LOW CARBON LIVING CRC

Energy, Transport, Waste and Water Demand Forecasting and Scenario Planning for Precincts.

Workshop 2 - Establishing a framework for integrated ETWW demand forecasting

Authors	Dr. Nicholas Holyoak
Title	Energy, Transport, Waste and Water (ETWW) Demand Forecasting and Scenario Planning for Precincts - Workshop 2 - Establishing a framework for integrated ETWW demand forecasting
ISBN	
Format	
Keywords	Demand Forecasting, Energy, Transport, Water, Waste, Modelling
Editor	
Publisher	
Series	
ISSN	
Preferred citation	

Acknowledgements

The development of this report is based on contributions from all participants of the second workshop for the Low Carbon Living CRC's Research Project RP2002 on ETWW demand forecasting and scenario planning for precincts project, and in particular those who developed papers, presented and participated in discussions.

Workshop Participants

Prof. Michael Taylor	*Dr Rocco Zito - UniSA*
Mr John Devlin - UniSA	*Mr Ivan Iankov - UniSA*
Dr Adam Berry - CSIRO	*Ms Olessya Vitkovskaya - DEWNR*
Mr Atiq Zaman - UniSA	*Mr Jason Ting - DPTI*
Mr He He - UniSA	*Mr Fernando Gamboa – Sydney Water*
Ms Michelle Philip - UniSA	*Mr Steve Kotz – SA Water*
A/Prof Tommy Wiedmann - UNSW	*Dr Nicholas Holyoak - UniSA*
Ms Kate Beatty – Sydney Water	

The project workshop on 'Establishing a Framework for Integrated ETWW Demand Forecasting' was held at The University of South Australia's City East Campus on 24th September 2013 from 10:00-16:00.

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Introduction

This project for the CRC for Low Carbon living is designed to develop a shared platform for integrated ETWW (energy, transport, waste and water) demand forecasting and scenario planning for ETWW under low carbon futures, focusing on gaps, synergies, alternative approaches and required research directions. It will include a series of facilitated national workshops on demand forecasting for ETWW utilities and services and on scenario generation and appraisal. The aim is to seek the development of integrated tools for demand forecasting and scenario evaluation covering ETWW with identified commonalities in data requirements and model formulation. It will first (Phase 1) develop an integrated framework for demand forecasting that will then be fully developed and implemented in Phase 2. A method for including the impacts of household behaviour change in demand forecasting will be a major component of the framework. In this way overall carbon impacts of urban developments or redevelopments can be assessed effectively and efficiently.

The following report presents the outcomes of the second workshop held for this project held on Tuesday the 24th September 2013 at Room BJ3-03 at the University of South Australia's City East Campus, Corner North Tce & Frome Rd, Adelaide from 10:00am until 4:30pm. The focus of this workshop is to follow on from the initial project workshop (CRC-LCL, 2013) and to address issues around and to establish a framework for integrated ETWW demand forecasting. This report discusses a collection of the of the presentations made and associated discussions during the workshop sessions with conclusions and a synthesis of these outcomes presented for the next stages of the research progress. For each of the presentations, the folowing summaries are based on notes are taken about the speaker's presentation and not made by the speaker directly.

Dr Adam Berry: Energy Demand Forecasting

Forecasting precinct energy demand is a complex task as there are a lot of influencing factors. It is important to identify data sets, modelling approaches and tool sets available for precinct energy demand forecasting and associated elements.

