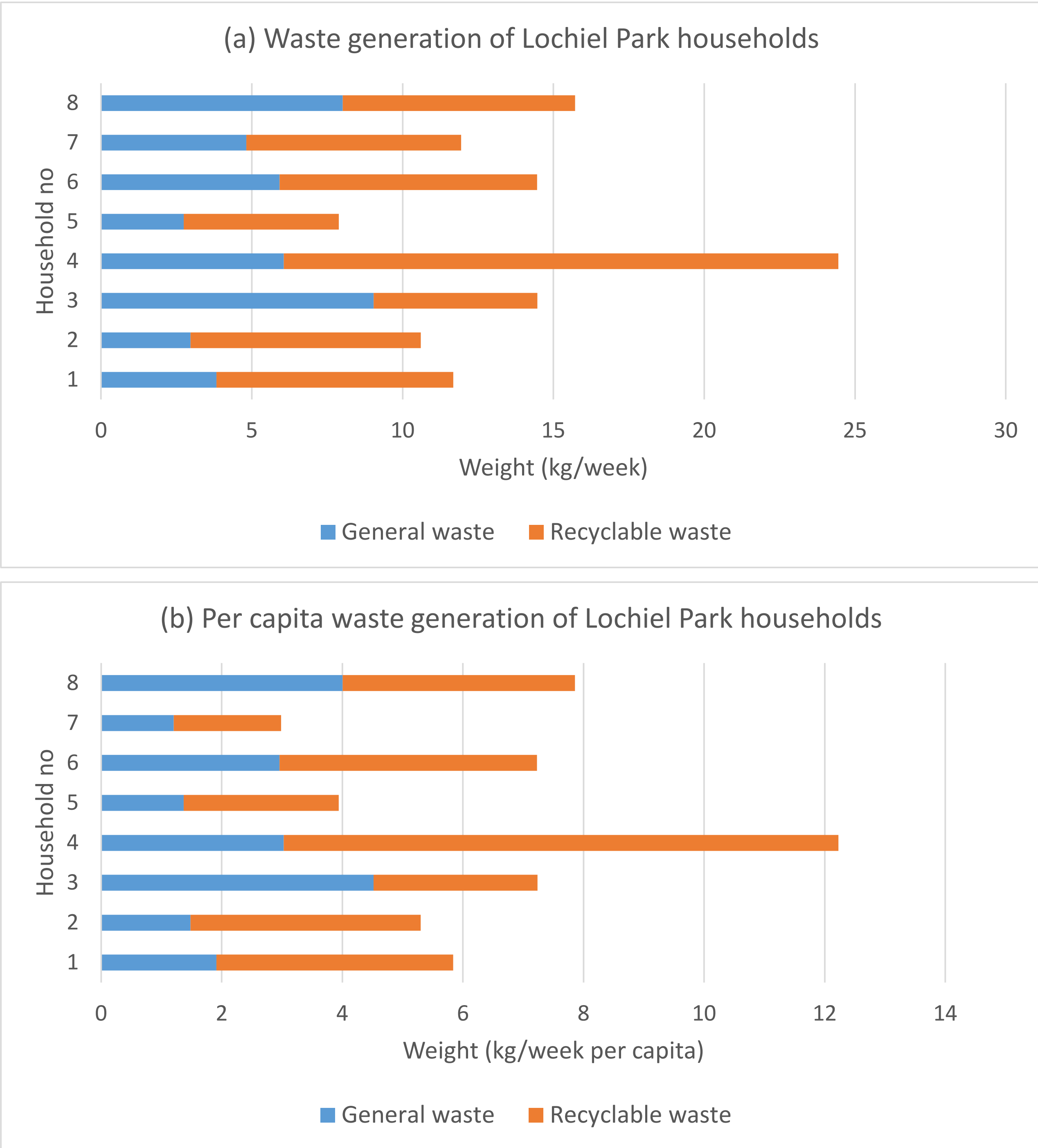


Figure 6.18: Weekly waste generation by (a) households and (b) per capita for Lochiel Park households (households as identified in Table 6.14)

6.2.3 Household economic activity and waste generation.

He He (2017) used the CWSU model (summarised by equations 6.1-6.5) with the household waste data collected in Lochiel Park (as summarised in Table 6.14) to indicate how the input-output modelling approach could be used to estimate levels of household economic activity and waste generation by household type. Given that the data from the Lochiel Park precinct only represent two (Mosaic) household types (D16 and B05) – and given the small sample sizes available – this analysis can only be used as a proof of concept at this stage. Given future extended data sets covering a wider range of household types, the development of such models would then lead to a more comprehensive modelling system for household waste generation that could be applied at the precinct level.

The CWSU model includes Landfill and Recovery sectors for its waste analysis. These may be taken to match with the general waste and recyclable wastes, respectively, in the Lochiel Park data set. The amounts of waste ($SW_{\cdot,F}$) generated by D16 and B05 household types and treated by the Landfill sector and the Recovery sector are shown in Table 6.14. The Mosaic weekly household expenditure data available to the project team covered 755 types of goods and services, which were then aggregated into eight intermediate sectors ($X_{\mathrm{I},F}$) corresponding to the number of intermediate sectors in the Australian IO table, as shown in Table 6.15. These weekly amounts were then converted into annual expenditures.

Mosaic types	Ag	Mi	Ma	EGW	Co	Pa	AOI	Waste	Total
	($AUD)								
D16	59.21	0	533.61	91.23	0	18.43	674.01	0.54	**1377.03**
B05	54.65	0	533.49	79.85	0	23.93	807.48	0.74	**1500.14**

Table 6.15: Aggregated household expenditure per week on intermediate sectors (D16 and B05)

Due to the different periods of the data sources, i.e. $X_{\mathrm{I},F}$ in 2013, $SW_{\cdot,F}$ in 2015–16, and the two Australian WIO coefficient matrices for 2009–10 and 2010–11, He He (2017) sought to demonstrate the utility of his model by building two scenarios for the calculation of the Australian WIO tables for different household types. Further, the comparative analysis based on these two scenarios was conducted in two stages: (1) comparative analysis illustrating the differences of inputs of Australian economy and waste generation caused by household consumption of B05 and D16 in each scenario, and (2) comparative analysis of household consumption of B05 or D16 in different scenarios to assess changes in inputs from the Australian economy and waste generation. Use of these two scenarios allowed assessment of the economic situations in different years on waste generation and treatment due to household consumption. In this way some idea of the possible impacts at the household level of changes in policies on waste management could be gauged. The two scenarios thus applied were:

1) Scenario I –input coefficient and Leontief matrix from 2009–10, year for $X_{\mathrm{I},F}$ 2013, with $SW_{\cdot,F}$ for 2015–16.
2) Scenario II – input coefficient and Leontief matrix for 2010–11, year for $X_{\mathrm{I},F}$ is 2013, with $SW_{\cdot,F}$ is 2015–16.

As summarised in Section 16 (Appendix D: WIO Tables for Lochiel Park Mosaic Household Types.) Tables D.1 and D.2 display the WIO tables for household type D16 in Scenarios I and II, while Tables D.3 and D.4 show the corresponding tables for household type B05. Note that these are reduced WIO tables because imports, exports, and some final demand categories are excluded because the research only calculated the domestic economic activities and waste generation caused by the Household sector. To provide comparisons, Tables D.5 and D.6 show the differences between B05 and D16 household types for Scenario I and for Scenario II. The differences shown in these tables were calculated using the WIO table of B05 type households (Table D.3) minus that of D16 type households (Table D.1) in Scenario I and Table D.4 minus table D.2 in Scenario II. Tables D.7 and D.8 show the differences between the two scenarios for D16 and B05 respectively.

The results are set out in three steps: (1) basic information regarding Australian economic activities and waste generation caused by household consumption (see Tables D.1, D.2, D.3 and D.4), (2) the first stage of the comparative analysis for the same scenario with different household types (see Tables D.5 and D.6), and (3) the second stage for the same household type with different scenarios (see Tables D.7 and D.8).

Summary information regarding Australian estimated economic activities and waste generation caused by household consumption of D16 type households is as follows, using the data laid out in Tables D.1 and D.2:

(1) The inputs of the All Other Industries (AOI) sector caused by D16 type household consumption was the highest inputs of intermediate sectors in Scenarios I and II, followed by the Manufacturing (Ma) sector and the Electricity, Gas and Water (EGW) sector
(2) The highest amount of waste was generated in the Manufacturing sector, which accounted for some 36 per cent of the total waste in Scenario I and 38 per cent of the total waste in Scenario II (Figure 6.19 and Figure 6.20).
(3) The total amount of waste treated by the Recovery sector was less than that treated by the Landfill sector in Scenario I while that treated by the Recovery sector was more than that treated by the Landfill sector in Scenario II. To be precise, in Scenario I the average recovery rate was 49.6 per cent, with the highest split achieved by the Household sector (59.8 per cent) followed by the Manufacturing sector (51.2 per cent), while the average recovery rate in Scenario II increased to 50.2 per cent
(4) The total amount of waste generation in the Australian economic system caused by consumption of household type D16 in these two scenarios was far greater than that directly generated on-site by household consumption, suggesting the importance of indirect effects on total waste generation.

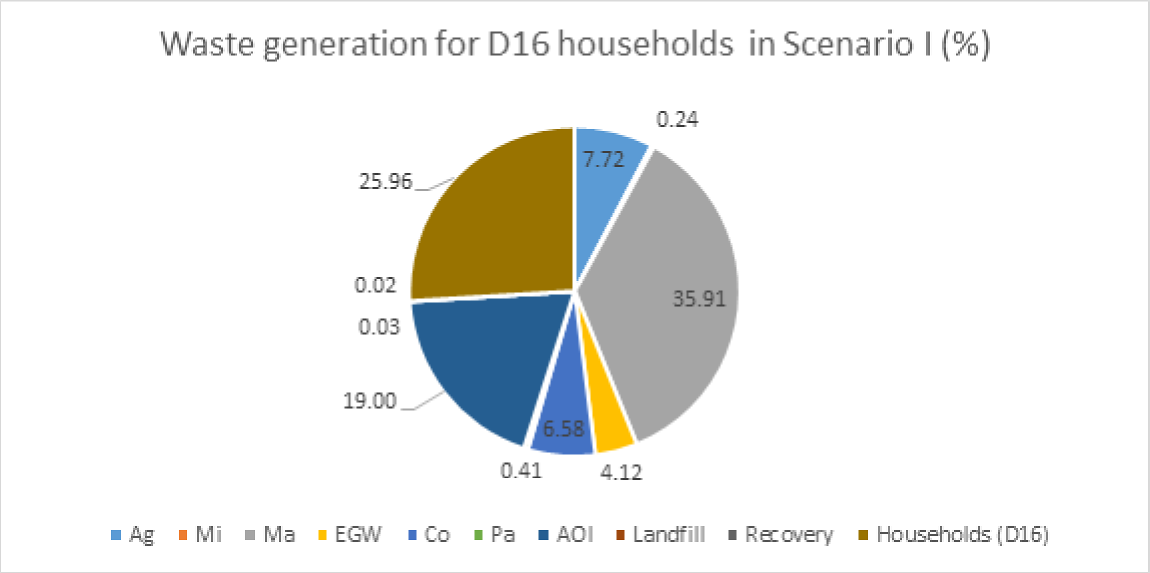


Figure 6.19: Waste generation of intermediate sectors for Mosaic household type D16 in Scenario I

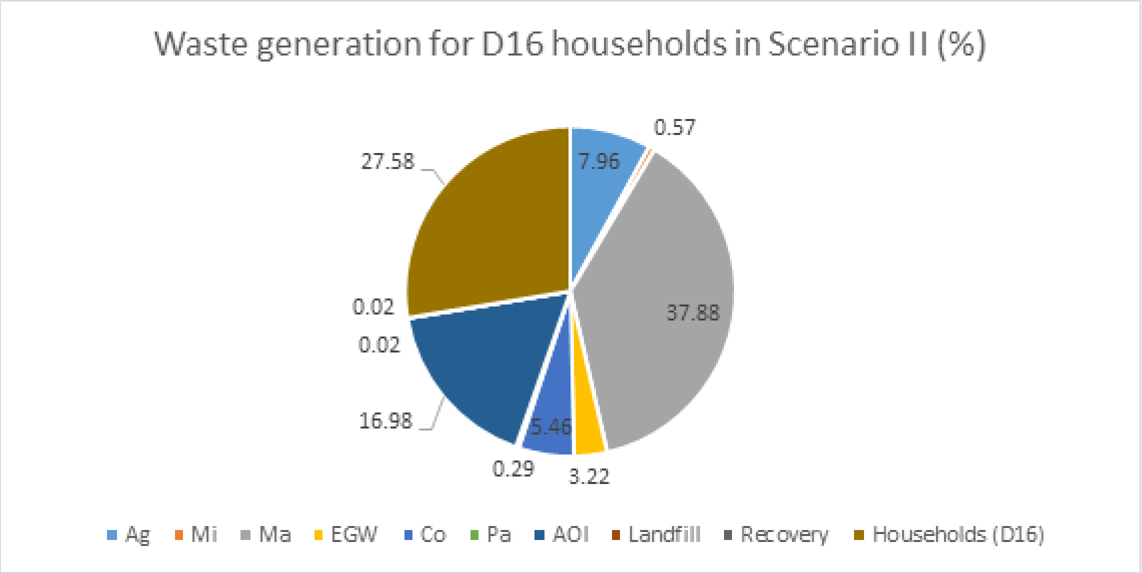


Figure 6.20: Waste generation of intermediate sectors for Mosaic household type D16 in Scenario II

The economic activities and waste generation caused by household consumption of B05 was similar to that of D16 except for the third finding (above) regarding the total amount of waste treated by waste treatment sectors. The total amount of waste treated by the Recovery sector was more than that treated by the Landfill sector in both Scenarios I and II (Tables D.3 and D.4).

Tables D5 and D.6 present a comparison of inputs of Australian economy and waste generation caused by household consumption of household types D16 and B05 in Scenario I and Scenario II. The main findings from this comparison can be summarised as:

1) The trend of changes of inputs from intermediate sectors is the same as the changes of waste generation from corresponding intermediate sectors. For example, the total inputs from the Agriculture, Forestry and Fishing (Ag) sector to other intermediate sectors caused by the consumption of household type B05 were less than that of household type D16. The amount of waste generated by the Ag sector for B05 household consumption was also less than that of D16 household consumption.
2) Although the total inputs from the intermediate sectors caused by consumption of B05 households were greater than that of D16 households, the total amount of waste generated by B05 type households was less than that of D16 households.

The final comparison of inputs of Australian economy and waste generation caused by consumption of B05 and D16 household types is between Scenarios I and II. Tables D.7 and D.8 indicate two major findings:

(1) To satisfy the consumption of B05 or D16 households, the total inputs from the intermediate sectors in Scenario II were less than those of Scenario I. In particular, the Manufacturing sector decreased by the largest amount, accounting for approximately $900 million in both Scenarios I and II.
(2) The amount of waste generated by D16 type households and treated by the Landfill sector as well as the Recovery sector decreased from Scenario II to Scenario I, with B05 type households showing similar changes. However, the changes for B05 households were greater than those for D16 households.

6.3 Discussion

In summary, the strength of the WIO model lies in its detailed description of economic activities and waste generation and treatment caused by the Final demand of the economic system, especially for the Household sector. However, the Australian WIO analysis presented in Section 6.2.1, (The 'Top-Down' Method) only quantified the total consumption of Australian households, and ignored differences in household consumption depending on different socio-demographic indicators. The economic activities and waste generation caused by the different types of household consumption have different consequences on a national scale that are important to take into account in the environmental policy-making process.

Section 6.2.3 (Household economic activity and waste generation) assessed the Australian economic activities and waste generation and treatment based on the Mosaic data for household consumption, on-site collection data for waste generation and treatment, and input coefficients and Leontief matrices of the Australian WIO model from Section 6.2.1. The findings from Section 6.2.3 indicate the characteristics of Australian economic activities and waste generation and treatment caused by two specific (Mosaic) household types, D16 and B05, under two scenarios. These are:

(1) For both B05 and D16 household types, the AOI sector inputs the greatest amount of funds to the Australian economy, and this is related to the household consumption of those household types. The D16 and B05 household types are characterized by couples without children[4]. In 2011, 25.3 per cent of Australian households were composed of couples without children (idcommunity 2017). The highest inputs of the intermediate sector to the total household consumption in Australia in Tables D.1 and D.2 were from the AOI sector. This suggests that more than a quarter of Australian household consumption has similar effects on the inputs of the AOI sector compared with the total household consumption.
(2) The amount of waste generated by the Manufacturing sector caused by D16 and B05 type households increased slightly from Scenario I to Scenario II. Tables D.3 and D.4 indicate that the amount of waste generated by per million AUS dollar of output for the Manufacturing sector in these two scenarios also increased.
(3) The increase of the average recovery rate from Scenario I to Scenario II suggests that the recovery rate may have improved with the development of technologies and the more recently implemented environmental policies in Australia.

[4] But do not necessarily exclude children, for membership of a specific Mosaic household type is determined on the basis of a probability distribution.

(4) The amount of indirect waste generation caused by consumption of D16 and B05 households was more than that of direct waste generation, which indicates that environmental policies should pay attention to the supply chain of goods and services as well as on-site disposal. In addition, this implies a substantial fraction of the waste generation is hidden from the end-user of products and services.
(5) The changes of inputs from intermediate sectors showed a similar trend to the changes of waste generated by the intermediate sectors caused by D16 and B05 households in the same scenario. This indicates that to satisfy different household demands the inputs of the intermediate sector increases and the amount of waste generation also rises, and vice versa.
(6) The total inputs of B05 households are greater than those of D16 households; however, the total amount of waste generated by B05 households is less than that of D16 households. A possible explanation of observation is in two parts. The first part is that providing only the inputs and waste generation from the intermediate sectors are calculated, it is easy to explain that the greater the inputs from the intermediate sectors, the greater the amount of waste generated, corresponding to finding (5) above. The second part is that the amount of waste directly generated on-site shows that the amount of waste generated by D16 households exceeds that generated by B05 households, perhaps because the D16 households tended to be retired couples and stayed at home while B05 households were generally at work during the day, based on information from the Lochiel Park survey.
(7) The decrease in the amount of waste treated by waste treatment sectors may possibly be due to the effectiveness of current environmental policies (National Waste Policy agreed in November 2009 and Environment Protection Regulations 2009) in Australia published for the two scenarios, in particular increases in the waste levy fees for the Landfill sector.
(8) Results of the increase of the average recovery rate from Scenario I to Scenario II, the decreases for the inputs of the Manufacturing sector for D16 and B05 households in the two scenarios, and the decrease in the amount of waste treated by waste treatment sectors provides some evidence that the Australian economy was perhaps moving towards a circular economy from 2009–10 to 2010–11.

The analysis of WIO tables for D16 and B05 households in Scenarios I and II indicates that a substantial fraction of the total waste production is hidden from the end-user of products and services. Policies aimed at reducing waste generation and implemented by governments should therefore focus on the supply chain or upstream processes in addition to on-site disposal. The comparative analysis was utilised to understand the effects of different types of household consumption on the development of economic activities and waste generation and treatment.

However, the limitations of data regarding household waste generation and treatment were a significant hurdle for the analysis process. As previously discussed, the waste mass and volume data for D16 households were collected from seven households and for B05 was collected from only one household. The number of samples for data collection is small, which affects the accuracy of analysis. In addition, the data were only collected in the Lochiel Park precinct, with the residents of that precinct belonging to just three of the 49 Mosaic household types (no survey respondents from the C13 household type agreed to participate in the weighing of their weekly wastes). Thus there was a lack of completeness and comprehensiveness of the comparative analysis.

To tackle these issues, further research directions based on the reported analysis are:

- Construct a database to include more samples and cover precincts in more regions in Australia to enhance the accuracy of analysis, and
- Collect different types of household waste data for a larger set of Mosaic households to form a series of WIO models to comprehensively analyse economic activities and waste generation by different household types.

The findings from this study do provide a mechanism for obtaining more information regarding relationships between household consumption and waste generation from the analysis of more types of household consumption and household waste generation.

7 Water Domain Forecasting

A rapidly urbanising world presents policy makers, planners and practitioners with challenges with respect to water conservation and carbon reduction. According to the latest projections, Australia's population will grow by 64% to 36 million in 2050 and double to 46 million by 2075 (ABS 2013; CSIRO 2015). At the same time, Australia's economy is projected to treble by 2050, with national income per person increasing by 12 to 15% above inflation per decade (CSIRO 2015; Hatfield-Dodds et al. 2015). Most of this growth is likely to take place in urban centres, which implies that the precinct should be the focus of demand forecasting efforts and emission forecasting to capture high levels of CO2e generated in urban Australia

Previous studies have shown that the combination of various factors such as technology, climate change impacts on temperature and rainfall, population and economic growth, changes in behaviour and socioeconomic attributes, and the nature of the water supply mix and electricity grid (including the benefits of renewables), can all have an influence on water-related carbon emissions of households (Cook et al. 2012; Kenway et al. 2013; Binks et al. 2016). The model developed as part of this project is sensitive to all the above elements, to ensure that the water domain of the ETWW model is sensitive to all the key variables driving water demand, enabling future forecasts that encompass the changes likely to occur in the Australian urban setting in coming decades.

7.1 Modelling water-related carbon emissions - overview

Figure 7.1 provides an overview of the overall structure of the water demand forecasting framework developed as part of this project, indicating the key water demand modelling parameters (models 1,2 and 3), and the main flows of water and water-related energy in the household, including energy for water supply and water treatment (see red text in Figure 7.1). The following sections of this report offer a more detailed description each of the individual demand forecasting modules for total water, hot water, rainwater and how these are translated into energy and carbon emissions for water supply, use, and wastewater collection and treatment (as shown in Figure 7.1). The energy (share of different electricity sources) and water supply mix (desalination, reservoir, etc.) are important and complex determinants of water-related carbon emissions. As a results, energy required in water and wastewater treatment and piping varies regionally and temporally (Cook et al. 2012; Marchi et al. 2014). Household size, lot size and socioeconomic status are important driving variables of water demand (Model 1) which in turn determine the energy used and carbon generated to heat, treat and supply water to the household. Technology, behaviour and climate change with end use interactions with other domains required consideration with hot water demanding around 23% of household-related energy (Kenway et al. 2015), while rainwater tank pumping also requires energy (often this can even be more energy-intensive per kL of water compared to mains water supply).

Wastewater volumes assume that outdoor use does not contribute to wastewater collection with a higher outdoor use percentage reducing the need for energy associated with wastewater treatment. The ratio of indoor to outdoor water use was a significant data gap in this project. It was therefore inferred on the basis of previous studies surveying apartments with similar garden sizes (Willis et al. 2011; Arbon et al. 2014). The energy requirements and carbon emissions associated with wastewater largely depend on the type of treatment (treatment can be primary, secondary or tertiary depending on the area) (Cook et al. 2012).

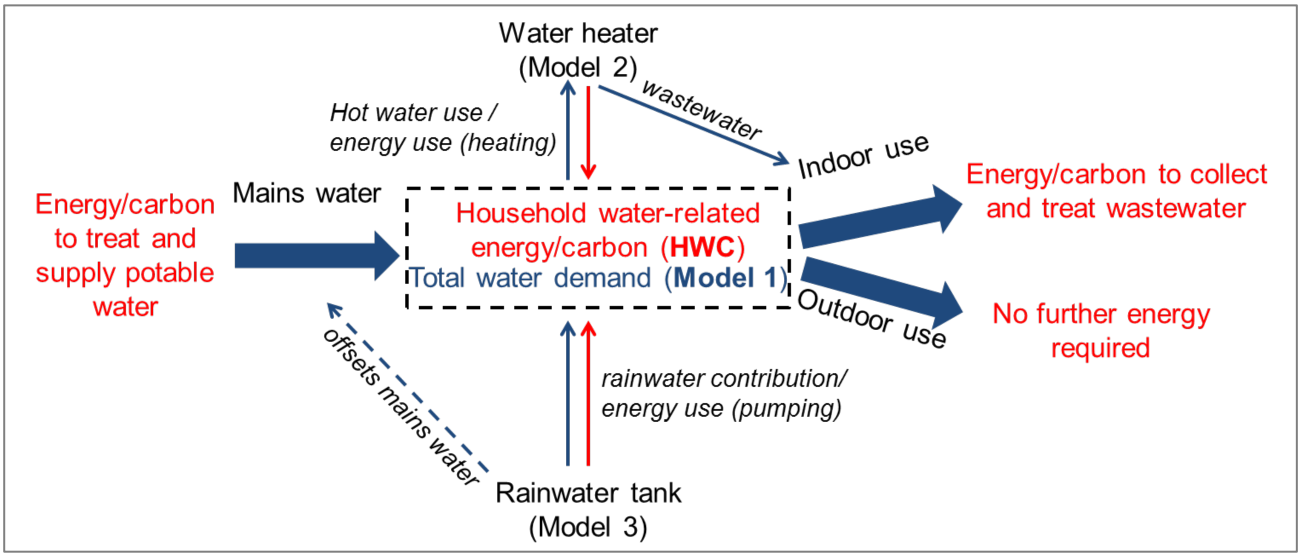


Figure 7.1. Conceptual framework of water demand forecasting model.

7.2 Forecasting Water Demand

Several types of water demand models are available and applied in practice with a selection of these provided in the following table. Each has a different level of sophistication and each method is fit for purpose, especially when considering the water supply utility's requirements. Table 7.1 lists the models and their underlying principles.

Model/method	Principle
Temporal extrapolation	Projection based on past trends
Unit water demand analysis	Unit water demand coefficient
Multivariate statistical models	Water use a function of multiple explanatory variables
End-use models	Simulation of end-use by domestic customers
Land use based models	Demand assessed on scale of uniform spatial entities

Table 7.1: Method and principles for water demand forecasting approaches.

The highlighted element of Table 7.1 highlights that the multivariate statistical model is the most suitable option considering the requirements of the ETWW forecasting tool and the data availability from Lochiel Park and other sources. This approach considers water use as a function of a number of variables, ie: Wd = f(driving variables), allowing for socio-economic variable inclusions such as Mosaic data variables in addition to temperature, precipitation and any other information available with regards to dwelling characteristics (Billings and Jones 2008; Worthington and Hoffman 2008; Rinaudo 2015; Sebri 2016). The water demand approach used in the ETWW model also draws on elements of end-use models and land use based models to better capture household energy use and interactions. End-use modelling allows estimation of uses such as hot-water use, an integral part of the carbon emissions estimate given its significant contribution to water-related energy use (Kenway et al. 2015). Land-use based models can account for what is happening at a precinct scale, as represented in the GIS environment.

7.3 Water Demand Model

The water demand forecasting model is coded in the 'R' open-source programming language and software environment for statistical computing (Dalgaard, 2002). It is composed of 3 linear mixed models at a monthly demand and supply resolution, which is well suited to a time-series application. The 'lme4' package was used to fit these models to the data and perform model validation and prediction (Bates et al, 2016). Training routines have been based on household water demand datasets acquired from the University of South Australia's Lochiel Park record database with 5 years (2011-2015) of data in one-minute resolution for 81 households (n = 4860) over five years.