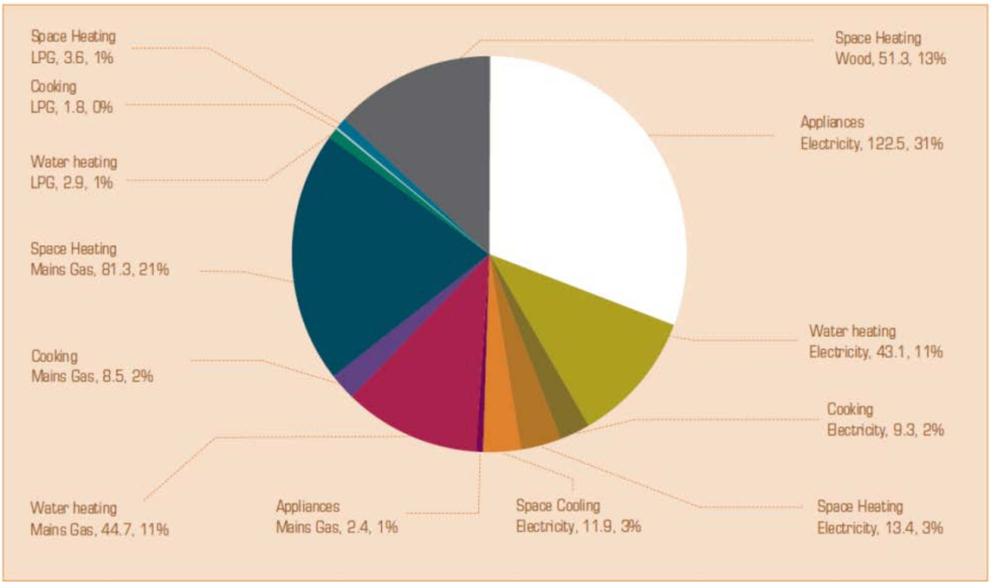
Data Sets

Much of the data that exists to detail residential energy use, is aggregate in nature and often explores high-level trends such as monthly aggregate energy use. The CSIRO is collating data sets to develop more realistic models of energy consumption. Residential energy usage is heavily influenced by the use of appliances accounting for the largest single proportion at 31% and expected to increase (Figure 1).

The Solar Cities program initiated by the Federal Government has allowed for a lot of data collection, which has occurred recently. Much of this data collection has occurred for the first time in Australia and illustrates the nature of peoples' domestic power use. Another program that has facilitiated data collection is the Low Income Energy Efficiency program. This represents a data collection exercise based on less homes but may be relevant and useful in the development of the ETWW project as does the data associated with the Residential Building Energy Efficiency Standards Repository. Other data relevant to this research includes that based on distribution network construction which may be used to plug-in to a precinct ETWW model to see what the distribution network will do.

Figure 1: Residential appliance usage estimates for 2007 [Source: DEWHA (2008)].

Note: Numerical values represent total peta-joules (PJ) per year of consumption by households and the percentage share of total energy consumption for the particular end-use. All values based on modelling.



Demand management trials are happening across Australia and although important, most are specific and one-off. Greenhouse gas emissions data is useful for short-term forecasting but may not be so appropriate for application in this research when considering forecasting into the future. Part of the reason for this is that there is much debate due to instability around policy associated with this subject and hence short-term future forecasting more reliable when compared to the longer term.

Modelling and Simulation

The modelling of power flows that occur at the precinct level commonly represent AC type power flow. Modelling processes were easier to accomplish in the past witht he presence of uni-directional power flows and traditionally radial networks. This is becoming more difficult with distributed generation and potentially bi-directional power flows. The Gridlab-D modelling platform exists as open source software that could potentially be applied in this project.

One technique for forecasting energy loads is neural

One approach to forecasting of energy loads can be based on a neural networks, utilising historical data sets. An issue with this approach is whether historical data is necessarily a good predictor for future energy use. Incorporation of behavioural type inputs into the modelling process is facitlitated through this technique, however this becomes more difficult when developing longer term forecasts, especially 10 to 20 years into the future. The modelling of individual building energy use is possible from the ‘ground-up’ with the CSIRO developed Accurate software. For application in the context of this project, there may be a need to develop a set of representative households and use to ‘plug-in’ as appropriate.

Residential Technology Trends

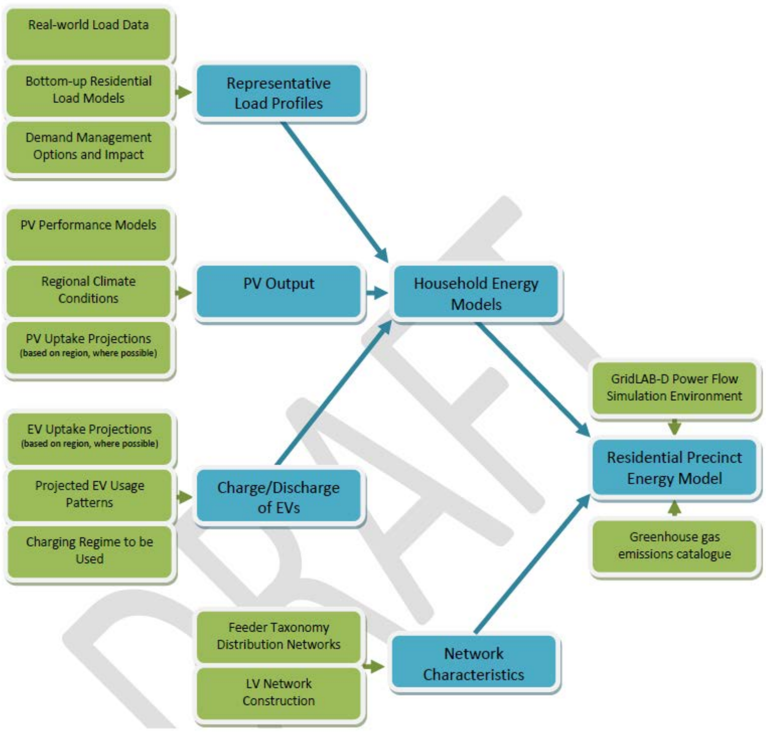
Trends in residential technologies that will impact on energy demand forecasting include the uptake of solar PV and electric vehicles in Australia. CSIRO has developed diffusion methods for forecasting both solar and electric vehicle uptake based on a variety of demographic and technology inputs for granular (post-code level) projections. These projections alone, however, will not be sufficient for fully assessing energy impact – for this, insight into specified charging regimens, PV penetration limits and generation ramp rate control efforts (amongst others) is required.

A Possible Path Forward

A possible path forward to establish an accurate and practical energy demand forecasting approach for this research will involve data and model fusion to provide representative load profiles, PV output, EV discharge/charge used to build household energy models combined with neural network characteristics to develop precinct energy models. One of the main dilemmas is that currently there is not much interaction with other domain forecasting approaches, these being for transport, water and waste.

Figure 2: Dependency map for the posited residential precinct energy model [Source: Berry and Percy (2013), Appendix A].

Note: Green shows inputs drawn from pre-existing data, tools or models. Blue shows outputs delivered through data, tool and model fusion.



Discussion on Energy Demand Forecasting

In relation to the use of electrical appliances in the household, there has been an increase in demand over time and is forecast to increase into the future. This is likely to be the as the result of more appliances present on the household rather than increased use of existing appliances. The forecast is not likely to account for the presence of electric vehicles These conclusions would need to be confirmed as the presented data is not the result of CSIRO-based research.

Mixed-use developments are experiencing promotion within and beyond Government policy and planning agencies. It is therefore essential that models account for the presence of mixed land uses and the inclusion of forecast scenarios that recognise this. The topic of mixed land uses should be recognised by all domains and scenario development will be required. In terms of energy demand forecasting, the models should account for mixed-use as forecasting for commercial buildings is more easily achieved when compared to residential. The Accu-rate modelling software can be applied to commercial land uses and more recent releases account for peoples

Behavioural aspects are captured through the development and analysis of surveys and hardware such as smart meters and (more rarely) cognitive metering. Smart meters may not provide as good a picture as surveys as they include whole of house demand. Living laboratories that are in existence such as Lochiel Park in Adelaide should be made use of in this context.

Dr Nicholas Holyoak: Transportation Demand Forecasting

Transportation demand forecasting is the estimation of present and future year transport behaviour patterns. Assisted by the use of software packages, it is influenced by socio-demographics, land uses and nature of transport network supply. Scales with increasing model resolution range from those with inclusions of National networks and operations to macroscopic models which include a whole metropolitan region, to micro and nano-scopic scale simulation which may include a small collection of intersections and person-based door-to-door travel.