Available water demand variables are the household Total Water (TW), Hot Water (HW) and Rainwater (RW) use – each of which serve as the dependent variables in the three linear mixed models. Other household and environment characteristics from a range of sources include lot size and household size, survey data from the waste domain research (income, education, household composition), and monthly weather data from the nearest weather stations (specifically daily maximum temperature and monthly precipitation). As part of the model, an automated historical weather data sourcing function was developed. The approach is detailed in the following section.

7.4 Temperature and Rainfall Data

Recent studies highlight the importance of reliable temperature and rainfall data to the accuracy of water demand forecasts (Haque et al., 2015; Sebri, 2016). Obtaining a long record of past weather data that matches water demand observations was one of the challenges of this domain. Weather data sourcing was achieved with the development of an automated routine that connects with the Australian Bureau of Meteorology (BOM) 'Climate Data Online' website. The model searches for the nearest temperature and rainfall stations in relation to the coordinates of the suburb centre and initially searches online for at least two nearby stations within a radius of 1, 2 or 5km from the suburb with a complete data record. Data from stations nearby are prioritised and the algorithm will stop looking for more stations if stations within 1-2km are available (see Figure 7.2). A higher number of stations ensures a more accurate final estimate. For the majority of urban locations, two or more weather stations are very likely to be available within a 5km radius. Temperature and rainfall series are finally generated using ordinary inverse distance weighting which dictates that the value of temperature or rainfall is given by the weighted average of the values available at any known point, where weights are inversely related to the distances between the prediction location and the sampled locations (Lu and Wong, 2008).

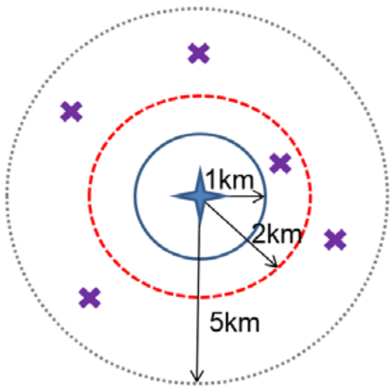


Figure 7.2: Example of weather station location and inclusion in the IDW calculation process.

Stations closer to the point of interest have a significantly greater effect on the estimated value than more distant points. This approach has been validated to provide accurate results sufficient for the domain water modelling.

7.5 Water Demand Forecasting using linear mixed models

While historically water demand forecasting carried out by utilities and academics relies on multiple linear regression, research supports the use of linear mixed models (panel data approaches) combining fixed and random effects. These have been shown to outperform multiple linear regression models overcoming problems of multicollinearity, and make it possible to control for unobservable heterogeneity of the cross-sectional units (households, in this case) (Arbués et al. 2003; Polebitski and Palmer 2009)

The first demand forecasting component (**Model 1**) predicts the total water (TW) demand for the household as the linear mixed model (LMM) accounts for fixed (predictor) variables and random effects as shown in the following equation:

$$y = \boxed{\underbrace{X\beta}_{fixed}} + \boxed{\underbrace{Zb}_{random}} + \underbrace{\varepsilon}_{error} \qquad \text{(Equation 7.1)}$$

Here, *y* represents the total household water demand, or TW. More specifically, the TW equation accounts for:

TW = f (income, education, rainfall, temp., bathrooms, hh_size, hh_comp) + (1|HH_ID) + (1|Season) (Equation 7.2)

Fixed effects are variables of income, education, rainfall, temperature, number of bathrooms, household size (hh_size), and household composition (hh_composition). As illustrated in Figure 7.3, there can be a great amount of variability in water demand, from household to household and also depending on the time of year. This model type includes a component to account for random effects based on the individual household (HH_ID) and season (Season) by creating different level intercepts for the household and for the season.

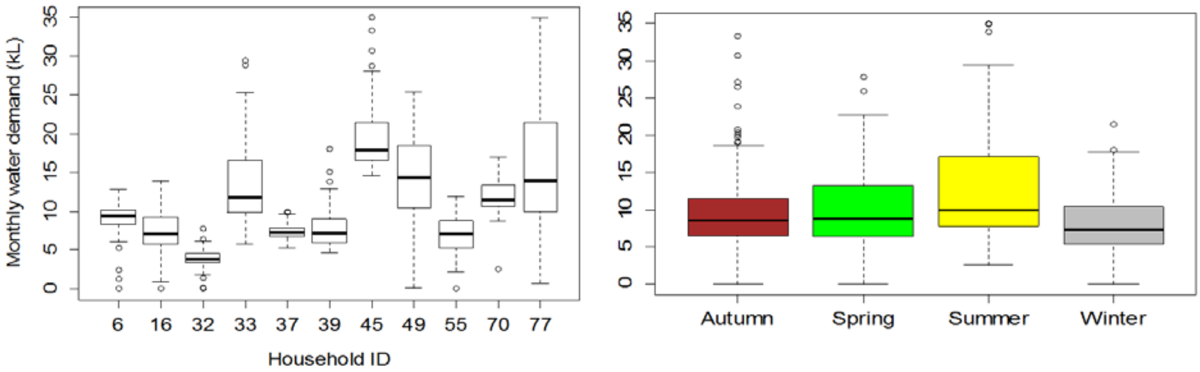


Figure 7.3: Example of random effects inclusions for household and seasonality effects.

The second model (**Model 2**) estimates the hot water (HW) demand for the household as:

HW = f (TW, temp., education, hh_comp, income) (1|HH_ID) + (1|Season) (Equation 7.3)

This uses the total water demand forecast from Model 1, and also variables for education, hh_comp, income and random effects from the household and seasonality.

The third model component (**Model 3**) estimates rainwater (RW) demand for the household as:

RW = f (Rainfall, tank size, roof area) (1|HH_ID) + (1|Season) (Equation 7.4)

Rainwater demand is a function of rainfall, the tank capacity and roof catchment area and, once again, includes random effects due to the household and seasonality.

7.6 Model Selection and Performance

A model selection process has been applied to select the best performance model to suit the domain forecasting process and provide a stable model and involved a comparison based on validation results. Stepwise regression was first used to determine the optimum mix of fixed effects variables. This model was treated as the baseline model for comparison purposes. Alternative linear mixed models testing different random effects were compared on the basis of RMSE and the Akaike Information Criterion (AIC) (Akaike 1992). Table 7.2 demonstrates this comparison for Model 1 for total water use. The Linear Mixed Model (LMM) was chosen as the most suitable however, LMM2 actually performed better but further testing has shown in to be highly sensitive and unstable under certain forecasting conditions.

		LM	LMM	LMM2
Fit	AIC	2941.768	2929.561	2926.251
	RMSE	2.581623	2.346627	2.337291
Fixed effects	HH size	7.43688***	1.57252	0.7207
	Lot size	1.37535***	0.08129	0.5761
	Rainfall	-0.01222	-0.2146	-0.3472
	Temperature	1.96034*	0.34574	1.9032
	Income (low)	-0.54165	-0.54748	-
	Income (medium)	9.17994***	-2.05242	-
	Education (university)	4.83751*	-4.89592	-
	Bathrooms	5.38046***	0.2946	13.243
Random effects	HH ID	-	4.221	39.6476
	Season	-	-	0.3138
	Residual	-	12.495	15.2063
	Observations (n)	525	537	863

*Note: *** indicates variable significant to 99% level.*

Table 7.2: Validation results for forecast approaches.

Validation plots in Figure 7.4and Figure 7.5 illustrate model performance across the year. The model captures the seasonal pattern well for households in the eight households that made up the validation dataset (these observations were not used as inputs to the model) with the exception of some unusual peaks in June and July.

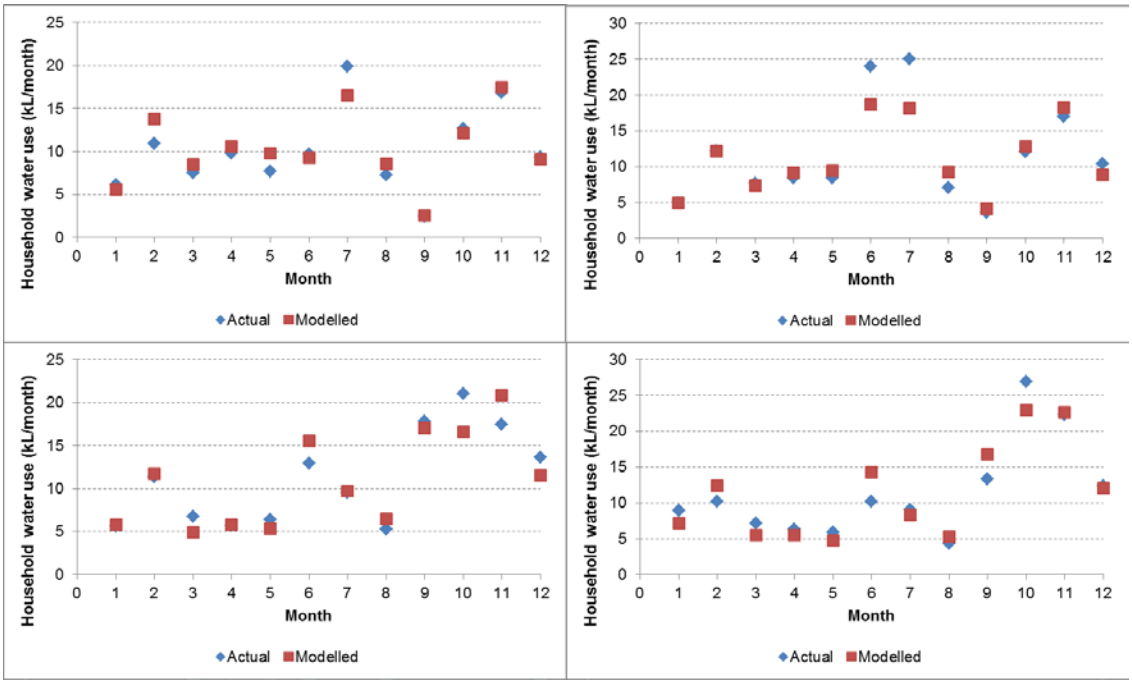


Figure 7.4: Water demand forecast validation plots (1-4).

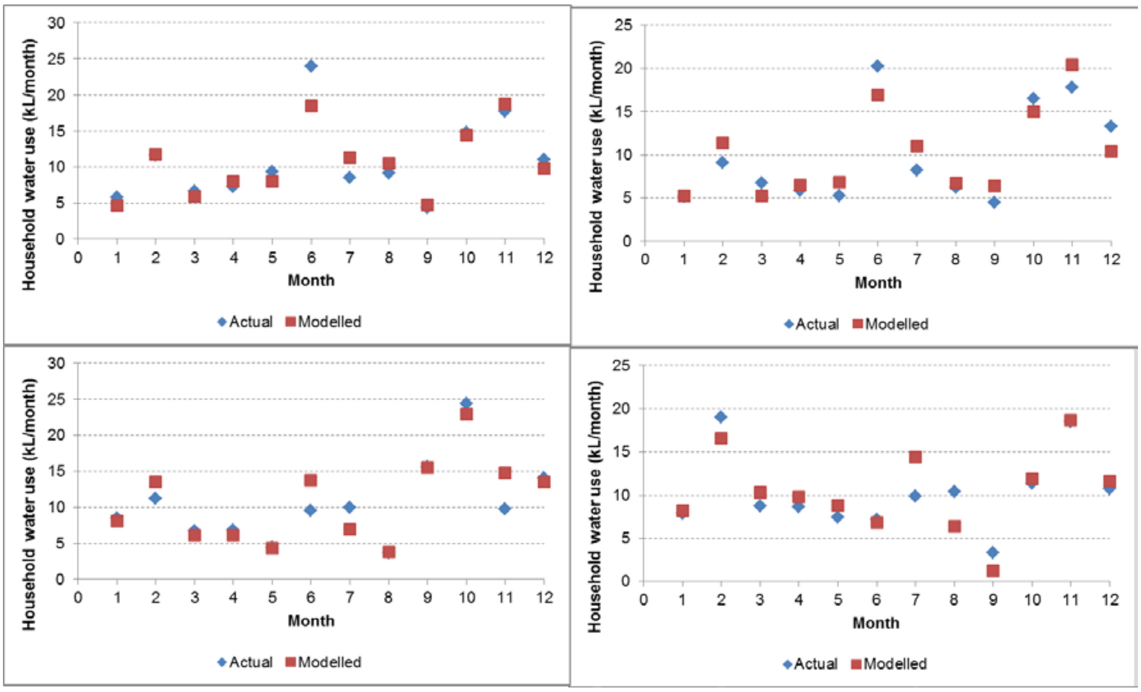


Figure 7.5: Water demand forecast validation plots (5-8).

The parametric bootstrap standard error, which applies to the standard error under 1000 resamples across all 12 months of the year over the available data period, is demonstrated in Figure 7.6. The standard error appears to be highest during the March-July period of the year.

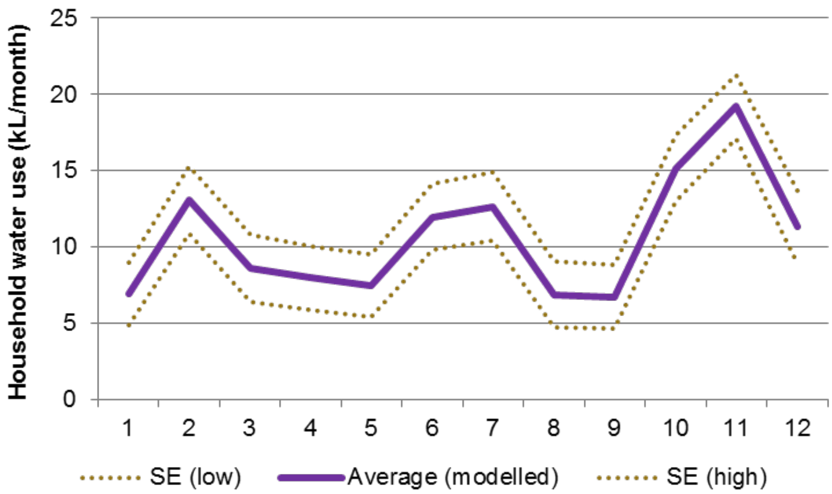


Figure 7.6: Parametric bootstrap error across 12 months.

7.7 Water-Related Energy Model

Once total water, rainwater and hot water demands have all been estimated using the respective linear mixed models, all necessary energy and associated carbon emissions can be modelled. This includes the energy required for water supply, water-related household energy use (for hot water and rainwater collection), and energy for wastewater (see Figure 7.1).

The energy kWh per kL of water supplied or wastewater treated is based on the 2009/10 water supply mix for Australian capital cities (estimated from Cook et al. 2012). This is combined with grid GHG intensity estimates. The grid GHG intensity is given as CO2-e per kWh in different states (DoE 2015). The following equations show how the carbon related to water supply and wastewater is calculated.

*Water supply carbon = kL (water use) * water energy factor * grid GHG intensity* (Equation 7.5)

*Wastewater carbon = kL (indoor use) * wastewater energy factor * grid GHG intensity* (Equation 7.6)

Models 2 and 3 (see Figure 7.1) provide demand estimates for hot water and rainwater use at the household. This is where interaction with the energy domain is most important as far as the water domain is concerned. Rainwater is also an important offset on total mains water input and hence an offset of water supply energy-related emissions. Hot water energy/GHG factors vary widely, depending on the heater type, from 44 gCO2-e/MJ to 501 gCO2-e/MJ (Whaley et al. 2014). In reality, emissions related to hot water use also depend on the specific mix of uses of that hot water, as different uses require different temperatures. The energy factor used for hot water production in this model is an Australian average of 26.8 kWh/kL for hot water (Kenway et al. 2015). For rainwater, the estimate of 1.5 kWh/kL by Retamal et al (2009) provides the most widely used energy factor associated with pumping operation. This factor is further supported by a more recent study by Umapathi et al (2013).Integrating Water Demand Modelling with the ETWW Model

Figure 7.7 provides the overall forecasting process and model work flow relating to other domains in the overall ETWW forecasting exercise.

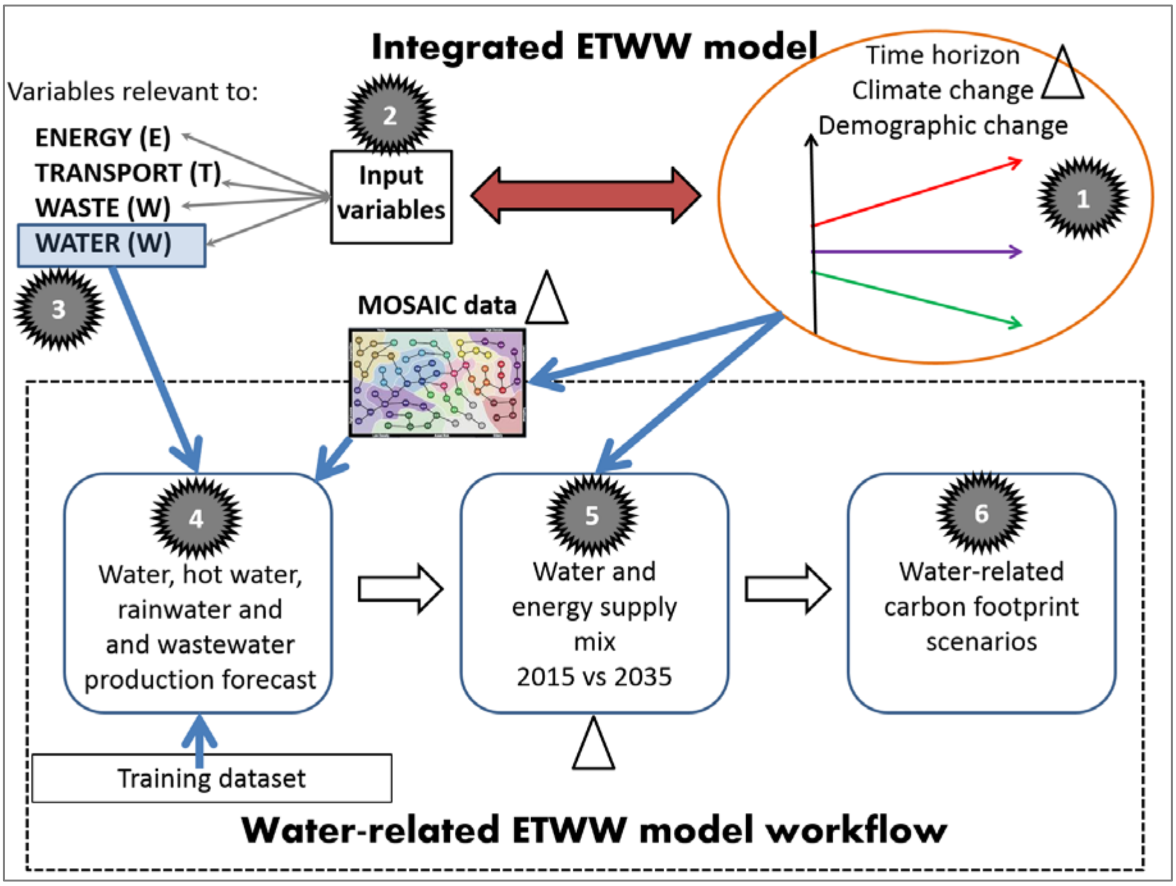


Figure 7.7: Overall water domain forecasting process and model work flow.

The illustrated conceptual model displays different model components along with the suggested order of tackling them. The diagram also depicts how scenario development could form a starting point for integrating the different modules of the ETWW project:

- Step 1 is to develop scenarios. These should in principle be common across CRC projects.
- Step 2 is decide on the scope of each model and which variables are necessary. Many are common between domains.

- Step 3 is to decide which variables are unique to each area.
- Steps 4-6 are the processes of estimating demands and associated energy and carbon impacts from these different types of water use and supply involving passing from a water demand model to estimates of carbon for each scenario.

Scenarios can then account for variations (Δ) to a range of these included elements.

This water demand and carbon impact modelling approach can be used to forecast water and water-related energy demand, recognising potential changes in household type/characteristics alongside other environmental/technological changes. There is an obvious connection with energy for hot water and care is taken to avoid double-counting. Hot water system choice is a significant factor for emission generation and where electrical water heaters are installed, the electricity grid is key to emissions reduction since it contributes to reductions in all aspects of water-related emissions.

This modelling process can be applied to forecast emissions from future populations (and associated sociodemographic changes) for large-scale urban areas (e.g. Sydney) with multiple water and energy supply mixes. Optimisation approaches could also be employed to find the optimum water and energy supply mixes to ensure reduced water-related carbon emissions under future scenarios. Scope 3 emissions outside the scope of this project but could be combined with our results to provide a complete inventory of precinct emissions under different scenarios.

8 ETWW Model Spreadsheet and Integration

Presented as a Microsoft Excel macro-enabled workbook format, the ETWW model provides a flexible, transparent, accessible, model environment which is easily and readily modified. It contains data and automated processes through the development of macros and is easily accessed by other software and extract and import data components from other environments. All sheets within the workbook are visible (ie. no sheets exist as hidden information) and allow for user interaction with all parameters.

Individual sheets within the workbook are broadly categorised as either an input, model or results sheet and are labelled with descriptions of each sheet contained in the following sections. Within each spreadsheet a colour coding convention applies to tables and tabular cell elements to allow the user to readily identify model elements as shown in Table 8.1.

Yellow Cells	Require values to be inputted by the user
Light Grey Cells	ETWW-model values that are set as default for modelling purposes
White Cells	Imported data and editable data
Blue Cells	ETWW forecast demand values
Orange Cells	ETWW forecast carbon impact values
No Formatting	Export data to GIS

Table 8.1: Excel spreadsheet cell colour convention.

8.1 Title Sheet

This simple sheet introduce the complete workbook in terms of the sheet content and process contained is provided to detail the colour coding convention and the step-by step process for ETWW carbon estimation.

8.2 INPUTS

Worksheets with the “INPUT” prefix identify content that is required as input to either the ETWW workbook modelling processes or external modelling processes. Input may be user-defined or selected from data table options or as default data parameters. The following section details worksheets that are INPUT operations.

8.3 INPUT_Environment

Precinct environment inputs are allocated in “Table A01: Scenario Definition” which requires user-based input for the precinct name, latitude and longitude. The sheet relates this information to a capital city location from “Table A03: Bounding Lat/Long”. The user is also required to define a base year and forecast year and a forecast month which in turn, determines the forecast season. The included Button labelled "Set Scenario Parameters" opens up an interface for input of required scenario definition data input from the user.

Average daily temperature range, monthly precipitation, solar irradiance and night-time hours are allocated by the spreadsheet into “Table A02: Climatic Conditions”, with the season allocated from “Table A04: Seasons” and based on the user defined forecast month.

8.4 INPUT_GISAttributes

The user is able to import the contents of the GIS precinct zone structure attribute table into “Table B01: GIS Precinct Zones” ensuring that the fields of the GIS table match those defined in B01. A GIS definition of the precinct land use structure as a collection of individual polygons, each with a unique identifier (Id), masterplan description, area in square meters and land-use code that must align with land use codes in INPUT_HHLandUseLookups. The included button "Import GIS Zone Attribute File" will open up an import text file dialog box to access the GIS attribute table.

"Table B02: GIS Precinct Road Links" provides a table structure for the importing of GIS attribute table from the GIS definition of the precinct road network. This exists as a collection of individual lines, each with a unique identifier (Id), length, speed, link type, and capacity index. The included button "Import GIS Road Network Attribute File" will open up an import text file dialog box to access the GIS road network attribute table.

8.5 INPUT_ScenarioOptions

Scenario options are provided to the user within "Input C01: Precinct Scenario Modelling Options" as a range of inclusion options for precinct scenario forecasting. They include option "OK" box turns the option on (yellow highlight) or off (grey highlight) with a number of required inputs for each option if selected. These options are:

- Electric vehicle ownership and use: for each residential precinct zone, define the EV Type and the Trip Purpose from the available drop-down options followed by the desired % travel by EV ,
- Rainwater tank water use: for each residential precinct zone, define the % rainwater use by the household,
- Wastewater recycling: for each residential precinct zone, define the % of greywater to be recycled,
- Activities from home: for each residential precinct zone, indicate whether or not the work, shopping, and/or education trip purposes are performed within the household,
- Water consumption behaviour: for each residential precinct zone, define the % change and if the behaviour represents an increase or decrease in consumption,
- Energy use behaviour: for each residential precinct zone, define the % change and if the behaviour represents an increase or decrease in consumption,
- Recycling behaviour: for each residential precinct zone, define the % change and if the behaviour represents an increase or decrease in consumption,
- Water supply variation: define the water supply mix to the entire precinct from the options of reservoir, desalination plant and localised network sources,
- Waste removal variation: define the one-way travel distance to the disposal site and removal vehicle capacity for the waste types of landfill, organic and recycling waste. [This distance then applies to the whole precinct],
- Solar panels: define the solar PV panel efficiency to apply to all panels used in the precinct,
- Battery storage: for residential land uses, define the in-home battery storage capacity,
- Grid energy and renewables: define the % of renewables (or green energy with zero CO2 impact) involved in the generation of energy supplying households and other land uses, water supply and recycling activity.

Summarised scenario option data applicable to each zone ID is presented in "Input C02: Input Parameters for Precinct Scenario Modelling Options". This table identifies relevant scenario attributes for GIS precinct zones as identified previously. The button: "Update INPUT_PrecinctScenario with Scenario Options" provides the 'INPUT_PrecintScenario' sheet with this information.

8.6 INPUT_PrecintScenario

This is a key data repository summarising all precinct zone attributes relevant to forecasting for residential land uses, non-residential land uses and scenario options within the table contained in this sheet. For all precinct zones, the land use type, built footprint area, number of building floors and resulting gross floor area is provided, requiring user inputs where appropriate. For residential zones, the residential structure type reference is provided and the Mosaic resident type is input, resulting in the allocation of adults/household, residents/household, workers/household, bedrooms/household, bathrooms/household, plot size, vehicles/household, residences/household, population and bin fill factor.

Data for non-residential land uses includes land use employment type, total employees for the zone, student type and students, water capture possibility with roof water capture availability, solar capture possibility with roof solar capture availability. This sheet also contains the zonal parameters for precinct scenario modelling options of

- EV ownership and use,
- Rainwater tank water use,
- Wastewater recycling,
- Water consumption behaviour,
- Energy use behaviour,
- Recycling behaviour.

Value entries for these fields are updated from the "INPUT_ScenarioOptions" worksheet.

8.7 INPUT_HHLandUseLookups

Lookup tables for non-residential land use types and demand factors are contained in this sheet along with key values for each Mosaic resident type and household structure types. “Table D01: Land Use Typologies and Characteristics” contains non-residential land use information on:

- Land use code, with a description of the type,
- Footprint build out proportion,
- Footprint green allocation proportion,
- Built out water capture area proportion,
- Built out solar capture area proportion,
- Number of floors,
- Employment type,
- Student type,
- Gross Floor Area (GFA) per employee.