Establishing Model Inputs

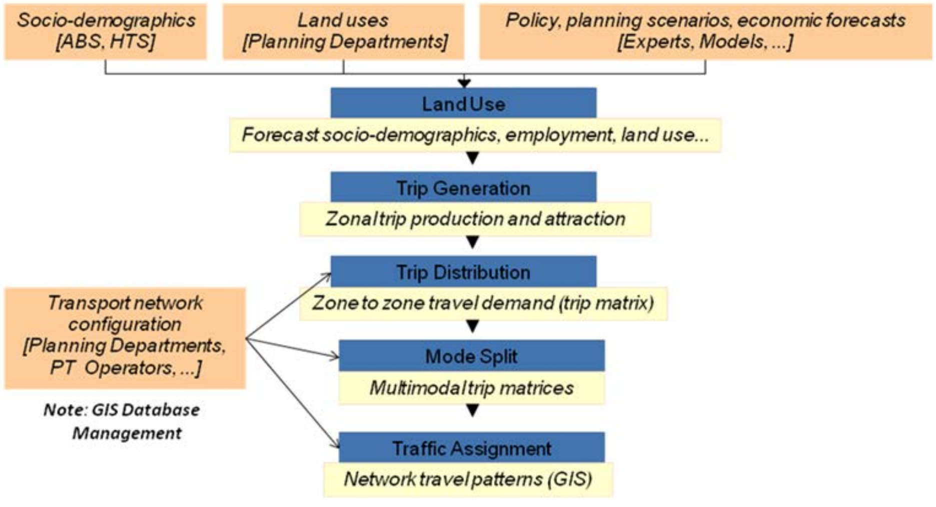
There are a number of essential stages for the forecasting of transport demands which are all well researched and are successfully applied in practice internationally and around Australia, mainly at the macro-scale, offering a weath of travel behaviour data available for inclusion inthe ETWW modelling process.

Prior to modelling activity, a Traffic Activity Zoning (TAZ) regime is applied to the study area to allow for the representation of land uses and demand distribution. Model inputs are based on the TAZ definition with data for each TAZ regarding land uses and household level socio-demographics. Transport networks with operational attributes including road, public transport, intersections, as well as other possible inputs such as freight-related demands. Examples of modelling output include travel demands disaggregate by trip purpose, household type, car ownership, time of day, mode, etc. and network travel patterns.

Macro-Level Forecast Stages

Once this has been established, first of these modelling stages (Figure 3) involves an application of land –use modelling where the key land use decision of individuals is 'where to locate homes or enterprises?'. Their decisions translate into travel and communications activity, affecting congestion and hence accessibility. Following on from this, the trip generation stage seeks to address the concern of the individual traveller's decision of 'shall I travel?'. Within the modelling framework, this stage establishes the total number journeys produced from and attracted to each TAZ, disaggregated by classifications such as purpose, time of day and traveller type. Next the trip distribution stage focuses on the decision of 'where shall I travel to?'. Application of models such as the gravity model results in a matrix of travel demand form origins to destinations.

Figure 3: Typical strategic modelling processes and data elements [Source Holyoak (2013), Appendix B].