Within this table, the energy use classification expressed as kWh/sqm/day for non-residential land uses are sourced from the following reference material:

- Baseline energy consumption and greenhouse gas emissions in commercial buildings in Australia (Commonwealth of Australia, 2012),
- US energy information administration commercial buildings energy consumption survey in US Energy Information Administration (2016).

In addition, the employment and student types are identified specifically for transport demand estimation purposes, as required in the strategic transport demand modelling routines.

Waste production classifications apply to landfill, organic and recycle material generation and is sourced from waste generation reference material references below:

- Commercial and Industrial Waste and Recycling in Australia by Industry Division in DSEWPC (2013),
- Recycling energy and the environmental impacts of reuse in Cooper and Gutowski, (2015),
- National organic waste profile in Department of Environment and Energy (2013),
- Emissions from waste treatment processes from DOE (2014),
- Survey data sources provided by the City of Marion and derived from project PhD research.

Within this table, the water demand classification expressed as kL/sqm/day for non-residential land uses are sourced from the following reference material:

- Benchmarks for water use from Sydney Water, (2016)

For all Mosaic resident type classifications A01 to M49 “Table D02: Select Mosaic Attributes” illustrates selected attributes and description of mosaic resident typology. Data items selected are re-formatted from the Mosaic Grand Index Table on a following spreadsheet (INPUT_MosaicGIT_Ref). This table provides the household:

- Adults,
- Residents,
- Worker factor and workers (estimated based on Mosaic classification and household descriptive datasets),
- Bedrooms,
- Bathrooms,
- Plot Size,
- Vehicles,
- Waste Factor (estimated for household based on survey data).

Physical attributes of the house structure are in “Table D03: Residential Structures Types” based on the following existing residential developments:

- Lights View: a CIC development in Adelaide’s inner northeast,
- Luminaire: a residential development at Bowden in central Adelaide,
- Park Central: a residential development at Bowden in central Adelaide,
- Bowden Seven: a residential development at Bowden in central Adelaide.

This table also allows for a user defined household structure definition. Residences report on the built area and percentage allocation for a range of house uses such as bedroom, living and kitchen areas as well as the included appliances, water storage capacity and solar PV size.

The “Table D04: Generalised Land Use Energy and Waste Reference Types” is provided here to relate energy and waste land-use types in the literature to ETWW defined land-use types. Some simple lookup tables are also included for Yes/No and Increase/Decrease lookup options, provided solely for model operational purposes.

8.8 INPUT_Demand Lookups

Lookup tables for domain-specific demand parameters relating physical characteristics of the precinct to modelling parameters and operational characteristics are included on this worksheet. Physical solar panel dimensions and electricity production capacity is included in “Table E01: Energy - Solar Capacities” whilst street and public space globe/lighting parameters are identified in “Table E02: Energy - Public Space Lighting”. A list of possible trip purposes for the transport domain is in “Table E03: Transport - Trip Purposes”, while a more detailed description of electric vehicle options is in “Table E04: Transport - Electric Vehicle Characteristics”. This table identifies the following characteristics for electric vehicle make and models of Nissan Leaf, VW e-Golf, BMW i3 and Tesla Model S:

- Battery capacity,
- Range,
- Energy consumption,
- Equivalent fuel consumption (equivalent energy consumption in petrol),
- Comparison car (conventionally powered car of similar size and capacity),
- Comparison car fuel consumption.

Electric vehicle and comparison vehicle characteristics are sourced from the Australian Government website for the Green Vehicle Guide (Commonwealth of Australia, 2016). If the user prefers a different vehicle type, the ETWW model provides an option for a user defined vehicle type.

Characteristics of the waste removal vehicles is provided in “Table E05: Transport - Waste Truck Characteristics” separately for landfill, organic and recycling waste types. Truck characteristics include:

- Load capacity,
- Fuel type used,
- Fuel use on an empty load,
- Fuel use on a full load,
- Fuel use emission rates.

Equally as important to determining the total emissions from waste removal are the parameters for travel associated with the waste removal activity. These varies for waste type and specific to the precinct location:

- Truck 'Home' location (TAZ),
- Home to precinct site distance,
- Dump/recycling locations and one-way distance,
- On-site precinct route distance,
- Collection interval.

For accurate truck collection estimations, additional characteristics for waste removal are identified in “Table E06: Waste - Household Waste Characteristics” as:

- Household bin capacity
- Uncompacted density
- Compaction ratio
- Waste CO_2e production

8.9 INPUT_MosaicGIT_Ref

This input sheet contains the Mosaic household typologies and attributes in the context of a re-formatted Mosaic Grand Index Table (GIT). All contents of this table are included however items of importance and relevance to ETWW forecasting are:

- Adults at the address,
- Number of persons resident,
- Annual household income,
- Number of bedrooms,
- Number of bathrooms,
- Plot size,
- Vehicles in the household.

The GIT is formatted so that all other items exist as hidden rows and \ supplementary calculation processes that estimate household averages are also hidden as to improve the ease of interpretation of only relevant information.

8.10 INPUT_Climate_Ref

Climate and environment reference data inputs within this sheet provide current and forecast climatic and environmental conditions. This is estimated for all Australian capital cities, with base and forecast data estimated using the Thornthwaite method (AUSTROADS, 2010).

Summarised Thornthwaite Moisture Index forecast year estimation results of average precipitation and temperature are made for all Australian capital cities. The 'hidden' columns Y to AP contain raw data responses from the Thornthwaite model operational runs for selected capital city locations. It is possible to refine these parameters based on exact latitude and longitude location of the precinct however this would require a re-run of the external Thornthwaite estimation process. The complete climate data for the forecast year are for:

- Ave monthly rainfall,
- Ave daily rainfall,
- Ave daily max temp,
- Ave daily min temp,
- Ave monthly global solar exposure,
- Ave daily global solar exposure,
- Ave daily solar irradiance,
- Ave night hours.

The composition, estimation and use of the Thornthwaite Moisture Index is described in Taylor and Philp (2016).

8.11 INPUT_EnergyCarbon_Ref

Energy and carbon relationships contained in this spreadsheet are divided into the forecast domains with relationship factors listed for each.

Scope 2 emissions for electricity purchased from the grid are physically produced by the burning of fuels (coal, natural gas, etc.) at the power station. The emission factor here is expressed as kg of CO2e/kWh and the proportion of renewable energy sources involved in the production process. Estimates are provided for all state capitals as the spreadsheet identifies the appropriate emission factor for the precinct location and the user is able to manually adjust this if required.

Tank to wheel emission rates and confidence intervals are the direct result of PhD research associated with this project (Iankov 2016) and detailed in other sections of this report relating to transport emission estimations. This section of the spreadsheet provides historic and forecast emission rates disaggregated by:

- Small, medium and large passenger vehicles,
- Residential street traffic load,
- Arterial road traffic load,
- Congested road traffic load,
- Highway traffic load.

Expected values and 95% confidence intervals are provided for tank to wheel greenhouse gas emission rates for traffic load occurring in a traffic condition represented by the US FTP speed-time profile (g CO2-e/vkt). Appropriate values are extracted and applied for the forecast year. Public transport emissions are provided a single value of 0.124 kg of CO2/passenger km, an emission rate sourced from Taylor *et al* (2010).

Emissions generated from waste treatments for landfill, recycling and organic wastes are expressed as kilogram of CO2e per kilogram of waste disposed although the waste types have quite different emission generation qualities. Landfill emissions are generated from the decomposition of waste whilst recycled waste generates Scope 2 emissions associated with grid-based energy used in the recycling processes for different recycled materials. Organic emissions are associated with the aerobic composting process required to turn organic material to garden compost.

Water supply and wastewater treatment requires energy and hence draws upon grid-based electricity to operate. Scope 2 emissions are therefore incurred in this process as energy in kWh required to supply or treat 1kL of water/wastewater. Energy use rates vary between capital cities and is therefore location-dependent for the precinct. The ETWW model recognises energy and emissions with:

- Water supply,
- Wastewater removal and treatment,
- Hot water generation,
- Rainwater tank water supply.

8.12 MODEL

Modelling routines contained within the ETWW workbook are identified with the “MODEL” prefix to identify content that is estimated through the application of models and use of input data, much of which relates to non-residential land uses. The following section details worksheets that are MODEL operations.

8.13 MODEL_NonResidential

Modelling routines on this worksheet forecast the demand and supply associated with each non-residential land use zone within the precinct for electrical energy, water and waste supply/demand. Energy routines determine internal building demand, outdoor precinct demand (as night time street and public space lighting requirements) and solar energy production. Water estimation processes estimate internal building demands, outdoor demands and water collection potential. Water collection is not included as part of the supply options for the precinct however they may do so if the routines are adjusted to account for collection tanks, pumping etc.

8.14 MODEL_TransportData

This spreadsheet has two main data components, the zoning and land use datasets used as input for the STM and the output data summaries from the STM. Strategic transport model critical input data components delivers data sourced from previous spreadsheets, describing the residential and non-residential zones in preparation for input to STM modelling routines. This data table contains the following items:

- Z: Allocated zone number. This will need to suit with the STM zone labelling convention
- Z_HHOLDS: number of residential households in the precinct sub-zone
- HH_PER: Average number of persons per household
- HH_WOR: Average number of workers per household
- HH_DEP: Average number of non-workers or dependants per household
- HH_CAR: Average number of privately owned passenger cars per household
- Z_POP: Total population of the precinct sub-zone
- Z_SER: Total employment in the service industry for the precinct sub-zone
- Z_MAN: Total employment in the manufacturing industry for the precinct sub-zone
- Z_TEC: Total employment in the technical/trade industry for the precinct sub-zone
- Z_TRA: Total employment in the transport industry for the precinct sub-zone
- Z_RET: Total employment in the retail industry for the precinct sub-zone
- Z_EDU: Total employment in the education industry for the precinct sub-zone
- Z_ENT: Total employment in the entertainment industry for the precinct sub-zone
- Z_OTH: Total employment in other industries for the precinct sub-zone
- Z_PE: Total enrolments in primary schools for the precinct sub-zone
- Z_SE: Total enrolments in secondary institutions for the precinct sub-zone
- Z_TE: Total enrolments in tertiary institutions for the precinct sub-zone

Strategic transport model forecasting results summaries relate to each sub-zone within the precinct, reporting on STM-estimated forecasts of total trips, total travel time and travel distance. These estimates are revised based on scenario options identified with revisions applied to the travel distances. Activities performed will influence the total travel performed and the presence of electric vehicles will sub-divide the total travel distance into that performed by conventional and electrically powered private transport modes

The “Import STM Demand Data” button will import the origin to destination data for the selected precinct zones and to all other internal and external to precinct zones contained within the STM. Associated travel demand, distances and times are imported in the form of person and vehicle trips and also disaggregated by travel purpose. This import occurs in columns BX to CS with the remainder as calculation fields based on this import, estimating the total vehicle hours travelled and vehicle kilometres travelled for all origin-destination pairing by both travel mode and trip purpose.

8.15 MODEL_WasteTransport

Transportation of waste forecasting routines utilise zonal activity data in terms of the population of households, the non-resident employment and land use for each type to estimate the total weight and volume of landfill, organic and recycling waste. It is important to note here that the spreadsheet estimates both residential and non-residential waste production.

For each land use type, compacted totals are estimated per collection period, which is then used to estimate the total number of trucks required to remove the waste for all three types. Each full truck in turn will need to dump the waste at the appropriate dumping or recycling facility. Travel is then related to energy use and carbon impact with totals for each waste truck travel then apportioned to each precinct sub-zone according to the proportion of waste each generates.

8.16 RESULTS

Forecast results of routines contained within the ETWW workbook and performed by external processes are identified with the "RESULTS" prefix. Estimates are reported for the demands and finally for the carbon impacts.

Interaction between the domains occurs depending on the identified scenario interaction options as identified in the following:

- Electric vehicle ownership and use: transport and energy domain interaction,
- Hot water use: water and energy domain interaction,
- Evaporative cooling: water and energy domain interaction,
- Rainwater tank water use: water and energy domain interaction,
- Wastewater: waste and water domain interaction,
- Activities from home: all domain interaction
- Water consumption behaviour: water and energy domain interaction
- Recycling behaviour: waste, transport and energy domain interaction,
- Water supply: water and energy domain interaction,
- Waste removal: waste and transport domain interaction,
- Grid energy generation: all domain integration.

In addition to these scenario interaction types, the structure and development of domain modelling routines allow for the representation of the following technologies and attributes of precinct structure, both at the household and precinct scale:

- Solar electricity generation technology,
- Battery electricity storage technology,
- Various household energy efficient devices,
- Supply of energy from renewable resources,
- Household water capture and re-use,
- Various household water saving devices,
- Alternative hot water systems,
- Water-efficient green areas at the household and precinct,
- Household recycling techniques and technologies,
- Public transport and non-motorised network alternatives, both contained within and connecting to the precinct.

Other behavioural interactions resulting in domain demand interactions that are represented are:

- Increased recycling behaviour,
- Reduced waste production behaviour,
- Increased work-form-home behaviour,
- Increased shop-from-home behaviour,
- Reduced water consumption behaviour,
- Reduced energy use behaviour,
- Reduced transport demand behaviour,
- Mode shift behaviour.

The following section details worksheets that contain forecast RESULTS, with interactions between domains represented in the final demand results quantified and presented for carbon estimation.

8.17 RESULTS_Demand

Demand data collated as outputs from the domain forecasting processes are initially utilised as the first iteration dataset, acting as a base data set for interactions

For the energy domain, the following demand and production components are provided, with all results expressed as daily kilowatt hours (kWh):

- Total demand,
- Energy used from the grid,
- Electricity generated from solar,
- Solar energy feed-in,
- Electricity stored in battery storage units,
- Battery capacity,

- Electricity demand for the electric vehicle (if applicable).

All residential and non-residential land uses produce demand estimates for total demand, grid energy and solar production with the remainder applicable to residential land uses only.

Demands for the transport domain are as follows with demands expressed the total daily kilometres of travel:
- Conventionally powered private vehicle (ie. fossil fuel energy source),
- Electric vehicle,
- Public transport, all modes combined,
- Bicycle,
- Walk,
- Waste truck/s.

All results here are expressed as total kilometres of travel although for private motorised modes the results are vehicle-kilometres and passenger kilometres for public transport modes.

The production of waste is classified into landfill, organic and recycling waste types with the total daily weight estimates for each in kilograms provided.

Water demand and wastewater production is classified into the following estimates in this spreadsheet:
- Mains demand,
- Rainwater demand,
- Hot water use,
- Outdoor use,
- Wastewater produced.

Results are expressed as daily water demand and wastewater production in kilolitres (kL) per household and total for residential sub-zones with total kL for non-residential land uses.

8.18 RESULTS_Carbon

Following on from the finalised demand estimation process (ie. accounting for any necessary feedback and iterations), daily carbon production estimates are produced for each domain and for all precinct zone locations as kg of CO_2e. This is initially reported for each demand domain and for each sub-zone within the precinct.

The energy and water domains provides a total CO_2e estimate with transport disaggregating to provide CO_2e estimates for conventional and electric cars, public transport and waste truck/s. Emissions associated with electric vehicle are included in the energy domain result. Waste disaggregates by waste type, with the following sources:

- Landfill: emissions from the decomposition of waste materials of different types,
- Organic: emissions from composting of organic waste,
- Recycling: emissions from grid-based energy required to recycle various recycling waste types.

8.19 OUTPUTS_GIS_Attributes

Finally, the summary outputs of CO_2e estimates are collated for the purpose of linking to the original GIS precinct structure and for displaying spatially on a precinct map and to utilise GIS analysis tool in the ArcGIS environment. GIS data linkage for all domains includes:

- GIS Zone Id,
- Mosaic resident type
- Residences
- Population
- Employees
- Energy_kg CO2
- Transport_kg CO2e
- Waste _kg CO2e
- Water_kg CO2e
- Total_kg CO2e
- Energy/HHold_kg CO2e
- Transport/HHold_kg CO2e
- Waste /HHold_kg CO2e

- Water/HHold_kg CO2e
- Total/HHold_kg CO2e
- Energy/m2_kg CO2e
- Transport/m2_kg CO2e
- Waste /m2_kg CO2e
- Water/m2_kg CO2e
- Total/m2_kg CO2

9 Case Study Application: Lochiel Park Precinct

To demonstrate the forecasting abilities of the ETWW model, two case study precinct locations were chosen for scenario development and reporting of forecast results, namely Lochiel Park and Tonsley in suburban Adelaide. Both of these precincts are part of the CRC's Adelaide Living Laboratory. The first of these concerns the Lochiel Park precinct located approximately 8 kilometres north-east of the Adelaide CBD. (Figure 9.1).

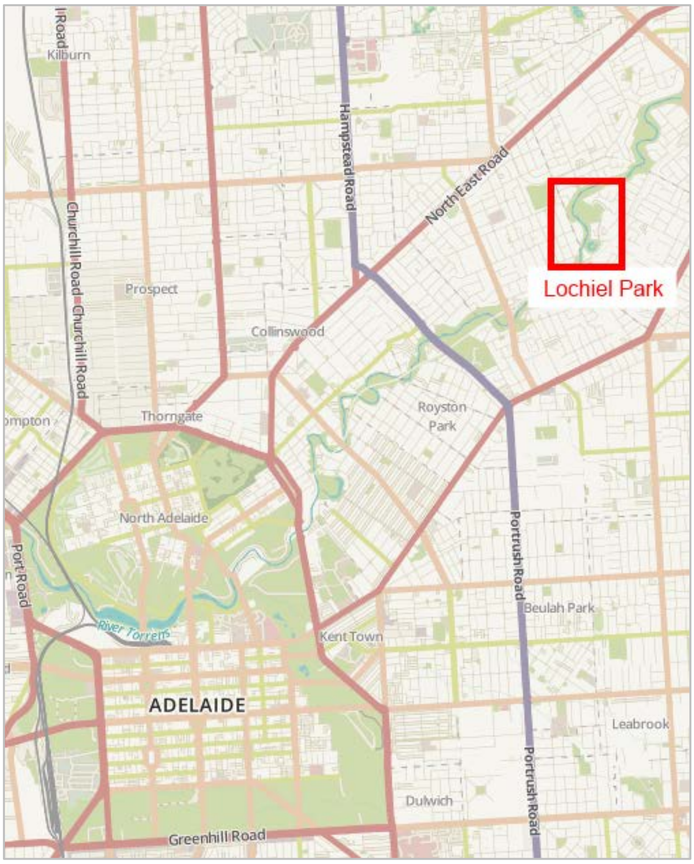


Figure 9.1: Lochiel Park site location.

Here, two scenarios were developed for forecasting tasks; a 'current' condition in 2015 and a future forecast condition in 2035 with specific attributes to demonstrate domain interaction. Both scenarios forecast daily demand profiles during the spring season. The results provided for this precinct forecasting focus on select results from the individual modelling domains with details mainly concerned with demand estimates from the forecast runs. Some interaction is estimated in this analysis, although interactions of domain forecasts are the focus of the second precinct case study location at Tonsley.

The 2015 Lochiel Park forecast or 'Scenario A' reflects current precinct with 106 households with 2015 Mosaic classifications in the following table and no other land uses. The current climate prevails with existing transport network connections, waste collection operations, household technologies etc., much of which is detailed by Experian's assessment of current household attributes. Scenario B relates to a 2035 forecast with the precinct expanded to 256 households with adjusted proportions of Mosaic types to reflect possible population change over 20 years. The assumed population change sees the introduction of more and different Mosaic typologies as the precinct matures. A proportion of residents present in 2015 are remain in the precinct whilst a range of new residents enter as the precinct ages and grows. Any number of possibilities could be represented here and align with future-oriented population research such as reported Bridge and Elias (2010) if desired in an alternative forecast future year scenario.

Additional simple land uses with small retail space and secondary education are also present and forecast climatic conditions prevail. In addition to the modified household profile of the precinct, Scenario B involves a secondary school with 300 enrolments and 15 staff and a small retail outlet employing 5 persons. Table 9.1 outlines the household types present in the scenarios of the Lochiel Park case study.

Mosaic Code	Description	Detailed Description	Households
		Scenario A - 2015	
B05	Educated Savers	Informed and educated wealthy families in desirable suburbs on city perimeters.	10
C13	Professional Views	Apartment dwellers with a social outlook living on the fringe of the inner city.	36
D16	Ageing Gracefully	Empty-nester couples living in large houses in sought after outer metropolitan suburbs.	60
		Scenario B – 2035	
B05	Educated Savers	Informed and educated wealthy families in desirable suburbs on city perimeters.	13
B06	Maturing Assets	Educated, maturing family households located in outer metropolitan suburbs.	38
B08	Multicultural Wealth	Multicultural adult households with good incomes in inner and outer city suburbs.	13
B09	The Good Life	Older couple households with simple needs living in suburbs that are more affordable.	51
C12	Wireless and Wealthy	Social young careerists in affluent city central suburbs.	13
C13	Professional Views	Apartment dwellers with a social outlook living on the fringe of the inner city.	38
D16	Ageing Gracefully	Empty-nester couples living in large houses in sought after outer metropolitan suburbs.	26
F21	Family Connections	Mixed family forms with substantial incomes located in new suburban estates.	13
H31	Extended Ethnicities	Extended families and home-sharers of diverse backgrounds living within easy access of major cities.	26
I34	Roaring Twenties	Singles at university or in early stages of their career in apartment outside of city centre environs.	5
K40	Community Conservatives	Elderly couples and singles with traditional values and low expenses in metropolitan areas.	20

Table 9.1: Household resident types present in the Lochiel Park precinct scenarios.

Physical attributes of household structure types are defined as the three possible households of apartments, medium and larger size detached houses. Table 9.2 provides a breakdown of the attributes for the house types present in both Scenarios A and B, with the assumption that future household attributes operate at the same levels of efficiency as they do in the base condition. Assessment of the household structure type considers the attributes in this table rather than a performance or efficiency ranking of the residence as a whole.

House Structure Type	1	2	3
General Description	**Apartment**	**Medium Size Detached**	**Larger Detached**
Roof Area/home (sqm)	45	190	240
Connected roof coefficient	0.9	0.8	0.7
Rainfall Collection/home (kL)	19111	71727	79277
Rainwater tank size (kL)	1.0	3.0	4.5
Panels/home	10.0	12.0	15.0
Bedrooms	2.0	3.0	4.0
Bathrooms	1.0	2.0	2.0
Parking allocation off-street	1.0	2.0	2.0
Parking allocation on-street	0.5	1.0	1.0
Plot Size (sqm)	150.0	300.0	300.0
Outdoor green space (%)	0	10	10
Elec - TV's	1.0	2.0	2.5
Elec - Cooking	1.0	1.0	1.5
Elec - AC	1.0	2.0	3.0
Elec – Hot Water	1.0	1.0	2.0
Elec - Washer	1.0	1.0	1.0
Elec - Dryer	1.0	1.0	1.0
Elec - Fridge	1.0	1.0	2.0
Gas - Cooking	0.0	0.0	0.0
Gas - Heating	0.0	0.0	0.0
Gas – Hot Water	0.0	0.0	0.0
Water - Showers	1.0	2.0	2.0
Water - Toilets	1.0	2.0	3.0

Table 9.2: Household structure type attributes.

The combined domain interactions for the forecasts are specified to only occur in Scenario B and are as follows:

- Energy and transport domains through the presence of electric vehicles,
- Waste, transport and energy domains through the physical pick-up and disposal of precinct waste,
- Water and energy from renewables and the energy used in the supply of water,
- All domains based on work-from-home behaviour, ie. spending the day in the precinct rather than at the work location.

9.1 Selected Forecast Results

The following provides a brief summary of selected scenario outcomes presenting the overall influence of forecast scenarios on the carbon production attached to the precinct. Estimation processes allow for detailed estimations at a household and individual land-use level.

9.1.1 Electric Vehicles

The electric vehicle scenario sees the introduction of an electric vehicle from no household ownership in 2015 to 100% household ownership for the Lochiel Park precinct in the year 2035, and assumes a growth of the precinct from 106 households in 2015 to 256 in the year 2035, along with other land uses as described previously. Travel over a complete day is considered and so this includes return trips as part of the journey. In this scenario the use of electric vehicles is for only for work-based trips performed from home-to-work and the returning work-to-home travel. A feature of the strategic transport modelling process is the allocation of an appropriate workplace location for all of the households within the precinct. Table 9.3 presents the 2015 and 2035 travel and carbon productions.

	2015		2035	
	Travel (km)	**CO2 (kg)**	**Travel (km)**	**CO2 (kg)**
Car - Conventional	18,071	3,397	58,093	10,921
Car - Electric	-	-	15,893	-
Public Transport	1,262	189	4,908	736
Bike	53	-	310	-
Walk	28	-	554	-

Table 9.3: Lochiel Park precinct multimodal travel and carbon impact for scenarios.

The 2035 scenario produces an overall growth in car travel of 55,915km with 15,893km of this attributable to electric vehicles. There is also substantial relative growth in travel from other modes which is not only related to an increase in home-based travel but also due to the presence of a secondary school and retail space. The introduction of electric vehicles to all households in the 2035 scenario for work-based travel sees a saving in CO2 of 2,988kg on a typical day if electricity is sourced from renewable sources such as solar.

As a result, the precinct requires a total of 2,861 kilowatt hours of electrical energy to power the daily electric vehicle needs. The ETWW foundation model allows the deeper investigation of this energy in terms of average energy per household within each Mosaic household class to power an electric vehicle, per home. Table 9.4 shows the average values for each household class.

Mosaic Classification	**kWh required for electric vehicle travel**
B05	6.0
B06	7.4
B08	6.7
B09	7.5
C12	4.1
C13	5.0
D16	6.9
F21	7.2
H31	9.2
I34	5.6
K40	4.7
Average	6.4

Table 9.4: Daily household power required for electric vehicle travel by house classification in 2035.

As a comparison to the average household electricity use, ACIL Allen Consulting (2015) reports that in 2014 the average Australian daily household electricity consumption was 15.9 kWh, and in 2011 was 18.2 kWh. Electric vehicle charging therefore represents an additional 40% to load to the average household energy demand.

9.1.2 Energy

The energy demand scenario investigates precinct energy demand for 2015 and 2035. For both scenarios we first determined the raw demand profiles, based on hourly outside temperature, information about the occupants and the homes. We then investigate the impacts of reducing demand, and CO_2 emissions, through the installation of solar and battery systems and how this effects the hourly demand profile shapes. Two demand reduction scenarios have been considered: 1) the reduction in grid reliance by 50% and, 2) the lowest cost energy supply solution. Table 9.5 summarises the yearly CO2 emissions and the 25 year net-present-value cost of energy. This cost includes the infrastructure costs of the solar and battery system, cost of energy imported from the grid and a small profit from energy exported to the grid; a discount rate of 5% was used. This table shows that there is only a small increase in lifetime energy costs to reduce grid reliance by 50%. Furthermore, the lowest cost scenario shows that both emissions and energy costs can be reduced by installing a solar panel only system.