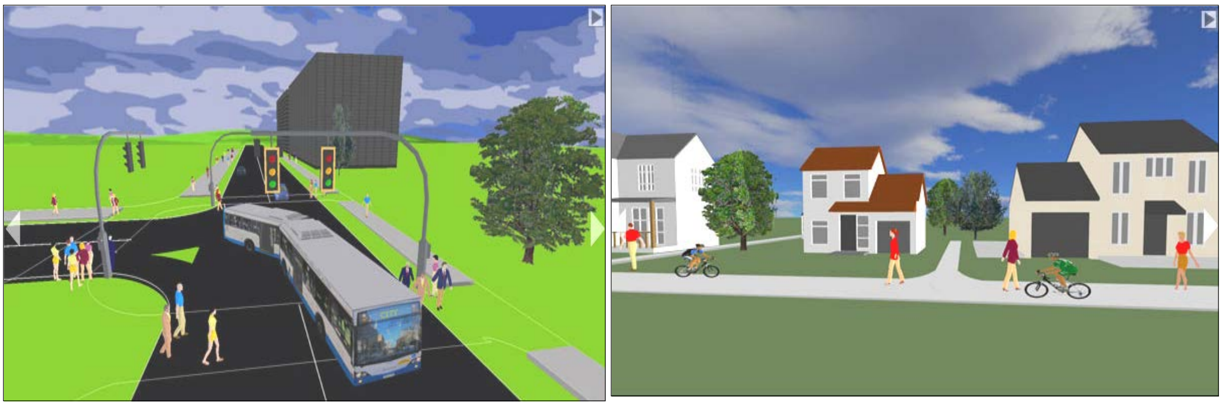
Mode choice follows on from this where the decision is 'how shall I travel?'. The traveller's discrete choice on which mode to select commonly uses a logit model. In this approach, it is possible to incorporate mode and person- specific variables with the development of a utility functions. The trip timing stage can also be addressed using a discrete choice model, where the decision is 'when shall I travel?'. The final stage, before an iteration of all stages is performed is the assignment where the decision is 'which route shall I take?'. Here network supply and travel demands are matched and the focus is on private vehicles (including freight). It is conducted using an optimization process that considers traffic conditions and congestion.

Altenative Approachesand Other Considerations

One alternative to the modelling approach depicted in Figure 3 is activity-based modelling which is a more detailed modelling approach that can recognise complex interactions, including those at the household and related to travel. Greater effort required to accurately calibrate such models that operate at a finer data resolution. These models often have a heavy reliance on discrete choice modelling.

For the purpose of representing travel demands at a precinct level, the Commuter software (www.azalient.com) is being researched by the transportation group. It is a nanosimulation modelling software, offering greater modelling detail than typical micro scale models including representations of door-to-door trips made by people.

Figure 4: Screen captures of Commuter software operation [Source: Azalient (2013)].



Other considerations for transportation forecasting in the context of this research and ETWW demand modelling includes the estimation of carbon impacts, data management and the use of GIS, inclusion of behaviour change, precinct definition and transport interactions with energy, waste and water.

Discussion

In the context of the ETWW project's need to represent precinct-level demand forecasts, the macro-scale models will be applicable with the potential for other inclusions, including micro-scale demand representations. Macro models are well developed and present for most of Australia's capital cities and so will provide a useful resource to draw on for this project. Data sources developed at the ABS Census 'mesh-block' zoning scale may be useful for inclusion in the transport (and other) demand forecasting tasks, however the zoning systems applicable to precinct-level demands (ie. TAZ) will likely be larger that these zones.

Meso-scale models that have recently received much attention in the transport modelling domain may be useful for inclusion in the forecasting task but as they are relatively new to the domain, their application will be limited due to the need for them to be more fully developed and refined. This is especially the case for precincts that exist in Australian capital cities.

The summary of Prof. Michael Taylor's presentation that follows provides more detail on some of the issues raised in this discussion.

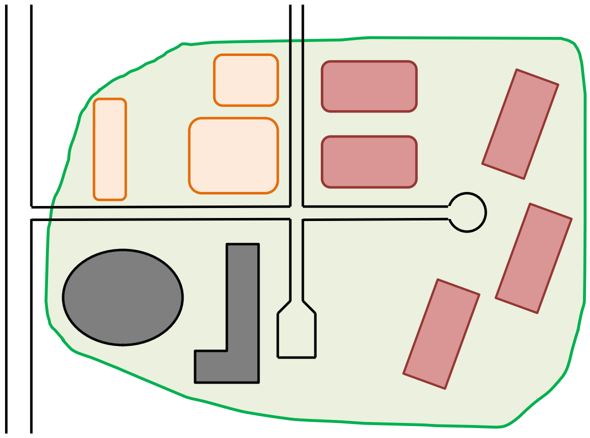
Professor Michael Taylor: Estimating Precinct Level Carbon Emissions from Transport