	Grid only		50% grid reliance reduction scenario				Lowest cost scenario			
Mosaic Group	Total cost of Energy from the grid ($)	Total Yearly CO_2 (TCO_2e)	Total cost of energy	Total Yearly CO2 (TCO_2e)	CO2 offset from Export (TCO_2e)	Net impact (TCO_2e)	Total cost of energy	Total Yearly CO2 (TCO_2e)	CO2 offset from Export (TCO_2e)	Net impact (TCO_2e)
C12	$ 12,744.81	1.63	$ 13,319.88	0.88	2.87	-2.00	$ 10,891.30	1.29	1.31	-0.03
C13	$ 7,629.41	0.53	$ 6,915.95	0.29	0.81	-0.51	$ 6,611.21	0.38	0.50	-0.12
I34	$ 12,744.81	1.63	$ 13,319.88	0.88	2.87	-2.00	$ 10,891.30	1.29	1.31	-0.03
F21	$ 13,478.63	1.45	$ 11,127.25	0.82	2.22	-1.40	$ 10,556.83	0.98	1.43	-0.44
B05	$ 15,894.44	2.19	$ 15,527.68	1.18	3.41	-2.23	$ 13,068.35	1.67	1.30	0.37
B06	$ 11,773.57	1.23	$ 10,132.85	0.69	1.78	-1.09	$ 9,505.44	0.86	1.05	-0.20
B08	$ 11,918.96	1.49	$ 12,493.59	0.79	2.77	-1.97	$ 10,262.30	1.17	0.96	0.21
H31	$ 11,321.01	1.29	$ 10,974.70	0.70	2.12	-1.42	$ 9,567.62	0.98	0.82	0.16
D16	$ 17,480.43	2.30	$ 15,257.97	1.26	3.71	-2.44	$ 13,664.06	1.64	1.97	-0.33
B09	$ 7,867.59	0.57	$ 7,123.56	0.32	0.81	-0.50	$ 6,789.75	0.40	0.54	-0.14
K40	$ 7,629.41	0.53	$ 6,915.95	0.29	0.81	-0.51	$ 6,611.21	0.38	0.50	-0.12

Table 9.5: CO2 Emissions and 25 year lifetime cost of energy.

9.1.3 Energy-Transport Interactions

An initial investigation of the interaction between the Energy and Transport domains was considered by adding the electric vehicle daily charging requirements to the base load profiles for each Mosaic Group. When generating the new profiles it was assumed that the charging of the electric vehicle is spread over the off peak pricing times, from 11pm – 6 am every day. Figure 9.2 shows a sample of the demand profiles produced by the model. The impact of electric vehicles can be seen by the increase in precinct demand during the off peak periods. The battery and solar optimisation model has been applied to these new profiles to analyse the impact of solar and battery systems on the precinct demand with electric vehicles. The 50% grid reliance scenario, shown by the blue line has increased the demand shape complexity significantly; this could have negative impacts on the electricity network.

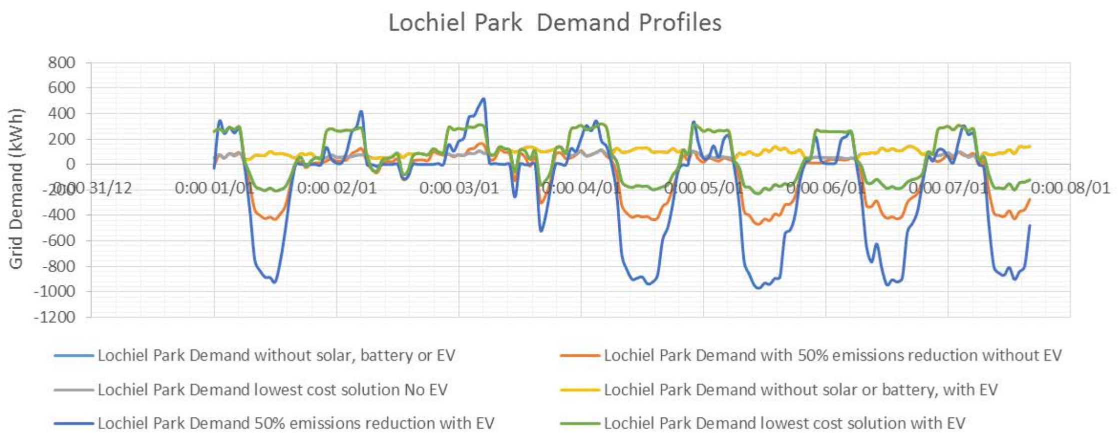


Figure 9.2: Sample of the precinct demand scenarios.

Table 9.6 shows the solar and battery capacities defined in the optimisation model. It can be seen that, no battery system has been defined for the lowest cost scenarios, an outcome that could change as battery prices reduce in the future.

					With Electric Vehicle			
			Lowest cost scenario no EV				Lowest cost scenario with EV	
Mosaic Group	Solar Capacity (kW)	Battery Capacity (kWh)	Solar Capacity (kW)	Battery Capacity (kWh)	Solar Capacity (kW)	Battery Capacity (kWh)	Solar Capacity (kW)	Battery Capacity (kWh)
C12	3.52	1.83	1.67	0.00	4.80	4.08	1.67	0.00
C13	1.04	0.35	0.67	0.00	2.98	3.10	0.67	0.00
I34	3.52	1.83	1.67	0.00	5.23	4.92	1.67	0.00
F21	2.85	0.67	1.95	0.00	5.96	4.47	1.95	0.00
B05	4.32	2.12	1.87	0.00	6.78	5.38	1.87	0.00
B06	2.32	0.72	1.47	0.00	5.34	4.72	1.47	0.00
B08	3.35	1.64	1.29	0.00	5.68	5.36	1.29	0.00
H31	2.65	1.21	1.16	0.00	5.95	6.33	1.16	0.00
D16	4.68	1.59	2.68	0.00	7.27	5.30	2.68	0.00

Table 9.6: Optimised system capacity

Table 9.7 summarises the yearly CO2 emissions and the 25 year net-present-value cost of energy when the homes have electric vehicles. An increase in emissions from the grid and energy costs can be observed in all scenarios. Since charging only occurs at night, to meet a grid reliance percentage of 50%, a large battery system is required to shift the solar generation from the day time to the night time to reduce the vehicle charging demand from the grid. This large battery accounts for the higher cost of energy for this scenario.

	Grid only		50% grid reliance reduction scenario				Lowest cost scenario			
Mosaic Group	Total cost of Energy from the grid ($)	Total Yearly CO2 (TCO2e)	Total cost of energy	Total Yearly CO2 (TCO2e)	CO2 offset from Export (TCO2e)	Net impact (TCO2e)	Total cost of energy	Total Yearly CO2 (TCO2e)	CO2 offset from Export (TCO2e)	Net impact (TCO2e)
C12	$15,014	2.44	$19,952	1.32	3.78	-2.45	$13,161	2.18	1.31	0.87
C13	$10,397	1.53	$15,234	0.84	2.32	-1.48	$9,378	1.47	0.50	0.98
I34	$15,844	2.74	$22,480	1.49	4.07	-2.58	$13,991	2.51	1.31	1.20
F21	$17,463	2.88	$22,090	1.61	4.74	-3.13	$14,541	2.56	1.43	1.13
B05	$19,215	3.38	$25,228	1.84	5.37	-3.53	$16,389	2.98	1.30	1.69
B06	$15,869	2.70	$21,985	1.50	4.18	-2.68	$13,601	2.48	1.05	1.42
B08	$15,627	2.82	$23,555	1.53	4.51	-2.98	$13,971	2.64	0.96	1.68
H31	$16,412	3.12	$26,418	1.71	4.63	-2.92	$14,660	2.99	0.82	2.18
D16	$21,299	3.67	$25,964	2.02	5.71	-3.69	$17,483	3.15	1.97	1.19
B09	$12,018	2.06	$19,749	1.14	2.98	-1.84	$10,940	2.05	0.54	1.51
K40	$10,230	1.47	$14,713	0.81	2.21	-1.40	$9,212	1.41	0.50	0.91

Table 9.7: Energy and Electric vehicle CO2 Emissions and 25 year lifetime cost of energy

9.1.4 Waste Disposal

The ETWW foundation model allows for the estimation of household waste production, the transport needs for waste removal and disposal/recovery with associated carbon impacts. Forecasting for both the 2015 and 2035 scenarios assumed that the on-road distance from Lochiel Park to recycling and dumping facility at Wingfield is 14.5km with *landfill* waste collection weekly, and bin capacity 140 litres; *organic and recycling* waste collection fortnightly and alternating with bin capacity of 240 litres. In this model estimation, it is assumed that populations in both scenario years exhibit the same recycling behaviour although this may be altered if future populations are expected to recycle more. Another scenario run could capture this behaviour in addition to on-site waste processing if desired.

Calculations were performed by waste type and again disaggregated by Mosaic household classification and reported here on a weekly basis. Transport based CO2 production is from the collection vehicle emissions with waste generated from landfill and organic is only from the decomposition of materials. Forecasts do not account for embodied CO2 or CO2 production from the recycling process. These emission types are beyond the present forecasting capacity of the ETWW model. Table 9.8 summarises the results.

	2015		2035	
	Transport Based CO2 (kg)	**Waste Generated CO2 (kg)**	**Transport Based CO2 (kg)**	**Waste Generated CO2 (kg)**
Landfill Garbage	112.6	365.2	337.9	915.6
Organic Waste	90.1	386.3	180.2	968.5
Mixed Recycling	90.1	0.0	180.2	0.0
Total	**292.9**	**751.6**	**698.4**	**1884.0**

Table 9.8: Weekly generation of CO2 associated with Lochiel Park precinct waste disposal for both scenarios.

It is evident from these results that in both scenarios transport is a significant component of carbon production associated with waste disposal, accounting for close to 27% of the total in both forecast scenarios.

9.1.5 Work From Home

The work-from home scenario only considered impacts related to the 2035 forecast scenario and assumed that a selection of household types will effectively 'work from home' and hence not contribute to commuting travel on the road. Table 9.9 presents the car-based travel and carbon saving disaggregated by Mosaic household type.

Mosaic Classification	Households	Work From Home?	Car travel saved (km)	CO2 saved (kg)
B05	13	All	5,332	1,002
B06	38	All	1,413	266
B08	13	All	860	162
B09	51	None	-	-
C12	13	All	249	47
C13	38	All	881	166
D16	26	None	-	-
F21	13	None	-	-
H31	26	None	-	-
I34	5	None	-	-
K40	20	None	-	-

Table 9.9: Work-from-home 2035 scenario car-based travel and carbon savings.

In total 8,734 kilometres of travel are removed from the roads as the selected cohorts do not commute, resulting in a reduction in carbon of 1,642 kg CO2 per day.

9.1.6 Water

The following is a short comparison of current (2015) versus potential future (2035) emissions scenarios in relation to water use for the Mosaic types at Lochiel Park. Climate change models predict a slight reduction in rainfall and increased temperature for Adelaide as shown in Figure 9.3.

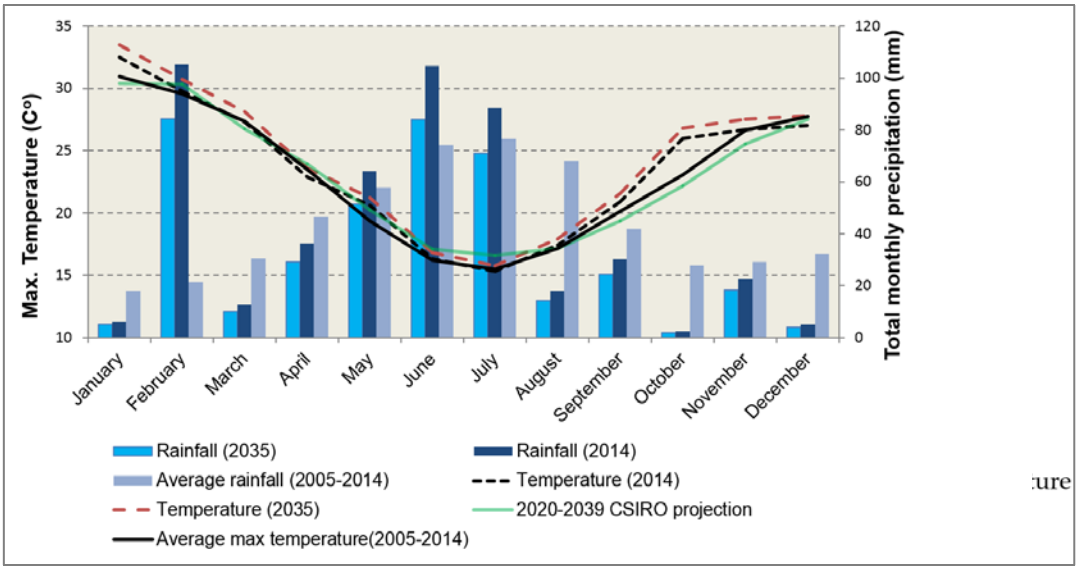


Figure 9.3: Assumed climate change forecast across 12 months.

9.1.6.1 Climate change – water demand impacts (Models 1-3)

The following model forecasts are with only climate change in the future scenario and minor changes with very similar overall patterns in demand. The hot water demand remains the same or reduces slightly whilst cold water demand increases due primarily to outdoor use. Mosaic classifications are provided on the y-axis in Figure 9.4(2015 Scenario) and Figure 9.5 2035 Scenario). Rainwater use is based on the availability of collected rainwater and the overall household demand for water.

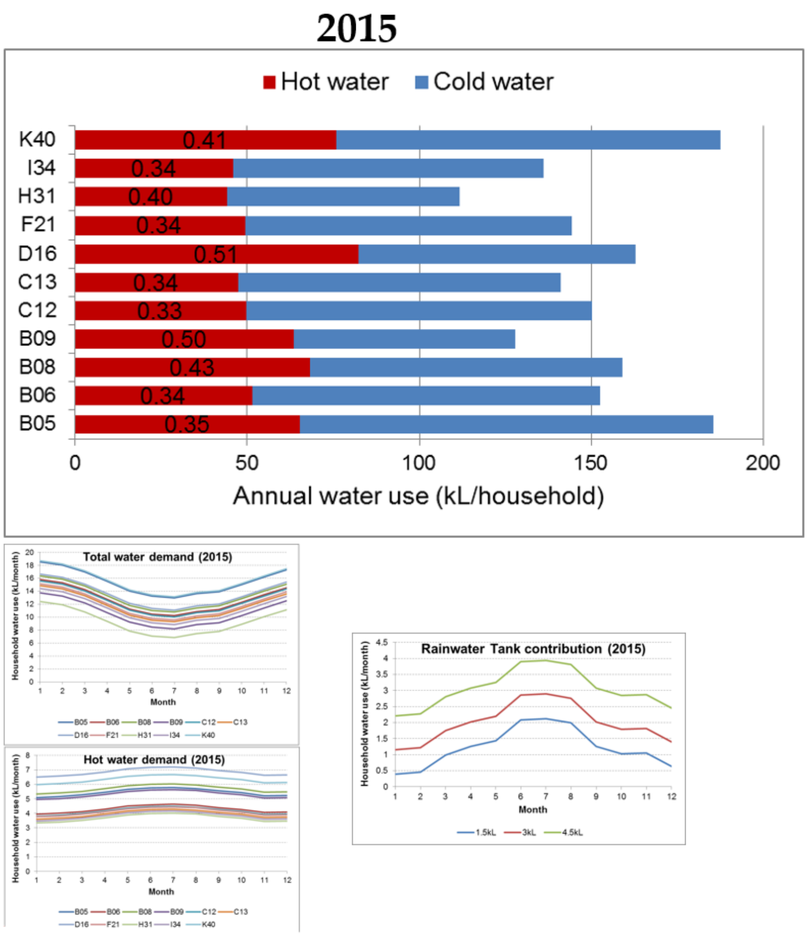


Figure 9.4: 2015 and 2035 water demand forecast results for each household type.

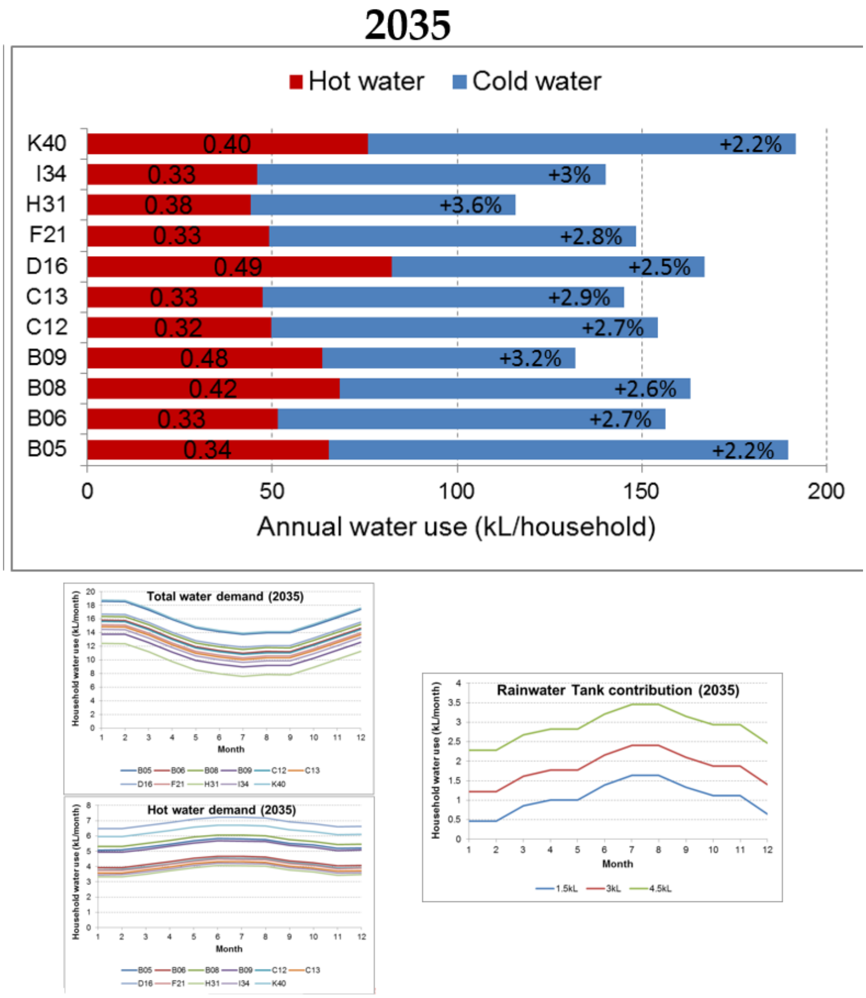


Figure 9.5: 2015 and 2035 water demand forecast results for each household type.

Mosaic classifications are provided on the y-axis in Figure 9.4 and Figure 9.5

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9.1.6.2 *Climate change – water-related energy impact*

Figure 9.6 indicates the carbon impact of water supply and use for each Mosaic household type in 2015.

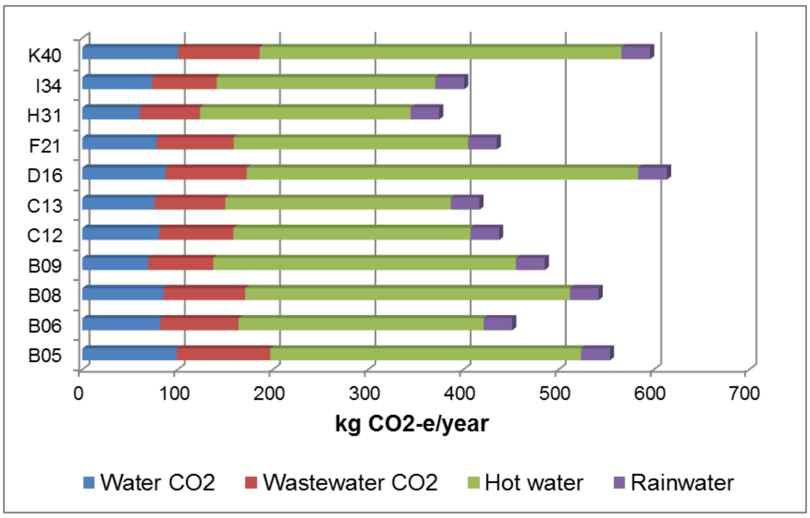


Figure 9.6: Carbon impact of water supply and use for each household type in 2015.

Based on the current household mix for 2015 precinct total emissions are 123.2 tCO2-e per year, with Figure 9.7 showing the relative shares of the different water components.

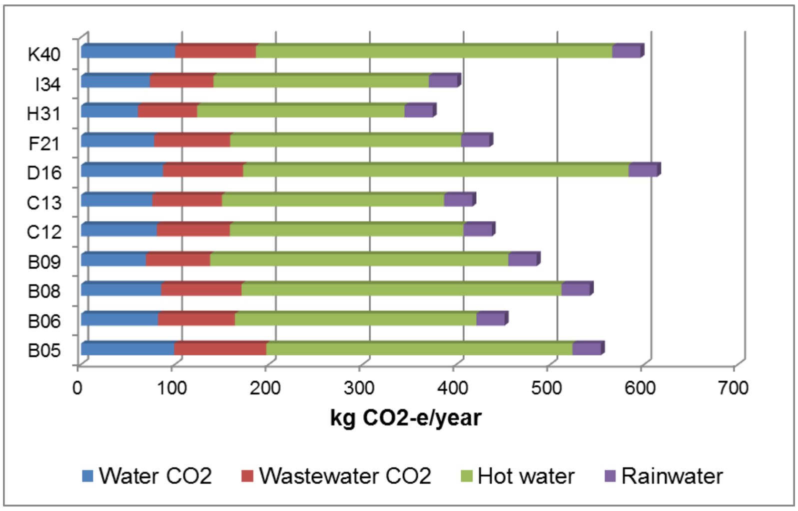


Figure 9.7: Carbon impact of water supply and use for each household type in 2035 with climate change effects only.

From Figure 9.7 with the 2035 household compositions in Lochiel Park, analysis indicates that If the same supply mix is maintained there will be a marginal reduction in CO2e emissions, with a precinct total of 122.9 tCO2-e. The reason for this is because despite the higher overall water demand (as shown previously), the reduced rainwater yield and lower hot water use, lead to this slight decrease in emissions

9.1.6.3 Water supply mix different – more desalination

Usage of more desalinated water in 2035 would lead to an increase in the intensity of carbon emissions for the water supply to the precinct. The 2035 precinct total is estimated at 164.8 tCO2-e, an increase of 34% over the amount for the base supply mix as in Figure 9.7. Figure 9.8 shows the new household consumption rates, and clearly indicates the increases in carbon impacts of the use of the desalinated water.

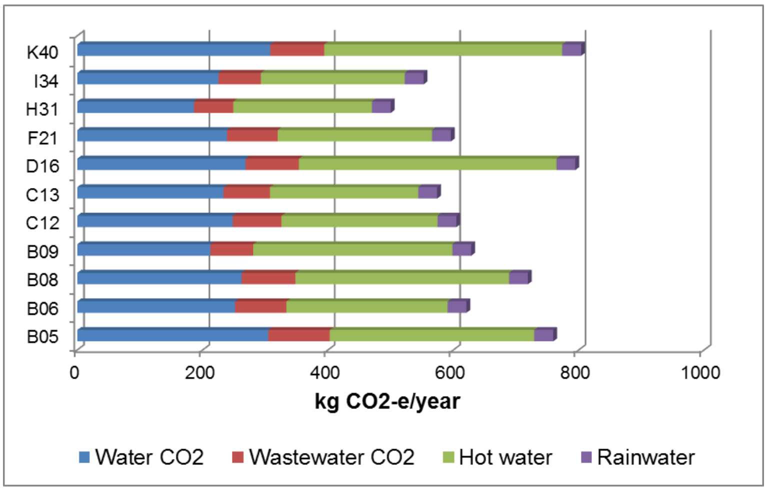


Figure 9.8: Carbon impact of water supply and use for each household type in 2035 with climate change effects and water supply mix change.

9.1.6.4 The same water supply mix but now with 80% renewables

Desalinated water may be more important in 2035 given the likelihood of a drier climate. To overcome the increase in carbon emissions predicted with the use of desalinated water, the increased use of energy from renewable sources should be considered. An analysis was therefore undertaken using 80% renewables. Figure 68 shows the carbon impacts on each household type under this situation. The overall impact is a reduction of 18% in the precinct total (water-based) carbon emissions (101.2 tCO2-e) when compared to the base case for 2035. Thus use of renewables can offset the effects of the desalination. In this case hot water now completely dominates the emissions profile, indicating a need to test the impacts of different hot water systems.

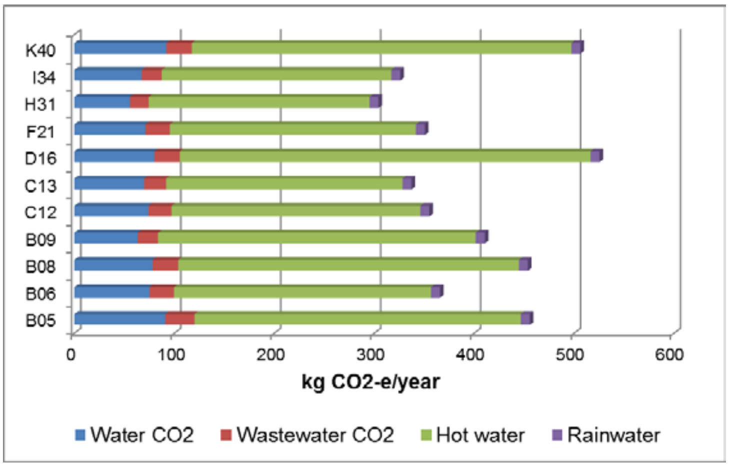


Figure 9.9: Carbon impact of water supply and use for each household type in 2035 with climate change effects and water supply mix change with 80% renewables.

Three alternative systems for hot water were then examined. These were:

1. Electrical storage hot water using the current grid
2. Electrical storage hot water with 80% renewables
3. Solar-gas hot water

The results for each of these alternatives are presented below.

9.1.6.5 Testing different hot water systems: Electric storage – current grid

Figure 9.10 presents the results for each household type, with climate change effects, water supply mix change and electric storage hot water. Using the water heater carbon intensity results provided in Waley et al (2015) and Moore et al (2017), the precinct total carbon emission is 188 tCO2-e, an increase of 52% over the base case for 2035. Electric storage water heating is inefficient and carbon intensive, certainly if using power from the grid.

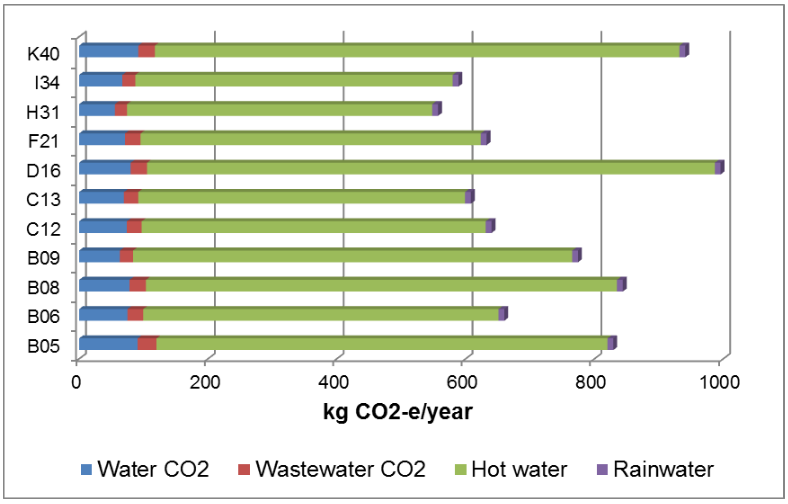


Figure 9.10: Carbon impact of water supply and use for each household type in 2035 with climate change effects, water supply mix change and electric storage hot water system.

9.1.6.6 Testing different hot water systems, Electric storage – 80% renewables

Use of 80% renewables for electric power supply is estimated to make a significant improvement in carbon emissions, as can be seen in Figure 9.11. Precinct total carbon emissions for water decrease to 107.4 tCO2-e, a decrease of 13% compared to the 2035 base case. This is another indication that use of renewable energy can offset emissions.

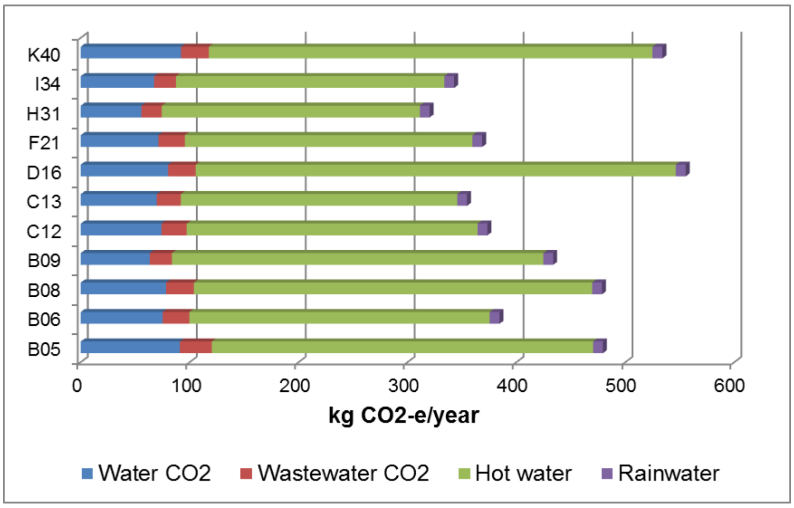


Figure 9.11: Carbon impact of water supply and use for each household type in 2035 with climate change effects, water supply mix change with 80% renewables and electric storage hot water system with 80% renewables.

9.1.6.7 Testing different hot water systems – solar gas

The use of solar-gas hot water systems along with 80% renewable energy is seen to provide the best alternative for water heating, as shown in Figure 9.12. Precinct total carbon emissions decrease by 45% from the 2035 base case, to 67 tCO2-e. Further, this result is independent of the grid carbon emissions intensity

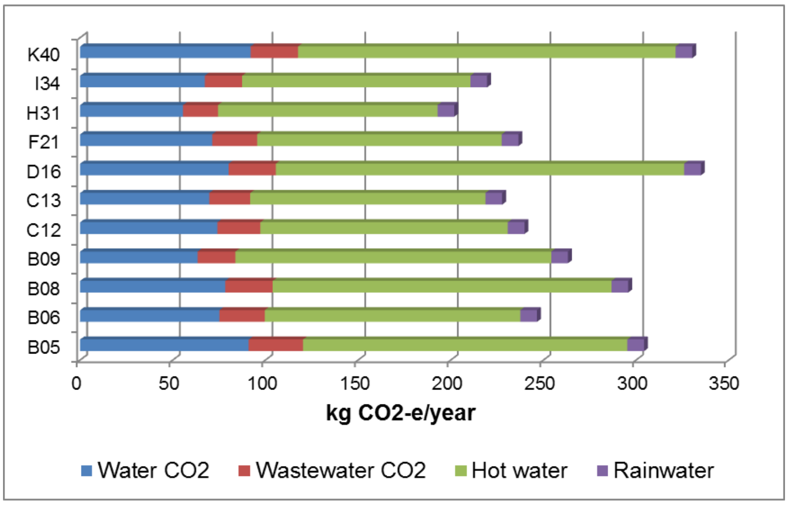


Figure 9.12: Carbon impact of water supply and use for each household type in 2035 with climate change effects, water supply mix change with 80% renewables and gas hot water system.

A number of useful conclusions can be drawn from this analysis of water usage in Lochiel Park:

- The model developed in this research can be used to forecast water and water-related energy demand
- Changes in household type/characteristics can be used in forecasting alongside other environmental/technological changes
- Obvious connection exists with energy for hot water, and care must be taken to avoid double-counting

- Hot water system choice is really important. Where electrical water heaters are installed the electricity grid is key to emissions reduction since it contributes to reductions in all aspects of water-related emissions
- This results in a question for further consideration: to what extent are water utilities responsible for GHGs from hot water?
- Given the use of the Mosaic household classification, the developed model can be used to forecast emissions from future populations (and associated sociodemographic changes) for large-scale urban areas (e.g. Sydney) with multiple water and energy supply mixes

9.2 Lochiel Park Household Performance Summary

In summary, the total annual carbon impact per household of each Mosaic household type in Lochiel Park is provided in Table 9.10 for both the 2015 and the 2035 forecast scenarios, with the total number of households of each type.

Mosaic Resident Type	2015		2035	
	Households	Total Annual kg CO2e/hhld	Households	Total Annual kg CO2e/hhld
C12	-	-	13	1,817
C13	36	2,514	38	3,340
I34	-	-	13	2,129
F21	-	-	51	4,217
B05	10	3,181	13	2,705
B06	-	-	38	3,803
B08	-	-	26	3,396
H31	-	-	13	3,091
D16	60	5,529	26	2,948
B09	-	-	5	2,052
K40	-	-	20	2,373
Totals	***106***	***4,284***	***256***	***3,265***

Table 9.10: Total annual CO2e emissions/household for the Lochiel Park 2015 and 2035 forecast scenarios by Mosaic household classification.

In total, for the 2015 base year, the combined total carbon for the precinct is 454,041 kg CO2e. This compares with the 2035 forecast year total annual carbon production of 836,395 kg CO2e for the whole precinct. However, the average carbon production per household drops to 3,265 kg CO2e in 2035 from 4,284 kg CO2e in 2015 Forecasting assumptions made for the 2035 forecast year include the scenario parameters of electric vehicle use, with 50% reliance on grid energy and 'lowest cost' energy supply arrangements. Also the carbon impact of water supply and use for each household type in 2035 recognises climate change effects, and water supply mix change with 80% renewables and gas hot water system in use. All types of waste are recognised with transport emissions including private, public and waste vehicle impacts. The greatest contributions to carbon are from the from the energy and transport components, followed by water and waste with larger household (more working adults living in larger house structures) contributing the largest proportion of CO2e.

10 Case Study Application: Tonsley Precinct

Adelaide's Tonsley precinct was selected as a second site for a case study application of the ETWW model. It is also part of the CRC's Adelaide Living Laboratory. The site is quite different in nature from Lochiel Park with much more mixed land use and less mature in its development with masterplan and site strategy information to guide much of the intended future development. Tonsley is located approximately 11km south-west of the Adelaide CBD. The general objective for redevelopment of the site is for it to become a hub for technical innovation with residential components as part of a thriving community.

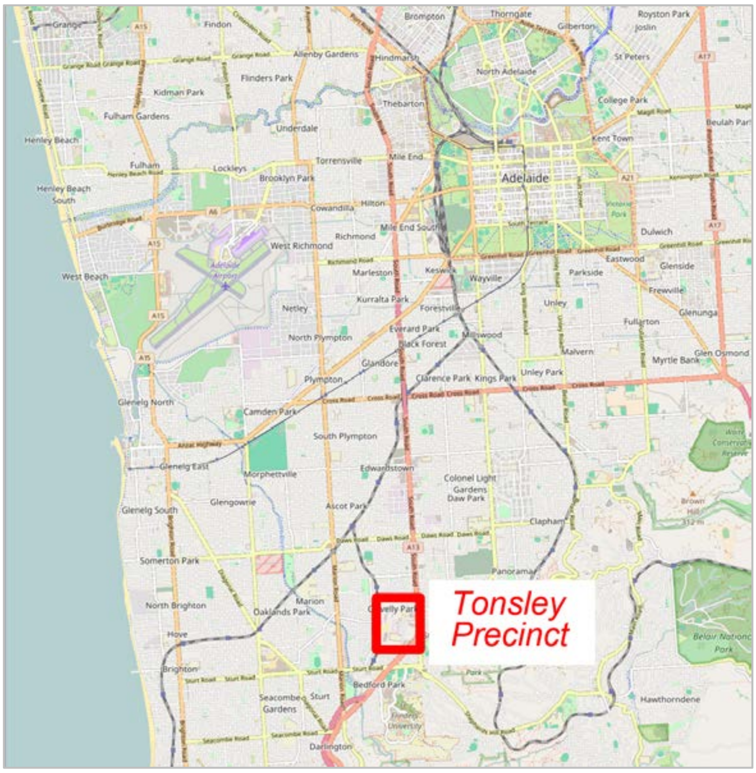
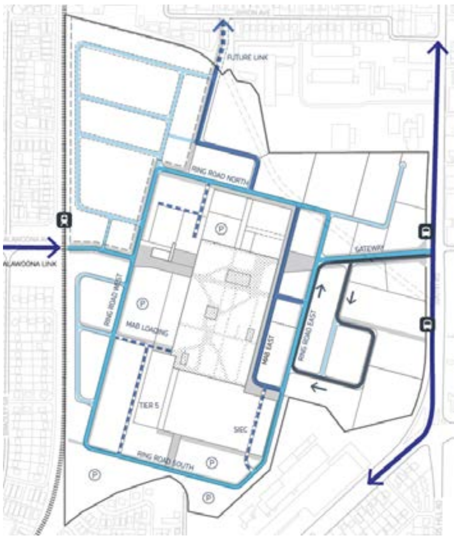


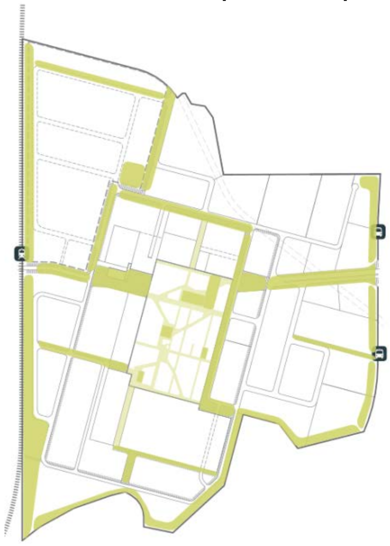
Figure 10.1: Location of the Tonsley precinct in Adelaide.

Much of the strategic precinct or masterplan information has been developed by the Government of South Australia (2013) with additional resources available through Renewal SA (2015). Such information sources provide guidance on land use allocations for roads and other site movement, building height, residential, high value industry, commercial, education, public space and green space. Collectively, these mapping resources along with technical guidance on the urban form are applied to develop the land use allocations in the precinct. Key items from the site masterplan documentation are represented in a mapping format in Figure 10.2.

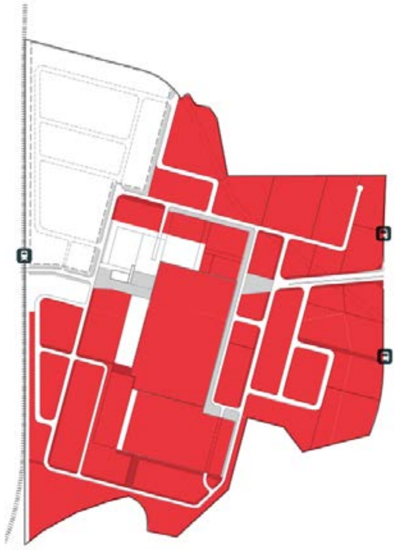


Internal road network and public transport stops

Residential land use allocation



Public space allocation



Non-residential land use allocation

Figure 10.2: Selected land use maps from Tonsley precinct masterplan information (source: Government of SA 2013 and Renewal SA 2015).

The available information on Tonsley was used in the development of the precinct site plan in a GIS for the scenario specification. Inclusions for open space, residential, non-residential and carparking uses with land use allocations for the Tonsley precinct are the same across all scenarios. Total land area is of the entire site, including open areas, roads and public space is 601,363 square metres with 862 individual household residences represented in the zones. The resulting GIS configuration as depicted in Figure 10.3, which formed the ETWW model based site land use plan.

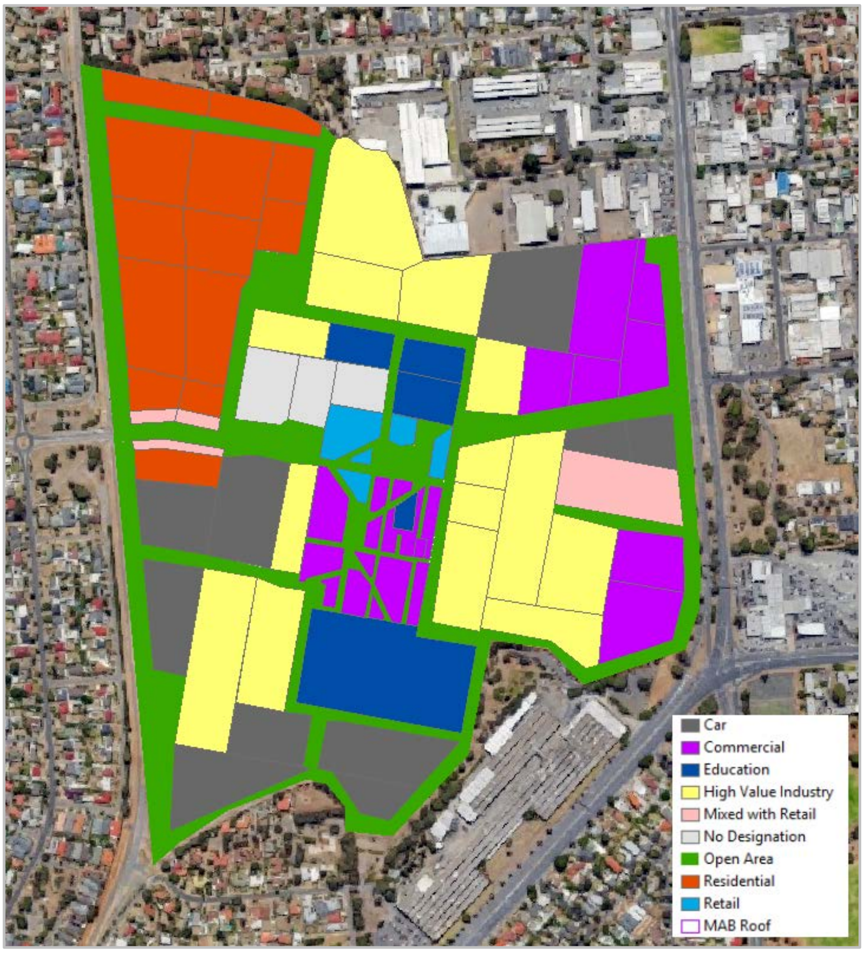


Figure 10.3: Configuration of Tonsley land uses according to available strategic precinct information.

In addition to these developed land uses, a model transport network was built for the site, again in a GIS environment (Figure 10.4). The network links allow internal transport flows for all modes and connections to external roads and public transport networks.

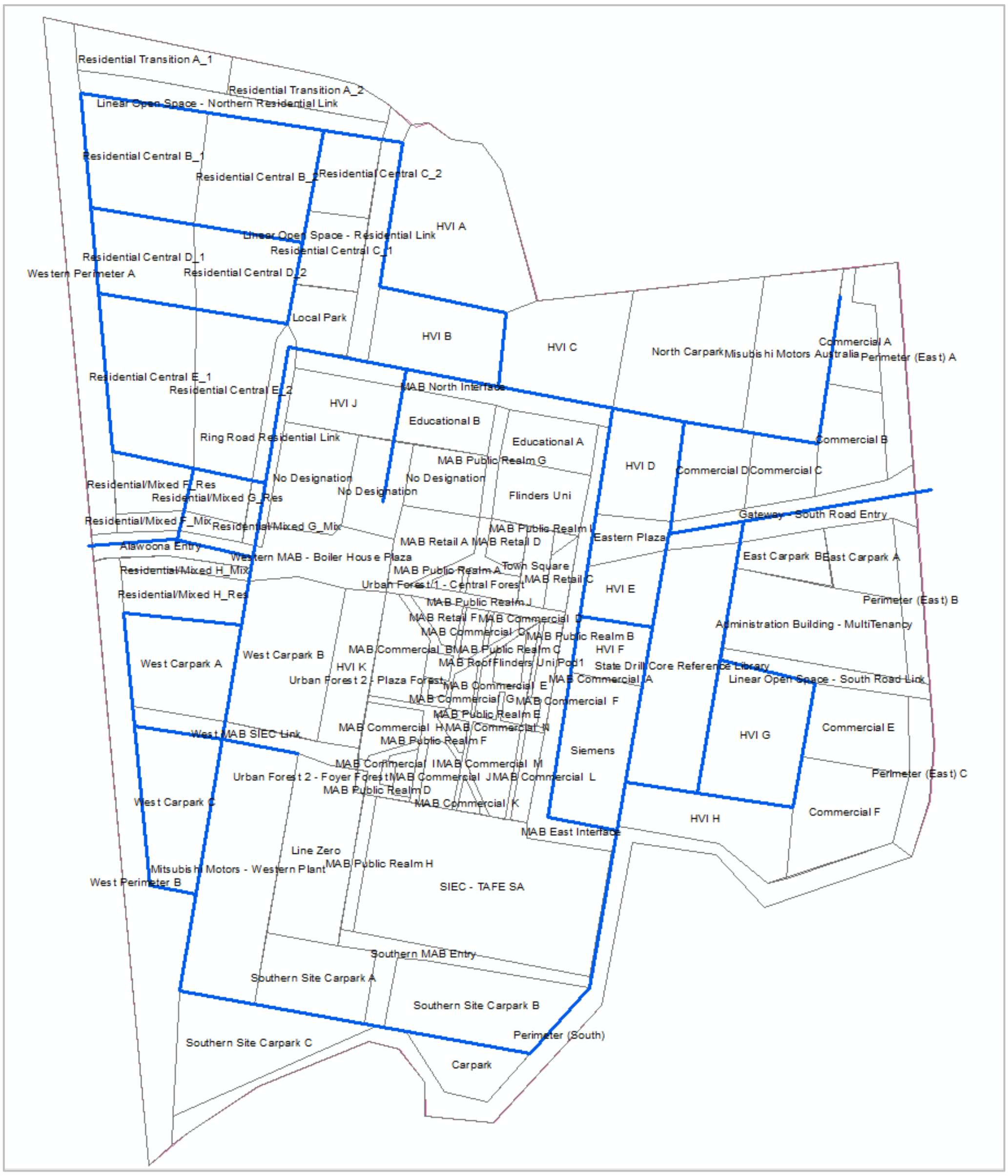


Figure 10.4: Configuration of Tonsley internal transport network (blue) with land uses identified.

10.1 Details of Forecasting Scenarios

There are three Tonsley precinct forecast scenarios, all developed for the year 2035 with specific interaction and residential attributes altered to demonstrate model operation and domain interaction. Road, cycle and walk networks are included with connections to public transport and the forecast represents 24 hour demand forecasting for a typical weekday in the month of October. The scenario also applies Scope 2 DOE (2014) emissions rates for grid energy supply, and utilises current waste dump and recycling locations. The detail of the three individual scenario applications are provided in the following sections

10.1.1 Tonsley Scenario 1

Tonsley Scenario 1 represents a baseline condition for the 2035 mixed-use precinct structure (Figure 10.3 previously) with the entire residential area developed containing all households in the north-western sector of the precinct (Figure 10.5 below) with associated attributes in Table 10.1. The residential component of Tonsley is assumed to represented with three household building types, to represent high-density semi-detached housing (Res_1), medium density apartments (Res_2) and high-density apartments (Res_3).

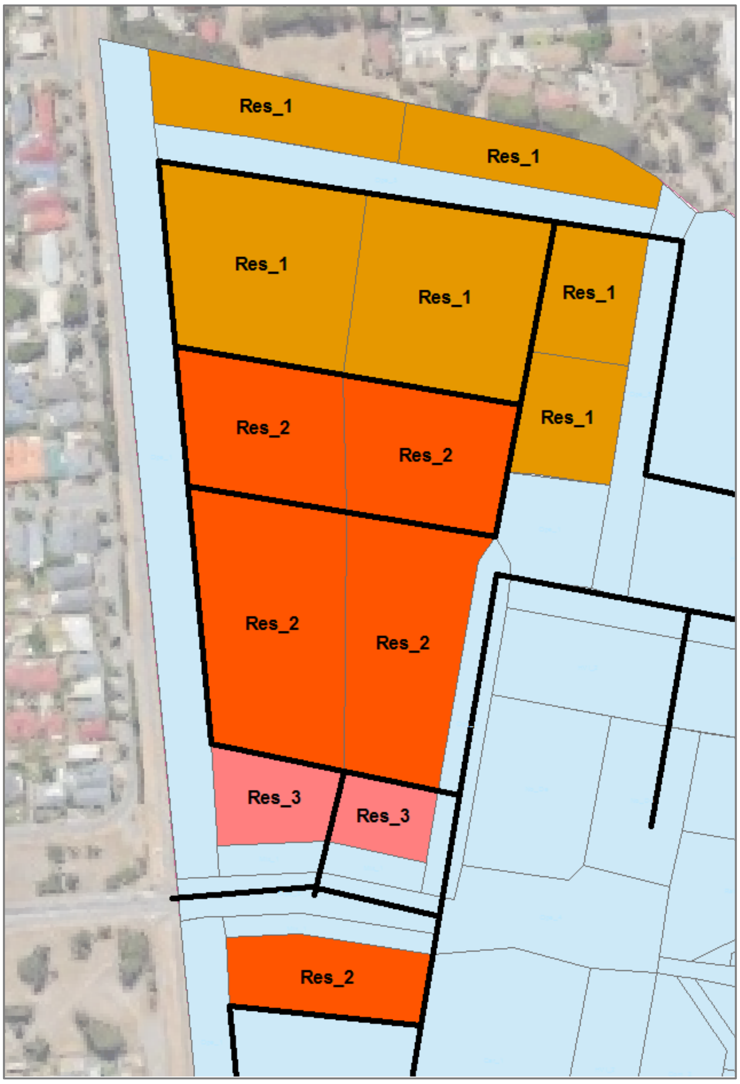


Figure 10.5: Detail of the Tonsley residential development components.

Attribute	Residence 1	Residence 2	Residence 3
Residence Type Code	Res_1	Res_2	Res_3
Reference Building	LightsView	Luminaire	Park Central
Residence Footprint	44.5 sqm	140 sqm	130 sqm
Floors	3	1	1
Total Floor Area	151 sqm	145 sqm	130 sqm
Bedrooms	2	2	2
Bedroom Area	18%	22%	25%
Living Area	28%	27%	30%
Kitchen Area	11%	12%	12%
Wet Area	5%	6%	6%
Green Area	2%	4%	3%
Carpark Area	15%	17%	14%
Other Area	19%	12%	10%
Rainwater storage	1	1	1
PV (solar) panels	4	4	2
Elec – Cooking	1	1	1
Elec – Aircond	1	1	1
Elec – HotWater	1	1	1
Elec – Washer	1	1	1
Elec – Dryer	1	1	1
Elec – Fridge	1	1	1
Water – Showers	1	1	1
Water – Toilets	1	1	1

Note: Residence Type Codes relate to those identified in previous figures

Table 10.1. Resident housing structure types with associated attributes.

All house structures in Tonsley have comparable floor area, with varying distribution of floor space and notably PV panels per residential building, assuming that space is available for their deployment. Residence type 1 are built to a height of 3 floors with the entire single house structure occupying all floors. Such residential structures are typical of those in the in the Lights View development in metropolitan Adelaide. Residence type 2 are built to a height of 4 floors with entire single house structures existing on two floors in a similar manner to residential structures in the Luminaire development in Bowden, Adelaide. Residence type 3 are taller structures built to a height of 6 floors with entire single house structures existing over two floors in a similar manner to the Park Central residential structures in Bowden, Adelaide. A complete build-out of other land uses includes:

- Commercial,
- Educational,
- High Value Industry,
- Open Space,
- Car parking,
- Mixed use,
- Retail,
- No Designation,
- Roof space.

In this base condition, no scenario options are applied. Resident typologies applied to all three Tonsley precinct development scenarios are presented with the relevant Mosaic codes in Table 10.2. Mosaic household resident typologies (Experian, 2016) provide the ETWW model with user with the ability to represent the household resident type as one of 49 unique segments, each with a representative Mosaic identification code. These typologies classify individual Australian households based on a range of socio-demographic and lifestyle attributes.

Mosaic ID	Mosaic Resident Type Description	Scenario Use
A02	Successful Spending	3
B07	Commuting Communities	3
B09	The Good Life	3
C10	Stylish Pursuits	1, 2
C11	Inner City Aspirations	1, 2, 3
C12	Wireless and Wealthy	1, 2
C13	Professional Views	1, 2, 3
C14	Leased Lifestyles	1, 2
D16	Ageing Gracefully	3
F21	Family Connections	3
F22	New Bubs, New Burbs	3
F24	Tykes and Takeaways	3
H30	Cultural Fusion	1, 2
I34	Roaring Twenties	1, 2, 3
I35	University Diversity	1, 2
J37	Aussie Grit	3
K38	Sensible Seniors	1, 2

Table 10.2: Scenario 1, 2 and 3 resident typologies.

For scenario 1, the total precinct resident population is 1,923 and residential land area allocation is 89,982 square metres.

10.1.2 Tonsley Scenario 2

Scenario 2 mirrors the Scenario 1 conditions detailed in the previous model application with the same land uses and resident population, however it also allows for a number of scenario option inclusions for the individual residential zones (Figure 10.6) represented in Table 10.3 and Table 10.4. This scenario also assumes that the household structure and included appliances (identified in Table 10.1) adopt the same performance characteristics as the previous scenario. Changes to energy or water consumption are therefore related to behaviour change.

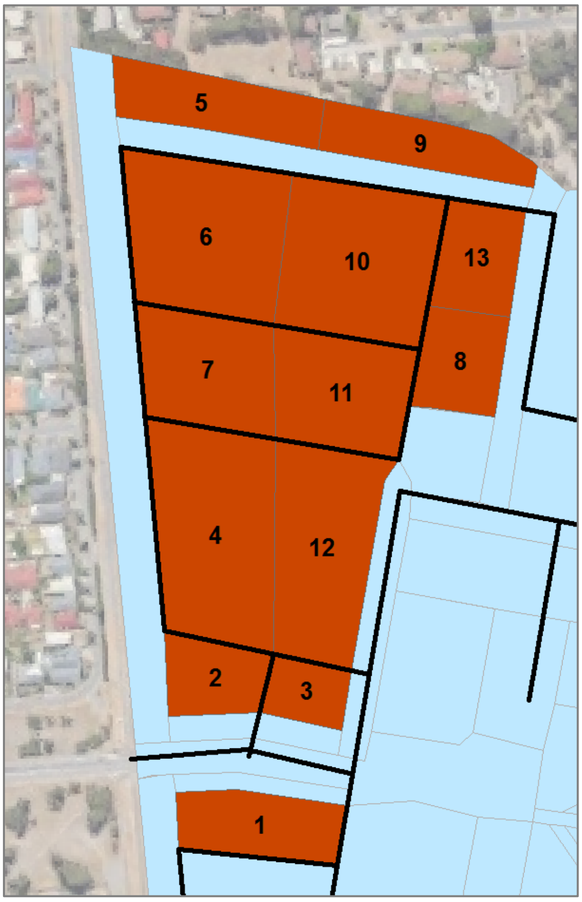


Figure 10.6: Tonsley residential land use and zoning IDs.