Carbon performance is a key consideration in precinct analysis and there is a need to estimate carbon emissions at this geographical scale. In terms of transport, the precinct is source of emissions that may occur across a much wider region. Travel demand models can provide basis for the estimates, but require readjustment. A definition of the precinct has been developed by Newton et al (2013) as the following:

'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'

In the context of this project, the precinct may be considered as a Traffic Activity Zone (TAZ) which are typically based on the Australian Bureau of Statistics definition of a Census Collection District or CCD. Therefore if we can assume that we would know CCD socio-demographic and population type information for a precinct within a TAZ.

Figure 5: Representation of a precinct as a connected set of buildings and facilities (which can be represented as 'micro-zones') [Source: Taylor (2013), Appendix C].



Regional travel demands can be represented by the transport modelling forecasts of Origin-Destination (O-D) matrices with additional descriptive data as travel cost matrices. Precinct travel demand may included in the regional O-D matrix, with rows representing travel originating in precinct and columns representing travel finishing in the precinct. It is also important to beware of double-counting intra-precinct demand in this context. The total travel cost of precinct-generated travel can be estimated, enabling estimation of fuel and emissions performance. Intra-precinct travel demand can utilise a micro or nano-level replication of regional analysis which would use different mathematical/computer models with the household as basic unit of analysis.

Precinct-level analysis can be performed using existing methods with modification. The outstanding issue is elastic travel demand and behaviour change.

Discussion

It is possible to represent the presence of transport infrastructure (such as light rail) within the precinct. This will be captured with the use of a modelling routine such as the mode choice model which can be applied within a macro-scale model. The results of such an application will be evident in the trip matrices that result and hence be recognised in the precinct.

Associate Professor Tommy Wiedmann: Review of Water Demand Forecasting

One of the main factors influencing water demand in urban areas is human behaviour and there have been attempts to simulate this in a modelling environment. It is important to note that behaviour associated with water demand can be influenced, as witnessed in demand changes associated with drought restrictions. Education can be a cost effective approach for influencing behaviour and reducing demand. End use surveys and measurement studies have been conducted in a number of locations around the world and provide some indication of the influence of behaviour on water demand.

Demographics and planning policies also have a significant influence on water demand. Total water demand is largely driven by population growth but because planning policies can influence both the density and water use efficiency of precincts, the influence of population growth can be somewhat balanced by policies that encourage efficiency.

Water source substitution (such as rainwater tanks, greywater and dual reticulation systems) will have an influence on future water supply infrastructure needs at both infill and brownfield sites. Efficient planning of infrastructure needs to consider the ability to adapt to future changes such as potential increases in decentralised alternative supply sources. Typically infrastructure planning is not well integrated with the regulation of the water industry relating to pricing and environmental licensing. There is a potential for future legislative change to better support more efficient infrastructure planning.

Types of urban water demand forecasting methods

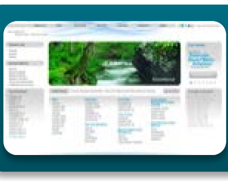
In the temporal domains there are 2 broad approaches to forecasting urban water demands, these being 'top-down' and 'bottom-up'. The complexity of the approach is based on the forecasting requirements and time series analysis can be long, short or cyclical with most approaches based on the short-term. In terms of long-term approaches, multivariate regression analysis is often utilised including independent variables such as climate (rainfall, evaporation, temperature) and population etc. Other approaches include computational intelligence methods, eg. neural networks and agent based approaches, however these are not widely applied in this area. System dynamics has also been used and Monte-Carlo simulation has been applied by some water utilities to quantify uncertainty.