ID	Electric Vehicles			Activities from home		
	EV Type	***Trip Purpose***	***% Travel by EV***	***Work***	***Shopping***	***Education***
1	VW e-Golf	Commute	50%	NO	NO	YES
2	none	none	0	YES	NO	NO
3	none	none	0	YES	NO	NO
4	VW e-Golf	Commute	50%	NO	NO	YES
5	VW e-Golf	Commute	50%	NO	NO	YES
6	none	none	0	YES	NO	NO
7	VW e-Golf	Commute	50%	NO	NO	NO
8	VW e-Golf	Commute	50%	NO	NO	NO
9	VW e-Golf	Commute	50%	NO	NO	NO
10	VW e-Golf	Commute	50%	NO	NO	NO
11	VW e-Golf	Commute	50%	NO	NO	NO
12	none	none	0	YES	NO	NO
13	none	none	0	YES	NO	NO

Table 10.3: Tonsley residential land use electric vehicle and activities performed from home parameters for Scenarios 2 and 3.

ID	% Rainwater Use	% Greywater Recycled	Water consumption behaviour		Energy Consumption behaviour		Recycling behaviour	
1	20%	15%	17%	Decrease	0%	-	25%	Increase
2	20%	15%	0%	-	15%	Decrease	20%	Increase
3	20%	15%	0%	-	15%	Decrease	20%	Increase
4	20%	15%	17%	Decrease	0%	-	25%	Increase
5	20%	15%	17%	Decrease	0%	-	25%	Increase
6	20%	15%	0%	-	15%	Decrease	20%	Increase
7	20%	15%	17%	Decrease	0%	-	25%	Increase
8	20%	15%	17%	Decrease	0%	-	25%	Increase
9	20%	15%	17%	Decrease	0%	-	25%	Increase
10	20%	15%	17%	Decrease	0%	-	25%	Increase
11	20%	15%	17%	Decrease	0%	-	25%	Increase
12	20%	15%	0%	-	15%	Decrease	20%	Increase
13	20%	15%	0%	-	15%	Decrease	20%	Increase

Table 10.4: Tonsley residential land use water use, energy consumption and recycling behaviour parameters for Scenarios 2 and 3.

From these tables it is possible to identify domain interactions that are included for:

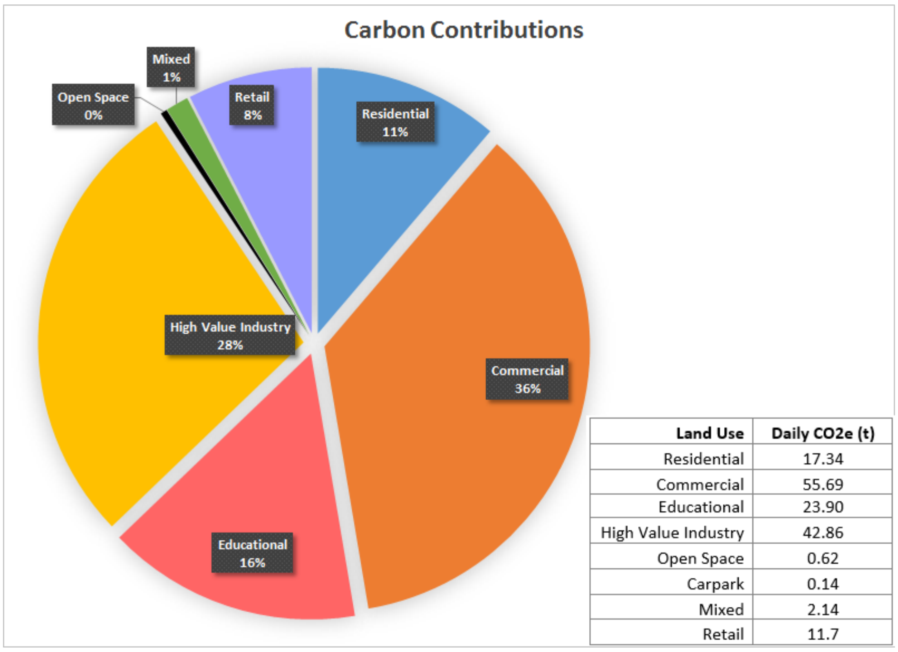
- Electric Vehicles: Transport and Energy,
- Activities from home: All domains,
- Rainwater use: Water and Energy,
- Recycling behaviour: Transport, Energy and Waste.

10.1.3 Tonsley Scenario 3

Scenario 3 is effectively a repeat of the Scenario 2 forecast with one major change. The resident population in this scenario is altered as specified previously. An overall effect of this is to present the model with a larger population of 2,293 residents, which by and large includes more families and larger household populations, as reflected in the new Mosaic typologies present. The precinct contains the same number and type of physical household structures as previous scenarios as well as the same non-residential land use allocations.

10.2 Demand and Carbon Estimates

Forecasting processes within the model produce a range of detailed outputs and results, hence for ease of interpretation and clarity of expression, this report will only focus on a synthesis of selected outcomes. Firstly, the scenario 1 baseline condition produces forecasts of carbon contributions from all land uses for the year 2035 represented in Figure 10.3.



Land Use	Daily CO2e (t)
Residential	17.34
Commercial	55.69
Educational	23.90
High Value Industry	42.86
Open Space	0.62
Carpark	0.14
Mixed	2.14
Retail	11.7

Figure 10.7: Scenario 1 baseline carbon impact contributions from land use types.

Non-residential land uses generate the majority of carbon emissions with commercial and high-value industry with a combined proportion of 64%, the largest component of the built environment and land use allocation at Tonsley. Carbon is generated across all the domains of energy, water transport and waste as employees undertake everyday activities associated with their work. Residential carbon impact is 11% of the total emissions which is due to the relatively small proportion of land use. This report focuses the remainder of the analysis on this residential precinct component.

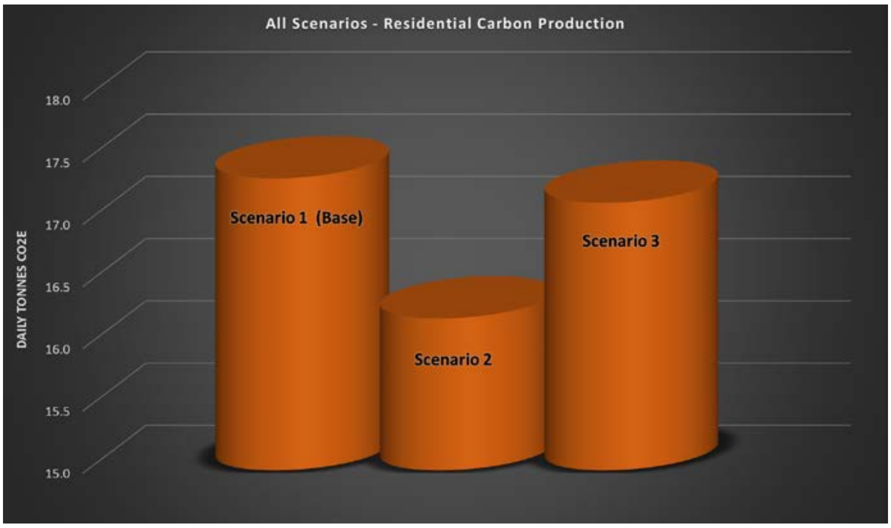


Figure 10.8: Total daily residential-only carbon impact of each scenario.

Analysing the daily CO2-e of the residential land uses, Scenario 1 produces a total of 17.3 tonnes CO2-e as a base condition for the 862 households, composed of three different house structure types and a resident population from a total of 9 Mosaic classification of resident types. Scenario 2 sees a significant reduction in CO2-e production to 16.2 daily tonnes. This reduction is due to overall effect of scenario inclusions related to household behaviour changes across the domains, recognising the interactive nature of the household demands. Scenario 3 produces an increase relative to scenario 2 to 17.2 tonnes CO2-e. This scenario recognises the impact of a changing population in the precinct with an increase in the total population and behaviour in relation to demand production form a change in household typologies.

Analysing the residential carbon impact component further, the ETWW model produces output to support the development of Figure 10.9, depicting the carbon impact of Tonsley scenario 1 as daily residential carbon by household type and domain.

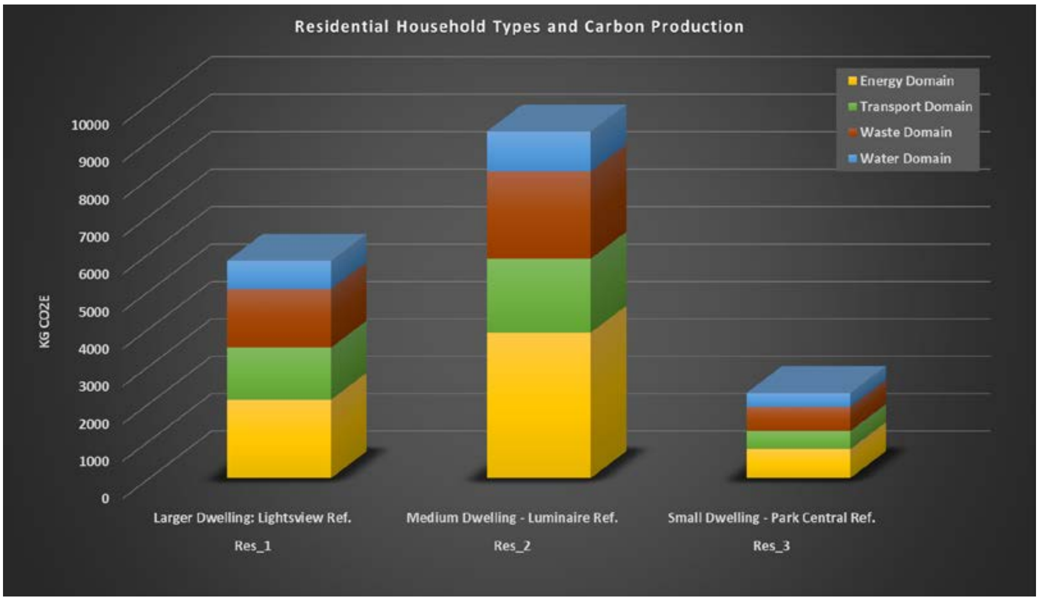
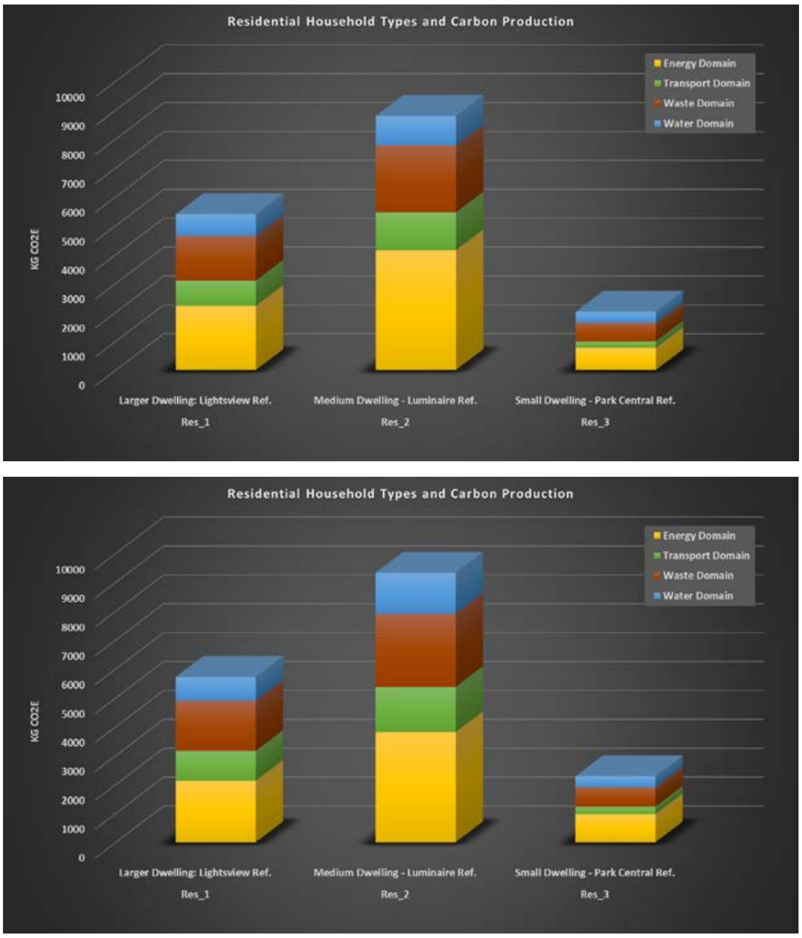


Figure 10.9: Carbon impact of Tonsley scenario 1 as daily residential carbon by household type and domain.

From this figure it can be observed that the energy domain is most significant contributor to carbon from all household structure types, followed by the waste domain. Transport is close to waste with the water domain contributing the least amount to carbon impact. Due to the majority of residences as type Res_2, this is the greatest contributor to carbon overall with residence type 3 contributing the least. Scenarios 2 and 3 are presented in Figure 10.10 for comparison.



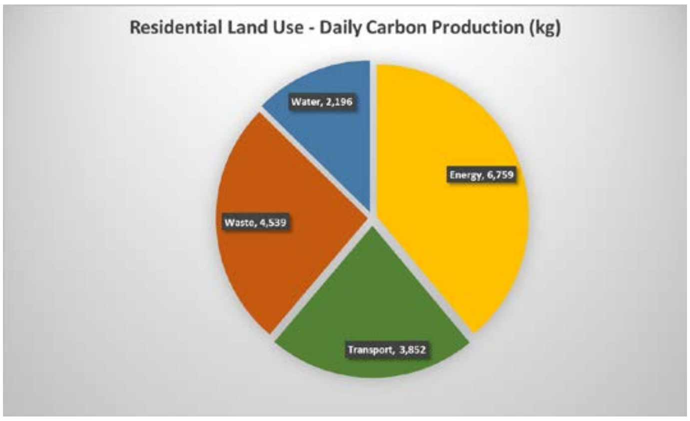
Scenario 2

Scenario 3

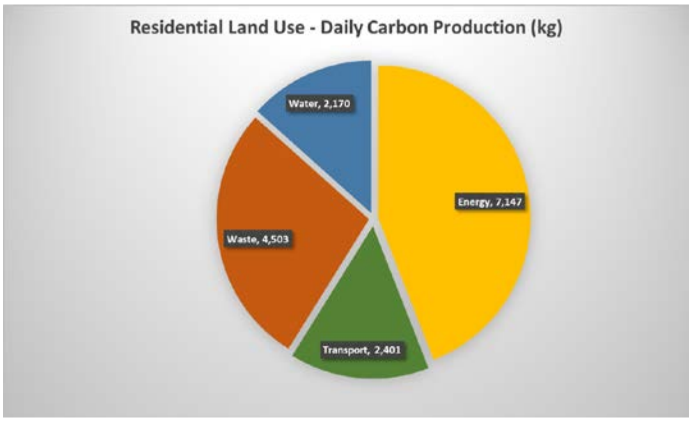
Figure 10.10: Carbon impact of Tonsley scenarios 2 and 3 as daily residential carbon by household type and domain.

The influence of scenario 2 inclusions is to reduce the overall emissions with proportionally less from transport due to electric vehicles, some of which has led to a relatively larger share of emissions from energy. The greatest impact on carbon reduction is due to residence type 2, which is due to the mix of population types residing in the residence and the physical characteristics of the residence. Scenario 3 sees increased emissions from water sector and an increase from transport due to changing population.

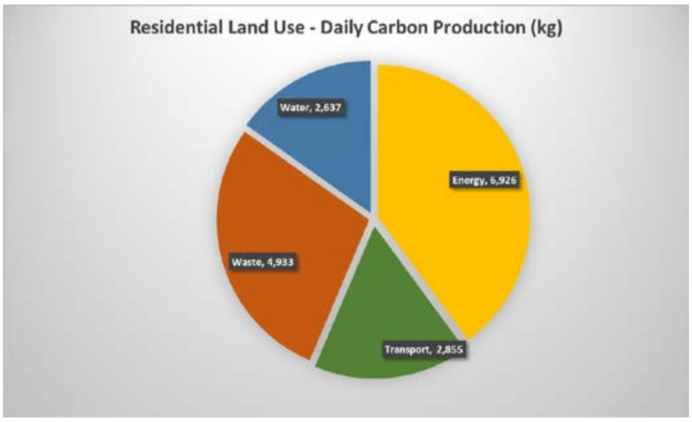
The pie charts in Figure 10.11 illustrate the proportion and weight of total carbon contributed by each domain to each of the three forecast scenarios.



Scenario 1



Scenario 2

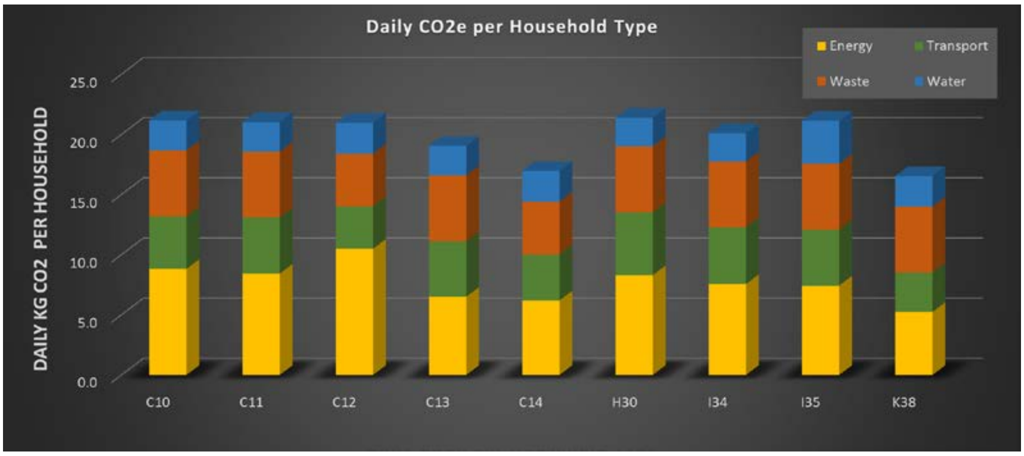


Scenario 3

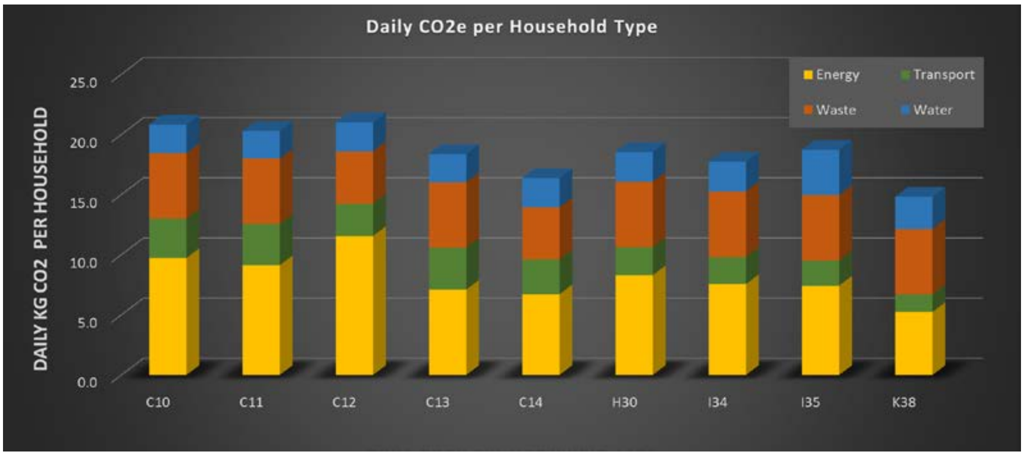
Figure 10.11: Carbon impact of 3 Tonsley scenarios as daily residential carbon by domain.

Results expressed previously in Figure 10.8 for the total scenario carbon impacts and observations made from bar charts of residence type contributions (Figure 10.9 and Figure 10.10) are supported by evidence from Figure 10.11. Scenario 1's greatest carbon contributor is energy domain (39%), followed by waste (26%) and transport (22%) with water (13%) the smallest contribution. Scenario 2 has an increase in energy to 44%, decrease from other domains, in particular transport to 15%. Scenario 3 has a contribution from energy decrease from scenario 2 but still higher than original base scenario. Other domains experience an increase when compared to scenario 2, emphasising the fact that household typology plays a significant role in carbon production.

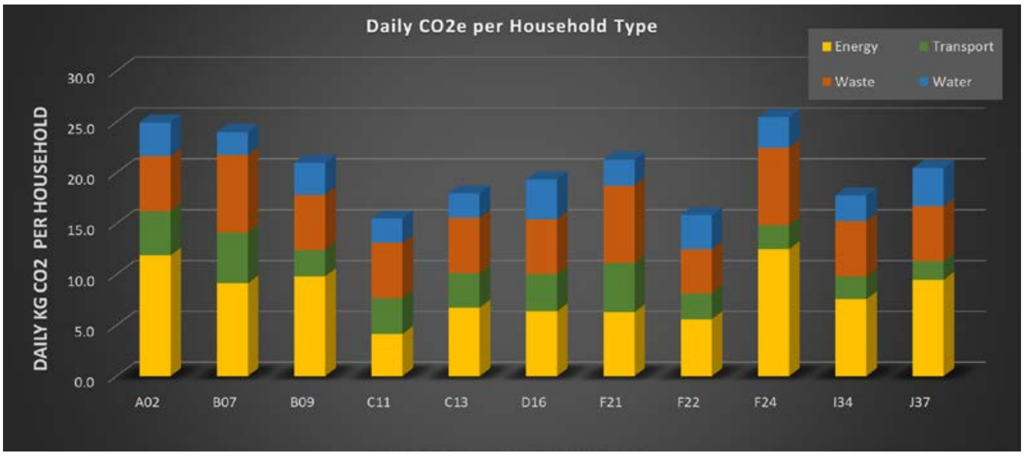
Another method to express carbon contribution from the ETWW model is to examine the carbon impact of 3 Tonsley scenarios as daily residential carbon by resident type and domain, as demonstrated in Figure 10.12.



Scenario 1



Scenario 2

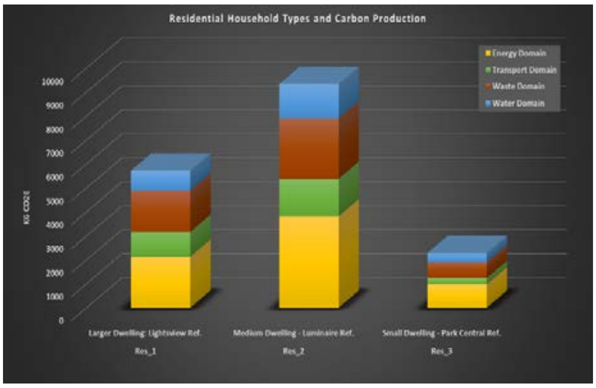


Scenario 3

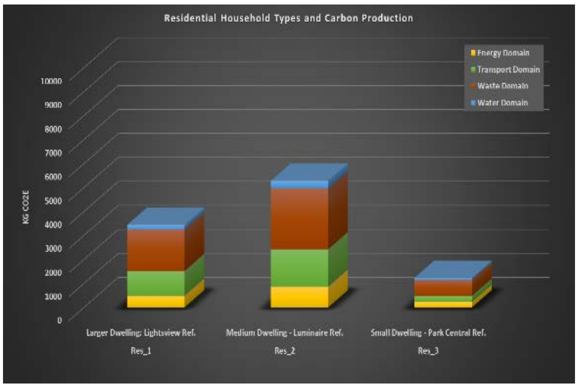
Figure 10.12: Carbon impact of 3 Tonsley scenarios as daily residential carbon by resident type and domain.

Scenario outcomes depicted in Figure 10.12 demonstrate similar characteristics to those observed previously, with most household types see a general reduction in the overall carbon contribution from scenario 1 to scenario 2. The biggest reduction is gained from household type H30 (Cultural Fusion) with a 2.85 kgCO2/day reduction per household. This is one of the larger household types containing (on average) 2.46 residents. Scenario 3 sees a change in household population types for Tonsley with an overall larger number of household types involved in the forecast process and hence a redistribution of the carbon production contributing to the scenario.

The process and modelling routines in the ETWW model make it possible to run comparative forecasting exercises such as alterations to the grid energy characteristics providing the precinct with electricity. In Figure 10.13, two carbon impact results for the daily residential carbon by household type and domain are provided. One is for Adelaide-based grid energy supply at 0.53 kg of CO2/kWh and the other for Tasmanian-based grid energy supply at 0.12 kg of CO2/kWh.



Scenario 3 with SA power 0.53 kg CO2/kWh



Scenario 3 with Tasmanian power 0.12 kg CO2/kWh

Figure 10.13: Carbon impact of grid energy powered by SA and Tasmanian sourced electricity

The results of the model forecasts show the total daily precinct carbon reduced from 154,337 kgCO2e to 60,078 kgCO2e with reductions made for all 3 resident structure types. As may be expected, the greatest reduction in carbon is from the energy domain and this is followed by the water domain. The waste and transport domains do not show as much reduction from powering the Tonsley grid from Tasmanian sourced electricity.

Another comparative forecasting exercises involves the comparison between precinct water supply types. Figure 10.14 displays the carbon impact of for the introduction of desalination plant water supply utilising South Australia's desalination plant to supply water networks, which is 100% offset with renewables in the energy use. Results provided in the following figure extend to all land uses.

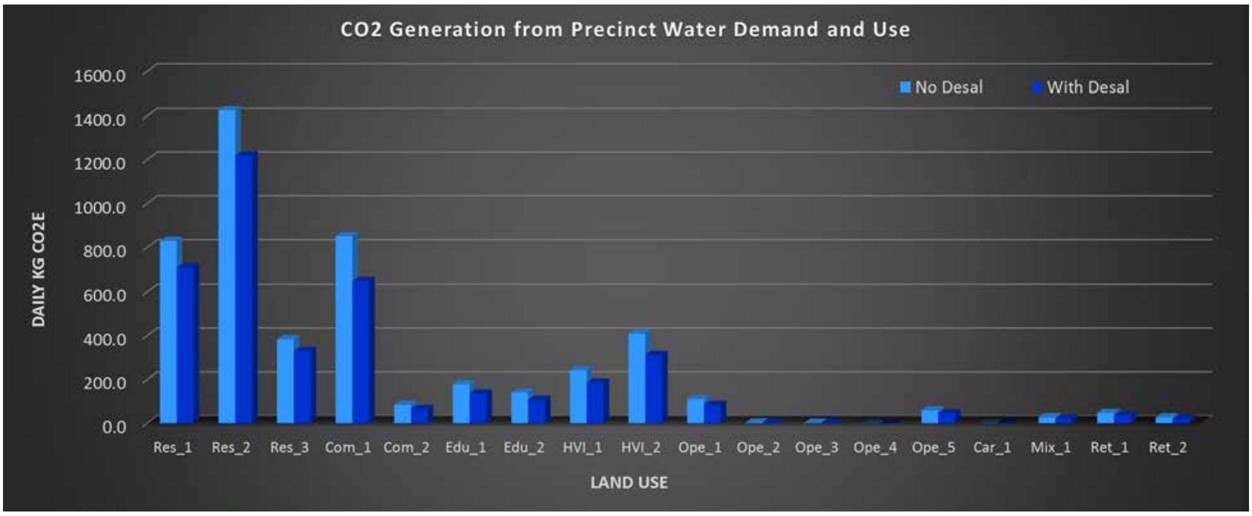


Figure 10.14: Carbon impacts of desalination plant water supply utilising SA's desalination plant to supply water networks with 100% offset with renewables.

In all land-use cases, a reduction in carbon is achieved from 4,811 to 3,916 kgCO2e daily across the precinct. This is most predominant for the residential land uses (Res_1 to Res_3). When investigated further (Figure 10.15), CO2e generation from residential water (with no desalination plant water) can be allocated to the different types of demand and use.

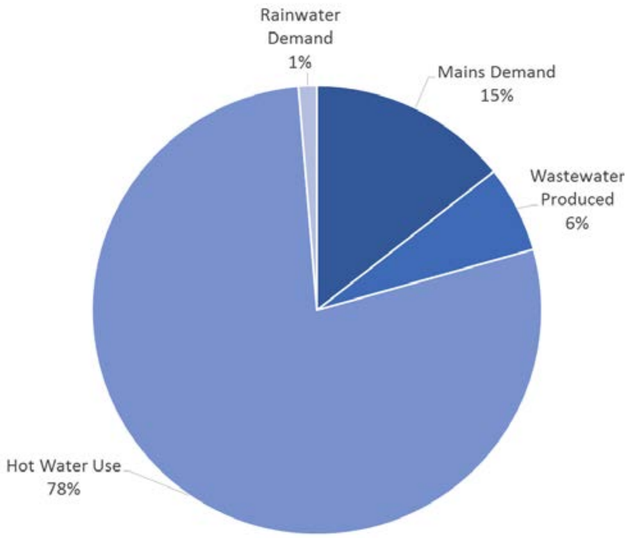


Figure 10.15: CO2e generation from residential water demand and use – no desalination plant water.

For the residential water domain, 15% of the carbon impact is from the energy used in mains supply process. This is the component that would reflect impacts of a desalination plant in the water supply chain and explains why the carbon reductions observed in Figure 10.14 are not greater (as may be anticipated). Hot water use is the largest household carbon contributor, supporting the previous scenario results where grid energy source at the household level is reflected by a significant reduction in carbon from the water domain. The choice of hot water system type can therefore have a significant impact on carbon emissions (as was indicated in the Lochiel park case study).

Figure 10.16 provides the total daily carbon for all precinct land uses resulting from the scenario 3 forecast. The GIS functionality combined with the ETWW model forecast data provides the user with the ability to define the CO2-e attributable to each land zone.

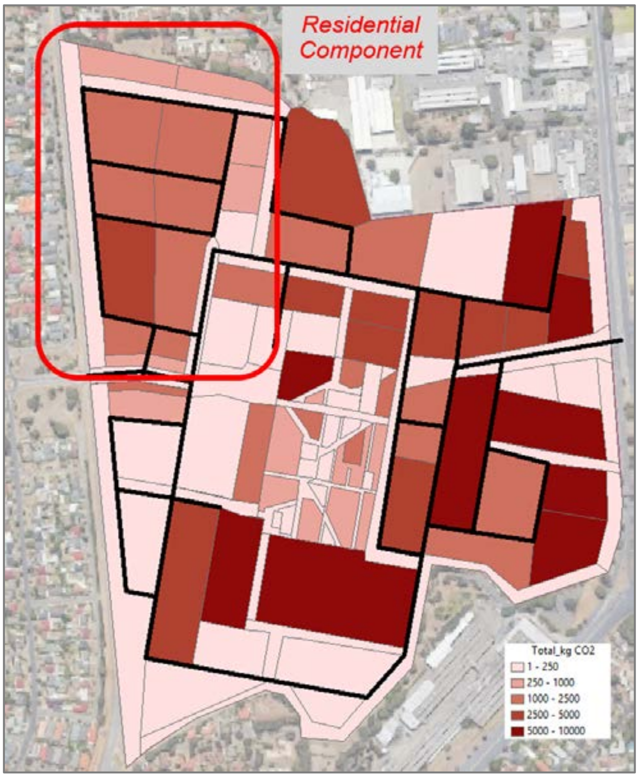


Figure 10.16: Carbon Impact of Scenario 3. Daily carbon for all precinct land uses.

The greatest CO2-e production is associated with commercial and education land uses, predominantly on the Southern and Eastern sides of the precinct. The residential components produce a range of total CO2-e however this is reduced in comparison to most commercial and HVI land uses. The lowest impact is from open and public spaces. A more detailed analysis of CO2-e, by domain, is possible for all land use types across Tonsley with Figure 10.17 illustrating the results for the residential components.

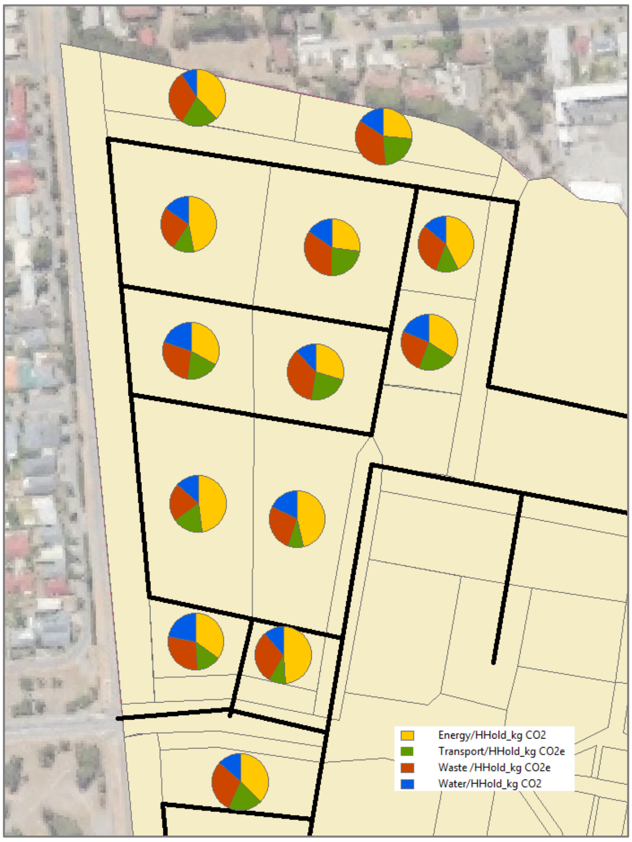


Figure 10.17: Carbon impact of Scenario 3 daily carbon proportions for all domains in residential zones.

From Figure 10.17 we can see that in most zones, CO2-e production from the energy domain dominates, often closely followed by the waste proportion with CO2-e associated with landfill and energy use for recycling purposes. Transport emissions are lower which is a direct result of the influence of the electric vehicle contributing to energy CO2-e rather than transport. Transport proportions are also from reduced overall transport from activities performed from the home, a behaviour that increases daily household emissions in other domains for the residences.

Considering only the transport contribution to carbon impact from the residential land uses only, Figure 10.18 expressed as the kg of CO2e generated per household from the transport task.

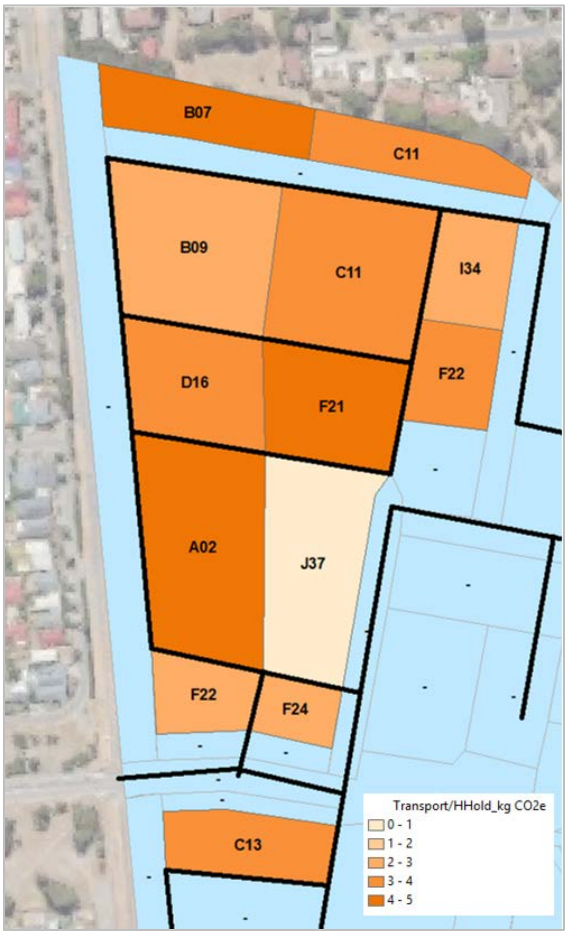


Figure 10.18: Carbon impact of Scenario 3 as daily transport domain carbon kg per household for the residential zones only, Mosaic codes included.

Emissions as daily CO2e generated by the transport task alone range from under 1 to 5 kg with the highest rates generated for zones with Res_2 type house structures. Although this example of mapping imagery is quite simple in nature, it can be used effectively in combination with other outputs and assessed further in the GIS environment.

The application of STM software such as Cube allows for further investigation of transport elements in relation to the road network. The software can allow the user to see what is occurring as patterns of travel behaviour and resulting carbon impacts if required. Entire strategic road networks represented in the Cube can appear as the Adelaide network does in Figure 10.19, with the Tonsley network addition circled in red. Tonsley elements of the network generated in GIS as provided previously. Road links here are coloured to indicate road links (blue) and centroid connector links (grey). It is noticeable that not every (single) road link is represented. This is a general characteristic of the strategic network representation in an STM, for which the general purpose of use is planning for the strategic transport systems of the metropolis.

Figure 10.19: Southern Adelaide section of MASTEM strategic network with Tonsley precinct addition circled.

It is possible to zoom into the Tonsley precinct from this figure and present the traffic volumes on the internal links expressed as a map visualisation as depicted in Figure 10.20. Here the lines represent road links with line width representing the volume of traffic on the link.

Figure 10.20: Resulting MASTEM AM peak volume flow bandwidths for Tonsley (with centroids).

Figure 10.20 shows the Tonsley internal network bounded on the left and right sides by Marion and South Roads respectively. Wider line representation represents higher vehicle flows, as they occur on these arterial links. Zone centroids are provided in red as a loading point for the land parcel allocated in the GIS map (Figure 10.4). This particular image represents the AM peak period of the day with generally higher volumes travelling on the left-hand side of the roads, out of the precinct and toward the CBD.

10.3 Tonsley Household Performance Summary

Summarising the carbon impacts of the Tonsley scenarios, the total annual carbon impact per household of each Mosaic household type in Tonsley is provided in Table 10.5 for all three 2035 forecast scenarios, along with the household structure type total number of households.

Household Structure Type	Households	Mosaic Resident Type (Scenarios 1 and 2)	Scenario 1 Total Annual kg CO2e/hhld	Scenario 2 Total Annual kg CO2e/hhld	Mosaic Resident (Scenario 3)	Scenario 3 Total Annual kg CO2e/hhld
Res_2	51	C14	4,056	3,936	C13	4,296
Res_3	70	I35	5,064	4,464	F22	3,672
Res_3	48	K38	3,960	3,552	F24	6,120
Res_2	128	C10	5,520	5,472	A02	5,976
Res_1	41	C13	4,560	4,392	B07	5,760

Res_1	86	H30	4,728	4,056	B09	5,040
Res_2	76	C11	5,376	5,184	D16	4,632
Res_1	30	C12	5,040	5,040	F22	4,104
Res_1	35	C11	4,320	4,128	C11	3,648
Res_1	84	C14	4,056	3,912	C11	3,744
Res_2	76	C10	4,344	4,176	F21	5,088
Res_2	104	H30	5,472	4,752	J37	4,896
Res_1	32	I34	4,848	4,272	I34	4,272
Totals	***861***		***4,829***	***4,506***		***4,825***

Table 10.5: Total annual CO2e emissions/household for the Tonsley 2035 forecast scenarios by Mosaic household classification.

In total, for the 2035 year forecast scenarios, the following total annual carbon production amounts, from the residential component only, are estimated as:

- 2035 Scenario 1: 4.157 tonnes CO2e for all households annually
- 2035 Scenario 2: 3.879 tonnes CO2e for all households annually
- 2035 Scenario 3: 4.154 tonnes CO2e for all households annually

Forecasting assumptions made for the 2035 forecast year include the scenario parameters identified previously with scenarios 1 and 2 adopting the same Mosaic population types and scenario3 allowing for a change in population as identified in Table 10.5. All scenarios have the same total number of homes with the same built structure type. The greatest contributions to carbon are from the households with larger numbers of residents and adults proportions and that are larger in physical structure size.

10.4 Summary of Carbon Impacts

To illustrate and compare the likely impact of the carbon-reduction interventions, which can be represented in the ETWW scenario options, two 'carbon staircases' have been developed based on the forecast scenario results and overall case study outcomes. The scenario options represented for each of the domains are previously identified in Section 3.0 with application to two precinct 'types' as follows:

- Residential: a precinct with residential land use only accompanied by supporting infrastructure and green space, similar to that found in Lochiel Park.
- Mixed use: incorporating residential along with commercial, retail, education, high-value industry, green space and required supporting infrastructure, similar to that found at Tonsley.

In the following Figure 10.21 and Figure 10.22, the carbon staircase depicts the likely impact of a range of carbon-reduction interventions on the 'typical' precinct. Each intervention contributes to the reduction of carbon in a 'Business As Usual' (BAU) case, accumulating in the total impact. Residual carbon is the remainder after the deployment of all interventions within the precinct.

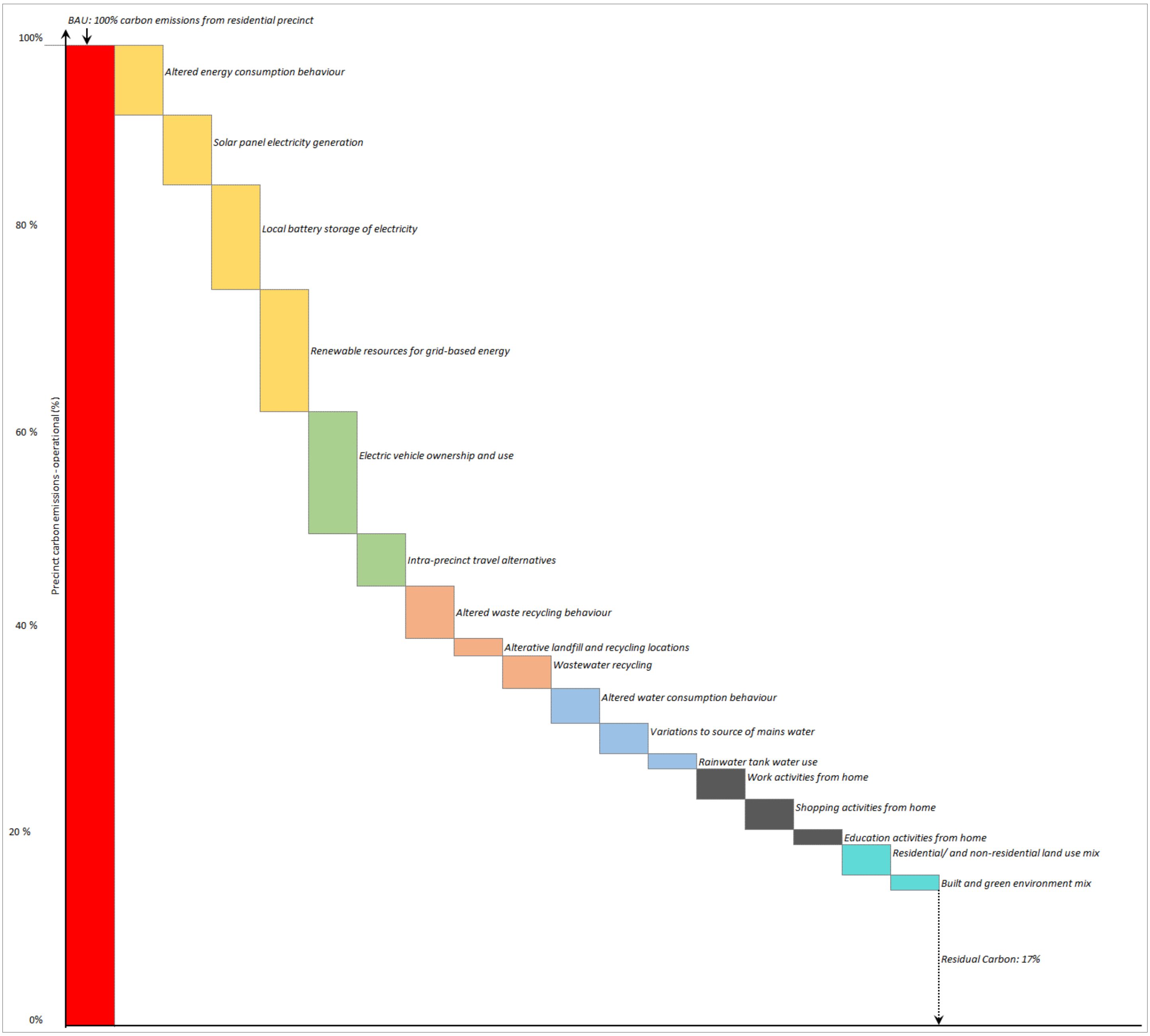


Figure 10.21: Carbon staircase for residential precinct.

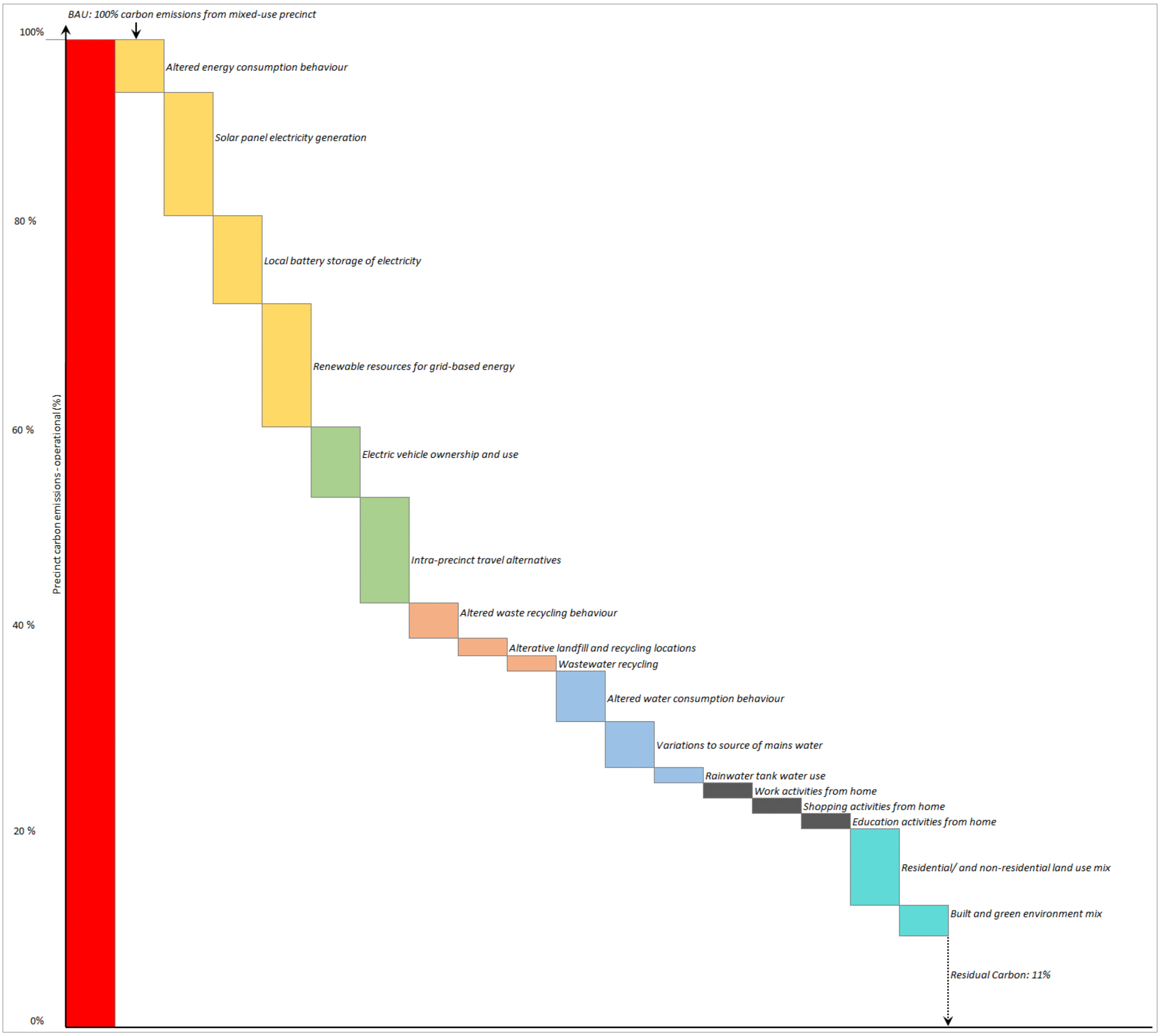


Figure 10.22: Carbon staircase for mixed use precinct.

From the carbon staircase estimations, it can be observed that overall, energy-related interventions (yellow) have the greatest potential for carbon-reduction impact at a precinct-scale. Both residential and mixed use precincts have a similar impact at around a 40% reduction to total carbon production. Residential has greater potential for behaviour change interventions and battery use while mixed use had greater potential for utilising solar energy to reduce carbon and both precinct types can benefit greatly from renewables present in the grid-based energy supply.

Although not as significant as the energy domain, transport interventions (green) related to electric vehicle use and intra-precinct travel alternatives can reduce carbon production. Mixed use precincts can benefit more from intra-precinct travel alternatives (such as walking, cycling or low-carbon share vehicles) whist residential precincts have greater potential for electric vehicle use at a household-level.

Waste interventions to carbon production (orange) have a relatively lower likely impact when compared to the other domains with residential having a greater carbon reduction impact in response to the interventions including behaviour change and wastewater recycling. The greatest water-domain impact (blue) relates to altered water consumption behaviour, followed by variations to mains water source in both residential and mixed use precinct types.

Activities from home have more potential for residential precincts to reduce carbon production, in particular the task of working from home. This considers the effect of the activity on all domains with reductions in transport-related emissions having a significant contribution here. Residential and non-residential land use mix has more potential when a greater number of land uses are represented in the precinct such as a in a mixed use precinct structure. The residual carbon from residential precincts exists at 17% whereas for mixed use precincts it is 11% of the total carbon in a BAU case. Mixed use precincts respond to the overall cumulative influence of all carbon reduction interventions better than residential-only precincts. Comparison is made in a relative sense only as two precinct types may have a significant difference in absolute carbon estimates.

11 Conclusions and Recommendations

Objectives of the CRC for Low Carbon Living's Program 2 for research activity include the creation of planning techniques, models and data for delivering low carbon developments at a precinct scale, with communication of best practice in sustainable city planning through precinct design and assessment tools. With such tools is should then be possible to plan for reduction to the carbon footprint of our urban systems, with key consideration being given to integrating the interlinked aspects of energy, water, waste, transport and buildings. It has also been noted that there is a need to provide the planning community with more advanced and scientifically validated models for use in precinct assessment.

The demand forecasting tool developed and reported herein seeks to address this need with the delivery of a demand forecast and carbon impact estimation tool for integrated demand forecasting of energy, travel, water and waste generation demand at the residential precinct level. This supports scenario planning for alternative development plans considering either existing or proposed residential precincts.

Drawing on existing research and industry-applied forecast routines and modelling techniques where appropriate, the project has also provided new forecast procedures delivered in the form of practical software applications appropriate for Australian urban conditions. Estimation techniques focus on the residential aspects of the precinct and recognise the household as the fundamental forecasting unit with demands accounting for factors such as the home structure type, technology applications, vehicle ownership and the characteristics of the resident population. Demand forecasts extend to other land uses including commercial, retail, educational, green infrastructure, open space and others, resulting in a holistic and integrated approach as a practical tool for industry. In summary the forecasting approaches taken for each of the individual domain research are:

- Energy: demand forecast process combined with battery solar optimisation model,
- Transport: utilises existing strategic transport modelling processes at a macro scale for demand representations,
- Waste: regression and factor analysis based forecasts of waste production,
- Water: demand forecasting with end use components.

Integration of forecast procedures across the domains, with specialised scenario options and information feedback processes linking modelling routines, have been critical inclusions in the model structure to enhance forecast detail and accuracy. Forecasting routines seek to utilise existing data sources where possible to ensure relevance and use by industry, now and into the future. Scenario options inclusions have been developed with guidance by industry project partners and reflect such things as electric vehicle use, water saving devices, solar production and energy storage options, waste removal vehicle and disposal location alternatives. In addition the model has abilities to recognise attributes of the built environment and population types, environmental considerations and climate change amongst other things.

Case study locations of Lochiel Park and Tonsley have provided a select range of forecast demand and carbon impact outputs with domain interactions highlighted. The Lochiel Park precinct lies approximately 8 km north-east of Adelaide's CBD and represents an established residential precinct, which is forecast to more than double in size with additional land uses in the future. Forecast estimations demonstrate the capabilities of the individual domain modelling methods and the utility of the integration operations. The Tonsley precinct is a mixed use region of Adelaide, approximately 11 km south-west of the CBD, currently under development with several core land uses present and masterplan documents outlining future development including s substantial residential component. The application of the ETWW demand forecasting tool to this precinct clearly demonstrated its capability to deliver demand forecasts and carbon impacts for scenarios o some complexity. Use of the tool with support from a GIS platform and graphical representations of its output provides urban planners and developers with a much enhanced capability.

As a result of the dedicated research efforts, this project delivers an advanced forecasting tool for the integrated estimation of precinct energy, transport, waste and water demand with associated carbon impacts. Model outcomes, including a connecting and integrating spreadsheet model provides a flexible and transparent forecast platform for industry application using readily available input datasets which may be collated from external resources (such as masterplan information, online datasets etc.) or by using default parameters already defined within the model.