Water modelling at a precinct level

Regression and time series are usually applied at a city or region wide scale. The effectiveness of AAN is mixed and it is important to quantify uncertainty. Polebitski and Palmer (2010) have developed a paper reporting on forecasting water demand for Census tracts. This is a particularly important publication as it is details a water demand forecasting approach that is relevant to this research.

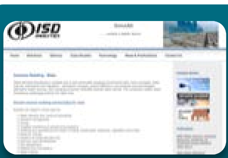
The survey of water providers conducted by the research team indicates that most providers use a top-down forecasting approach, most use macro-scale models and prefer simpler models. Quantifying uncertainty and modelling behaviour change is important. In terms of the precinct the most concern is about infrastructure. Software used (Figure 6) includes Innovyse (Sydney), SimulAlt (Melbourne), IWR-MAN, DSS (California) and ForecastPro.

Figure 6: Software used for water demand forecasting [Source: Cooke (2013), Appendix D].



Innovyze (formerly Wallingford Software)

- Demand Watch - for urban water demand forecasting. Uses historical demand data, time series autoregression & Fourier Trans for short-term water demand forecasts
- Adaptive demand forecasting updated in real-time
- Included in a suite of software for hydrology: InfoWater, InfoWorks WS, InfoWorks CS, InfoWorks SD, InofWorks RS, FloodWorks
- http://www.innovyze.com/

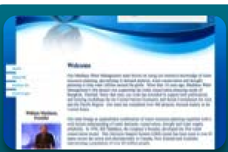


SimulAlt Water Forecasting & Barwon Model Configuration (intelligent software)

- Does NOT rely on historical data.
- Micro-Simulation model includes; agent based modelling, micro-economics, cognitive reasoning
- Bottom up approach
- Includes human behaviour / consumer model
- Allows for senario testing
- http://www.isdanalytics.com

IWR-MAIN

- Sectorial forecast software based on US historial data.
- Used by Metropolitain Water District of Southern California **(Billings & Jones, 2008, p. 33)**
- Provides water demand forecasts disaggregated by sector & time periods
- Can be used to test differnt senarios
- Designed by US Dept of Energy
- http://apps1.eere.energy.gov/buildings/tools_directory/software.cfm/ID=74/pagename=alpha_list



Decision Support System (DSS) Model

- Least cost planning demand management decision support system
- Top down & bottom up to calibrate end-use models
- Developed by Maddaus Water Management California
- Microsoft Excel Based Software **(Billings & Jones, 2008, p. 33)**
- Long-term forecasts can be developed for 10 to 30 years

Forecast Pro

- Generic forecasting software used in many areas of business
- Statistical basis, uses various methodologies, inlcuding; Expert selection, Exponential smoothing, Box-Jenkins, Dynamic regression, Event models, Multiple level models, seasonal simplification.

Conclusions

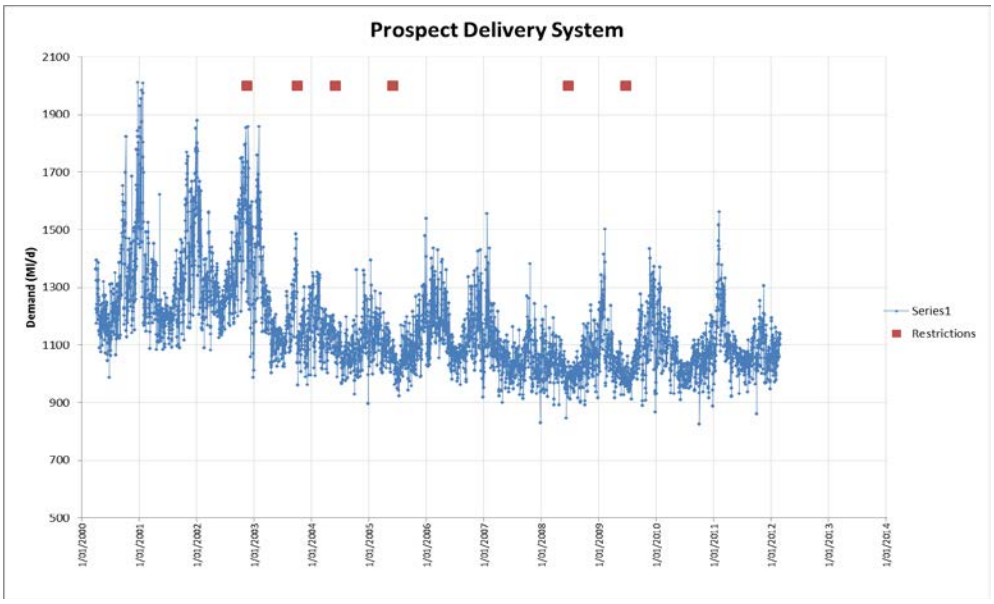
Conclusions are that for precinct infrastructure sizing the peak-day forecast is of greatest importance. The methodology described in the Polebitski and Palmer paper provides an approach with good potential for this research although carbon outcomes and some model for human behaviour would still need to be integrated.