11.1 Further Research Opportunities

As an operational modelling suite accompanied by published research outcomes, the ETWW model offers industry a practical and flexible demand and carbon forecasting tool for residential precincts. Extending on this work would provide the model with enhanced capabilities, applications, flexibility and ease of use. Outcomes of the industry partner panel session of the *ETWW Project National Symposium* to communicate results (Appendix B) indicated a range of these and initially, further opportunities exist to extend the research outputs in the following directions:

11.1.1 Further refinement of forecast estimation processes for non-residential land uses.

Transport estimations performed as part of the STM routines sufficiently account for non-residential land use travel demands however modelling associated with the water, waste and energy domains does not, at the same level of refinement as residential routines. This aspect of the ETWW model could be improved with additional forecast processes that recognise land use activity associated with commerce, industry, retailing and education as well as green and public spaces.

11.1.2 Complete forecasting operations on a single or cloud-based platform.

Currently, while the tool provides an integrated [platform for assembling and disseminating its outputs, the operation of the domain forecasting is fragmented with individual applications for each estimation process. Combining all of these processes on a single platform would enhance estimation efficiency and reduce run times as the integrated domain forecasting becomes closer in an operational sense. This could be achieved through either the development of a single software tool (in the same software environment and coding language) or as a single point of access and operation on a cloud-based environment containing all modelling elements. These two approaches differ in nature and would require differing perspectives for further model development, however they would be capable of achieving the same goals.

11.1.3 Further synergies and connections with other CRC-LCL based research activity.

Outcomes of the ETWW research provides a great opportunity to enhance other CRC-LCL based research activity and vice versa through strengthened connections between projects. Several current research that have been involved with the ETWW project to date, and offer potential in this regard include:

- RP3017: Adelaide Living Laboratory Hub. Data from this hub has assisted in the development and refinement of household demand forecasting tools in the ETWW project and could continue to present data for future model refinements and calibrations. Other CRC projects with a living lab/community focus could also do the same. The ETWW project could benefit these types of projects by providing future forecasting abilities associated with living lab-type precincts.

- RP2011: PIM - An Open Digital Information Standard throughout the Urban Development Lifecycle: Data utilised in the ETWW forecasting process can be closely associated with the data recognised in a precinct-information model platform. Data definitions developed in the ETWW project should be recognised by a PIM to assist in the data management for the model and to connect with other reported and forecast data types in the PIM. Operations and processes for both research projects would benefit from continued collaboration.

- RP2007: ICM Scoping study results: Carbon-based forecast outputs from the ETWW model report on ‘operational’ type forecasts without recognition of embodied energy and carbon required in the production of building materials, precinct development and maintenance. Integrated carbon metric estimates can add to the ETWW estimates to provide a more complete picture of precinct carbon impact.

11.1.4 Financial impacts.

Current demand forecasts developed in the ETWW model are utilised to produce carbon impact estimates for the user to analyse as part of precinct development scenarios. Model users would also benefit from integrated and complete cost estimates based on these demands. Costs that are not currently in the modelling process could recognise the financial dimension for energy, water, waste treatment and transport operation supply as well as the provision of the infrastructure required to support these supplies over time. Estimates of costs may relate to energy and water supply, waste removal and treatment as well as multimodal transport provisions as well the provision and maintenance of associated infrastructure. Cost estimates may also extend to the carbon components, as represented by a carbon ‘tax’ for example.

11.1.5 Improved estimation of freight transport modes

Transport demand forecasts would be further refined by the representation of light and heavy freight demands required for the operation of a precinct. The degree of this demand is not only affected by the residential precinct components but also the non-residential activities, especially in the case of heavier freight modes. In a future urban world where a majority of household purchasing may be done online, with small consignment deliveries to households an integral part of the online service, much of the transport activity associated with the precinct (and hence precinct carbon performance) will come from light freight vehicles.

11.1.6 Forecasting scenarios

A number of additional forecast scenario applications and beyond those represented at Lochiel Park and Tonsley in the case studies reported would benefit industry and all users of the forecast tool. These scenario applications include:

- Representing a CBD within the model as a precinct, as either a full CBD or part-representation, to demonstrate residential forecasting abilities and also the potential for more detailed non-residential forecasting procedures,
- Scenario runs with variations to the energy and water supply mix, focussing on the potential for micro grid assessments,
- Scenario runs with variations to grid-based energy reliance,
- Abilities for the model to represent car-sharing activity within and beyond the precinct.

11.2 Recommendations

Based on the research outcomes and findings, the research team has made the following set of recommendations that relate to furthering the ETWW project research. These are as follows:

- Continued development of the tool into a single platform for use, either as a cloud-based application or existing in a single software environment. This will allow for improved impact and utilisation across industry, enhance estimation efficiency and reduce run times.
- Further refinement of the forecast estimation processes to allow for accurate estimation of non-residential land use carbon impacts. This extends to CBD land uses and applications.
- Continued synergies and connections with other CRC-LCL based research activity. Other such CRC research activity includes that associated with RP3017, RP2011 and RP2007.
- Application of the tool to additional forecasting scenarios. This may include residential precinct developments across Australia and (with improved non-residential estimations) more detailed estimations of mixed land use precincts.
- Expansion of estimation routines to allow for financial/economic impact assessment and to recognise freight modes in the forecasting process.

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13 Appendix A: Operational Processes for the User.

Operational processes involved in the develoment of forecast estimates largely involve the processes provided in the operational flowchart with the development of a precinct scenario and associated datasets, running of modelling routines, iterative processes for data feedback and integration and estimation of carbon impacts from resulting demands. Throughout these processes the ETMM model spreadsheet detailed in this section forms a central component for model runs and data management and is therefore the focus on user operation.

Step 1: GIS model development

- Develop GIS map of the precinct, including all land use allocations as zones and road networks with appropriate attributes. Refer to INPUT_GISAttributes for data specification requirements in the GIS model development.
- Attributes required for linking to the GIS model are the:
    - unique identifier (Id),
    - masterplan description,
    - area in square metres and
    - land-use code that must align with land use codes in INPUT_HHLandUseLookups.

Step 2: Import GIS attributes

- Import the GIS precinct zone identifications and the GIS precinct road links into the INPUT_GISAttributes sheet. This can be accomplished with the assistance of the "Import GIS Zone Attribute File" button to open up an import text file dialog box to access the GIS attribute table.

Step 3: Set scenario parameters

- Set the required scenario parameters through the INPUT_Environment sheet. This will require the user to define
    - input for the precinct name,
    - latitude and longitude,
    - forecast year and
    - forecast month.
- included Button labelled "Set Scenario Parameters" opens up GUI for input of required scenario definition data input from the user.

Step 4:Set precinct scenario options

- Select the desired precinct scenario modelling options and identify relevant attributes in the INPUT_ScenarioOptions sheet for the following scenario options
    - EV ownership and use,
    - Rainwater tank water use,
    - Wastewater recycling,
    - Water consumption behaviour,
    - Energy use behaviour,
    - Recycling behaviour.

Step 5: Provide detail for the precinct the land uses

- For each of the residential and non-residential land uses, define the following parameters as they relate to each land use zone utilising the INPUT_PrecintScenario sheet
    - Identify the building floors,
    - mosaic resident types (residential only),
    - students,
    - solar capture,
    - water capture potential.

Step 6: External domain model runs

- Externally run the energy, transport and water domain forecasting routines, linked to relevant parameters defined within the workbook.
    - Energy: Energy demand model for residential precinct components. Non-residential estimates are automatically forecast within the ETWW spreadsheet model following on from the precinct and scenario definitions.
    - Transport:The STM base run will provide both the residential and non-residential demands forecasts.
    - Water: Water demand model for residential precinct components. Non-residential estimates are automatically forecast within the ETWW spreadsheet model following on from the precinct and scenario definitions.
    - Waste: The ETWW spreadsheet model will provide both the residential and non-residential demands forecasts. automatically following on from the precinct and scenario definitions.

Step 7: Demand data import

- Extract the relevant demand data profiles for each of the domains that are not automatically generated within the spreadsheet model. These are included in the RESULTS_Demand spreadsheet.

Step 8: Model iteration

- Re-run the external aind internal modelling operations with recognition of the interacting demand components, as per the scenario specifications identified in the INPUT_ScenarioOptions sheet.re-import and overwrite demand data in the RESULTS_Demand spreadsheet.

Step 8: Final Results

- Demand results and carbon results provided in RESULTS_Demand and RESULTS_Carbon respectively.
- Export GIS data from OUTPUTS_GISAttributes and connect with GIS spatial dataset.

14 Appendix B: ETWW Symposium Industry Perspectives Session Outcomes.

Representatives:

Mr Leigh Dalwood
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AECOM

Mr. Scott Manning
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Main Points – Summary:

- Along with forecasting the carbon impacts of future precinct design, the financial aspects associated with infrastructure provision and operation is also valuable to the industry partners. For water infrastructure providers and operators, financial aspects are often at the forefront for infrastructure planning, carbon may play a larger role in the future.

- Scenarios considering variations to the energy supply mix, not only for household use energy but used in the supply of water (with its relationship with carbon and cost impacts) are of interest to both the energy and water sectors. Localised micro-grid assessments may also be considered in this context.

- The ETWW model should have a role to play in providing carbon impact forecasts for developers which would be used in the procurement process and assessment of development options. Such developers and government bodies who consider such aspects are clients of AECOM.

- An issue facing forecasters across the domains is defining a 'base-case' from which to compare development options in the future.

- Industry partners have short and longer-term forecast horizons and it is viewed that the ETWW model forecast may be better suited to long-term forecasts. These long-term horizons can align with government perspectives represented in documents such as the SA state strategic plans and land use plans (30 year), Future Grid Forum (up to 50 years), Network Transportation Roadmaps (10-15 years). Beyond these horizons, uncertainties may be too great to forecast accurately.

- The ETWW model could be applied to investigate potential energy sector performance of greenfield developments providing information on grid-based energy reliance and reducing connection costs to the grid.

- The ETWW model may be applied to address questions related to centralised versus decentralised energy and water supply. Centralised supply provides security/reliability but is costly whereas decentralised can reduce infrastructure costs. A mix of both could be a good proposition for a precinct but what is the 'mix'? How much local infrastructure can provide a proportion of decentralised supply?

- Non-residential land uses are an important consideration for AECOM who are involved in 'Rockerfeller resilient cities' with mixed-use focus. It is viewed that mixed use developments provide a range of benefits over purely residential precincts and the ETWW model could be used to demonstrate these. Current sites such as the Royal Adelaide Hospital redevelopment and Bays Development in Sydney can provide a platform for the tool to investigate trade-offs between mixed use site configurations. For the water supply sector, residential supply is the greatest (around 80%) of demand with a small number of large industry users with Adelaide per capita residential water use remaining constant over past 5 years. Prior to the last drought, use was 420 L/pp/day, after drought 320 L/pp/day.

- Model abilities around car-sharing precinct initiatives are of interest to industry and others. Refinements to model abilities could assist in the investigation of car-sharing programs.

- Embodied energy and carbon is of interest however in the past it has often been estimated with priority over operational impacts, which are of more concern to the industry representatives. A tool that incorporates both operational and embodied would allow for assessments of best 'bang-for-buck' precinct inclusions. Making the tool fully dynamic would help in this process with a multi-criteria analysis to provide diversity in the tool and useful to a range of audiences. Questions may also exist here around what is the baseline embodied energy and what is the lifetime to assess.

- Assessing behaviour change is of interest to the energy sector, in particular the uptake of technologies such as solar PV and electric vehicles. Beyond the uptake, the use and potential behaviour change associated with the use would also be a useful inclusion, for example investigating and quantifying whether households use more energy if they have their own solar provision. Price and demand elasticities with sensitivity testing also important especially in relation to uptake and behaviour change.

15 Appendix C: Waste Behaviour and Attitudes Questionnaire.

My research focuses on the waste management. Municipal solid waste generation has become a serious burden for cities all over the world. It has been estimated that the waste generation in Australia has increased by 145 per cent from 1997 to 2012.Due to a fast growing of the material-intensive economy and the significantincreases of material consumption, the amount of municipal solid waste generated in Australia will continue to rise in the future. In order to protect our environment from destroying, accurate projection of the future waste generation from households is important for any urban development.

The following survey will collect the information about the facts, which affect the amount of municipal waste generation.The aim of this survey will assist me to perform my research.

Thank you for your help!

1. **Please select your gender**

Female	Male

2. **Nationality**

•

3. **House type**

Apartment	
Duplex	
House	
Townhouse	

4. **Net Floor Area**

The size of Net Floor Area	m^2

5. **Could you select disposable income group in $ (weekly)**

$0~170	$170~270	$270~370	$370~470	$470~670	More

6. **The number and gender of the family members**

The number of the family members	

The number of male	
The number of female	

7. The number of different age in the family members

The ages	The number
0~6	
7~17	
18~40	
40~65	
65 ~ more	

And the highest education degree in the family members

8. The status of work of the family members

Status of occupation	The number
Work at home	
Work at office	
Fly in fly out	
Student	
Retired	
Unable to work for some reasons	

•

9. Which type of eating habit is your family used to choosing?

Eating habit	Times in a week (7 days)
Cooking at home	
Eating outside	
Delivery (Take away)	

10. What is your main responsibility for your family?

Food purchase	
Waste disposal	
Food storage	

11. Please tick the box(es) which is (are) appropriate for you

Question	Every day	Every week	Fortnightly	Monthly	Yearly	Never
If you are responsible for food purchase, how often do you go shopping for food?						
How often do you hold a party?						
How often do you take the waste to the recycling Bin?						
How often iskitchen waste collected by the municipality from your premise?						

-

12. Which of these sources do you get your information from about waste?

- **(Select more than one response)**

Sources	
TV	
Radio	
Local press	
Leaflet/Brochure	
Website	
Please show other sources (If you have) :	
Not APPLICABLE	

-

13. Do you make a weekly food menu?

Yes	No

Do you make a weekly food menu

14. **Do you ever take part in some environment focused activities?**

- **(For example, planting trees as a volunteer)**

Yes	No

If yes, could you tell me the name and content of this activity?

15. **How important do you consider each of the following environmental issues?**

Items	Extremely	moderately	Neutral	Slightly	Not at all
Global warming					
Ozone layer depletion					
Desertification					
Water pollution					
The pollution of General waste					

16. **If your council offers a food waste collection service, which items could you put them into the benchtop container?(Select more than one response)**

Teabags		Yoghurt		Vacuum dust	
Vegetables		Shredded paper		Plastic bags/oven bags	
Dishcloths/sponges		Coffee grounds		Bones	

17. **What can you put in your green organics bin?(Select more than one response)**

Dirt/rocks		Polystyrene or foam	
Metal		Garden prunings	
Batteries		Small branches	
Household chemicals		Building material or permapine	

Leaves		Medical waste	
Twigs		Nappies	
Lawnclippings			

18. Do you know the website "www.zerowaste.sa.gov.au"? When and how?

19. Could you introduce some tips, which you carry out, about how to recycle and reuse municipal waste?

•

20. Do you know if other people (such as your neighbours, friends and peers) have special methods to recycle, reuse and minimize? Briefly explain

•

21. How often do you do the following?

	Always	Often	Sometimes	Rarely	Never
Buy product with as little packaging as possible					
Use my own bag when going shopping, rather than one provided by the shop					
Look for packaging that can be easily reused or recycled					
Buy fruit and vegetables without packaging					

Buy products that can be used again, rather than disposable items					

22. How often do you do the following?

	Always	Often	Sometimes	Rarely	Never
Try to repair things before buying new items					
Reuse paper					
Reuse glass bottles and jars					
Wash and reuse dishcloths rather than buying them new					
Reuse old plastic containers, such as margarine tubs					

23. How often do you recycle the following?

	Always	Often	Sometimes	Rarely	Never
Glass					
Paper/magazine/Newspaper					
Plastics goods					
Textiles					
Foil					
Metal goods					
Books/ DVDs , CDs					

24. Please indicate the relevance of the following aspects for appropriate waste management systems at your household.

Items	Extremely relevant	Highly relevant	Moderately relevant	Slightly relevant	Not relevant
Knowledge and awareness on waste recycling activity					
Time for separating and recycling					

Willingness of all members at home for recycling					
Information on waste recycling activities					
Appropriate separate waste bins (organic, recycle, disposal bins)					
Waste collection facility					
Location of recycling facility/depot					
Waste management fees					

25. There are many ways to avoid the creation of household waste. Please indicate your opinion of the following methods of avoiding waste.

Items	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Avoiding buying items that you would never used					
Selling/renting/borrowing items that are rarely used					
Donating rarely or never used items to relatives/other					
Managing or storing food properly					
Sharing and redistributing of used products by collaborative consumption					

26. Could I weigh the bins once per week in the following six months (from October 2015 to February 2016)?

Yes	No

16 Appendix D: WIO Tables for Lochiel Park Mosaic Household Types.

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recovery	Households (D16)	Total output
	($AUD)										
Ag	1561.78	5.19	2677.39	4.23	6.66	2.43	333.53	0.00	0.00	3078.92	7670.12
Mi	7.67	505.02	3202.36	452.22	16.65	1.46	140.08	0.00	0.00	0.00	4325.47
Ma	593.43	192.84	7862.55	250.67	520.57	61.35	3148.54	2.90	2.28	27747.72	40382.85
EGW	122.67	66.59	670.36	2282.29	15.54	8.90	553.66	0.44	0.28	4743.96	8464.69
Co	128.81	201.49	331.14	562.32	960.48	94.54	1414.17	3.92	3.13	0.00	3699.99
Pa	7.67	13.84	137.30	19.48	12.95	44.52	426.92	0.00	0.00	958.36	1621.03
AOI	1472.07	630.41	7539.48	1021.31	837.64	441.44	19698.37	11.03	8.69	35048.52	66708.97
Treatment methods	(units: kilograms)										
Landfill	135.71	4.76	504.79	66.06	96.94	6.64	333.53	0.58	0.43	300.22	1449.64
Recovery	86.64	2.16	529.02	52.51	92.50	5.18	213.46	0.29	0.28	447.09	1429.13

Table D.1: The WIO table for Mosaic household type D16 in Scenario I

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recover y	Households (D16)	Total output
($AUD)											
Ag	1496.47	6.86	2668.28	3.46	5.57	1.94	280.07	0.00	0.00	3078.92	7541.57
Mi	12.06	440.65	3560.34	376.06	21.24	1.46	160.04	0.13	0.00	0.00	4571.98
Ma	545.06	217.12	7389.09	206.62	491.34	45.61	2827.34	2.56	1.90	27747.72	39474.36
EGW	116.10	71.76	738.12	2382.60	14.28	17.47	560.13	0.54	0.41	4743.96	8645.37
Co	145.50	217.12	299.98	468.57	928.36	72.94	1346.99	2.69	2.04	0.00	3484.19
Pa	6.79	21.03	142.10	18.15	13.93	39.62	420.10	0.00	0.00	958.36	1620.08
AOI	1380.37	776.16	7329.88	1129.92	742.76	382.65	19864.76	14.81	11.15	35048.52	66680.97
Treatment methods	(units: kilograms)										
Landfill	142.49	9.60	517.08	40.63	69.30	3.72	266.73	0.40	0.27	300.22	1350.44
Recovery	73.13	5.94	509.18	46.68	78.70	4.20	193.38	0.27	0.27	447.09	1358.85

Table D.2: The WIO table for Mosaic household type D16 in Scenario II

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recovery	Households (B05)	Total output
($AUD)											
Ag	1524.27	5.23	2717.44	3.89	7.13	2.97	383.90	0.00	0.00	2841.80	7486.63
Mi	7.48	509.51	3250.27	415.88	17.82	1.78	161.24	0.00	0.00	0.00	4363.99
Ma	579.18	194.55	7980.18	230.53	557.27	75.05	3623.99	2.82	2.28	27741.48	40987.33
EGW	119.73	67.18	680.38	2098.89	16.63	10.89	637.27	0.42	0.29	4152.20	7783.89
Co	125.71	203.28	336.09	517.13	1028.19	115.65	1627.73	3.80	3.14	0.00	3960.72
Pa	7.48	13.96	139.36	17.91	13.86	54.46	491.39	0.00	0.00	1244.36	1982.78
AOI	1436.72	636.01	7652.28	939.25	896.70	540.02	22672.99	10.70	8.70	41988.96	76782.32
Treatment methods	(units: kilograms)										
Landfill	132.45	4.80	512.34	60.75	103.77	8.12	383.90	0.56	0.43	199.09	1406.19
Recovery	84.56	2.18	536.93	48.29	99.02	6.34	245.69	0.28	0.29	408.20	1431.77

Table D.3: The WIO table for Mosaic household type B05 in Scenario I

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recovery	Households (B05)	Total output
($AUD)											
Ag	1457.25	6.93	2704.64	3.18	5.97	2.37	322.31	0.00	0.00	2841.80	7344.46
Mi	11.75	445.38	3608.85	346.36	22.78	1.78	184.18	0.13	0.00	0.00	4621.20
Ma	530.78	219.46	7489.76	190.30	526.88	55.74	3253.78	2.45	1.90	27741.48	40012.53
EGW	113.06	72.54	748.18	2194.40	15.31	21.35	644.62	0.52	0.41	4152.20	7962.56
Co	141.69	219.46	304.07	431.55	995.51	89.14	1550.15	2.58	2.04	0.00	3736.19
Pa	6.61	21.25	144.03	16.72	14.94	48.43	483.46	0.00	0.00	1244.36	1979.80
AOI	1344.19	784.50	7429.75	1040.67	796.48	467.65	22860.89	14.20	11.13	41988.96	76738.42
Treatment methods	(units: kilograms)										
Landfill	138.75	9.70	524.12	37.42	74.31	4.55	306.96	0.39	0.27	199.09	1295.56
Recovery	71.21	6.01	516.12	43.00	84.39	5.14	222.55	0.26	0.27	408.20	1357.14

Table D.4: The WIO table for Mosaic household type B05 in Scenario II

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recover y	Households (B05 - D16)	Total output
($AUD)											
Ag	-37.51	0.04	40.05	-0.34	0.47	0.54	50.37	0	0	-237.12	-183.49
Mi	-0.19	4.49	47.91	-36.34	1.17	0.32	21.16	0	0	0	38.52
Ma	-14.25	1.71	117.63	-20.14	36.7	13.7	475.45	-0.08	0	-6.24	604.48
EGW	-2.94	0.59	10.02	-183.4	1.09	1.99	83.61	-0.02	0.01	-591.76	-680.8
Co	-3.1	1.79	4.95	-45.19	67.71	21.11	213.56	-0.12	0.01	0	260.73
Pa	-0.19	0.12	2.06	-1.57	0.91	9.94	64.47	0	0	286	361.75
AOI	-35.35	5.6	112.8	-82.06	59.06	98.58	2974.62	-0.33	0.01	6940.44	10073.35
Treatment methods	(units: kilograms)										
Landfill	-3.26	0.04	7.55	-5.31	6.83	1.48	50.37	-0.02	0	-101.13	-43.45
Recovery	-2.08	0.02	7.91	-4.22	6.52	1.16	32.23	-0.01	0.01	-38.89	2.64

Table D.5: Differences between Mosaic household types B05 and D16 for Scenario I

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recover y	Households (B05 - D16)	Total output
(AUD)											
Ag	-39.22	0.07	36.36	-0.28	0.4	0.43	42.24	0	0	-237.12	-197.11
Mi	-0.31	4.73	48.51	-29.7	1.54	0.32	24.14	0	0	0	49.22
Ma	-14.28	2.34	100.67	-16.32	35.54	10.13	426.44	-0.11	0	-6.24	538.17
EGW	-3.04	0.78	10.06	-188.2	1.03	3.88	84.49	-0.02	0	-591.76	-682.81
Co	-3.81	2.34	4.09	-37.02	67.15	16.2	203.16	-0.11	0	0	252
Pa	-0.18	0.22	1.93	-1.43	1.01	8.81	63.36	0	0	286	359.72
AOI	-36.18	8.34	99.87	-89.25	53.72	85	2996.13	-0.61	-0.02	6940.44	10057.45
Treatment methods	(units: kilograms)										
Landfill	-3.74	0.1	7.04	-3.21	5.01	0.83	40.23	-0.01	0	-101.13	-54.88
Recovery	-1.92	0.07	6.94	-3.68	5.69	0.94	29.17	-0.01	0	-38.89	-1.71

Table D.6: Differences between Mosaic household types B05 and D16 for Scenario II

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recover y	Households (D16)	Total output
($AUD)											
Ag	-65.31	1.67	-9.11	-0.77	-1.09	-0.49	-53.46	0	0	0	-128.55
Mi	4.39	-64.37	357.98	-76.16	4.59	0	19.96	0.13	0	0	246.51
Ma	-48.37	24.28	-473.46	-44.05	-29.23	-15.74	-321.2	-0.34	-0.38	0	-908.49
EGW	-6.57	5.17	67.76	100.31	-1.26	8.57	6.47	0.1	0.13	0	180.68
Co	16.69	15.63	-31.16	-93.75	-32.12	-21.6	-67.18	-1.23	-1.09	0	-215.8
Pa	-0.88	7.19	4.8	-1.33	0.98	-4.9	-6.82	0	0	0	-0.95
AOI	-91.7	145.75	-209.6	108.61	-94.88	-58.79	166.39	3.78	2.46	0	-28
Treatment methods	(units: kilograms)										
Landfill	6.78	4.84	12.29	-25.43	-27.64	-2.92	-66.8	-0.18	-0.16	0	-99.2
Recovery	-13.51	3.78	-19.84	-5.83	-13.8	-0.98	-20.08	-0.02	-0.01	0	-70.28

Table D.7: Differences between the two scenarios for Mosaic household type D16

	Ag	Mi	Ma	EGW	Co	Pa	AOI	Landfill	Recovery	Households (B05)	Total output
($AUD)											
Ag	-67.02	1.7	-12.8	-0.71	-1.16	-0.6	-61.59	0	0	0	-142.17
Mi	4.27	-64.13	358.58	-69.52	4.96	0	22.94	0.13	0	0	257.21
Ma	-48.4	24.91	-490.42	-40.23	-30.39	-19.31	-370.21	-0.37	-0.38	0	-974.8
EGW	-6.67	5.36	67.8	95.51	-1.32	10.46	7.35	0.1	0.12	0	178.67
Co	15.98	16.18	-32.02	-85.58	-32.68	-26.51	-77.58	-1.22	-1.1	0	-224.53
Pa	-0.87	7.29	4.67	-1.19	1.08	-6.03	-7.93	0	0	0	-2.98
AOI	-92.53	148.49	-222.53	101.42	-100.22	-72.37	187.9	3.5	2.43	0	-43.9
Treatment methods	(units: kilograms)										
Landfill	6.3	4.9	11.78	-23.33	-29.46	-3.57	-76.94	-0.17	-0.16	0	-110.63
Recovery	-13.35	3.83	-20.81	-5.29	-14.63	-1.2	-23.14	-0.02	-0.02	0	-74.63

Table D.8: Differences between the two scenarios for Mosaic household type B05