Mr Fernando Gamboa: Water Demand Forecasting in Practice

Practitioners planning and sizing infrastructure needs for precincts have generally gained a better result using 'top-down' water demand forecasts than 'bottom up' approaches. General sources of data used as inputs to the forecasting process in Sydney include population and dwelling forecasts from NSW Department of Planning and Infrastructure (DoPI), historical consumption trends, census data and development applications. For Sydney, the top-down demand forecasting process currently involves analysing and deriving demand rates for each lot allowing for the relative efficiency in water use due to the DoPI's Building Sustainability Index (BASIX) requirement for new housing. For greenfield locations, these rates are informed by similar development in adjacent areas, for infill, these rates will already be known for existing housing within the zone. Hydraulic modelling is then used to determine infrastructure needs including a sensitivity assessment and risk profile.

Generally the forecast maximum hour demand is required for infrastructure sizing however, the smaller the zone size, the higher the temporal resolution required and this can be up to the peak minute. Challenges for forecasting have been the shift in demand during restrictions, the drop in peak day demand in recent years and the changes in when the peak occurs during the day (previously was afternoon, currently it occurs in the morning).

Figure 7: Forecasting challenges – water demand between 2010 and 2012 [Source: Gamboa (2013), Appendix E (presentation)].



The Water Servicing Association of Australia (WSAA) outlines six planning phases for water and wastewater services:

1. define objectives
2. generate options
3. select sustainability criteria
4. screen options
5. perform detailed options assessment
6. recommend preferred option.

There area number of comonly used water demand forecasting and planning tools that help to facilitate these phases. Tools currently in use in Sydney include the energy and carbon estimator which estimates the life-cycle greenhouse gas emissions and energy costs for water and wastewater assets. Construction and operating costing tools include a capital costing tool and economic options evaluation tool. In practice given time, cost and quality contraints, simpler forecasting tools are better. Hydraulic modelling tools provide Sydney Water with a hydraulic model and map.

Areas for future focus will be to continue to refresh the planning process, monitor consumption, improve understanding of dynamic changes in water use behaviour and focus on parameters that have the biggest impact on consumption and on forecast uncertainty.

Discussion

The presence of water saving technology within the home (such as water-saving toilets, showers and washing machines) over the past 20 or so years has had a large impact on average day residential demand. Twenty years ago, these three highest water using appliances in the home were around 50% less efficient and in next 15-20 years they are expected to get around 15% more efficient than today. The drop in peak day and hour demand recently seen in Sydney is however largely behaviour related. People have made big changes to the way they use water outdoors on high demand days.

The impact on rainwater tanks is that they have offer an alternative source of water but the use and effect of this on demand from the traditional reticulated system is limited. Rainwater tanks are only connected to certain uses and are unlikely to provide an alleviation of peak demands, in particular the annual peak-hours as they are highly likely to be empty at the time of year when this occurs in most situations. In terms of water supply cost, the largest component is the fixed component (ie. supply and sewerage charges), and therefore the payback period for the cost of a rainwater tank is very long or infinite (that is, involves a net cost to the household).

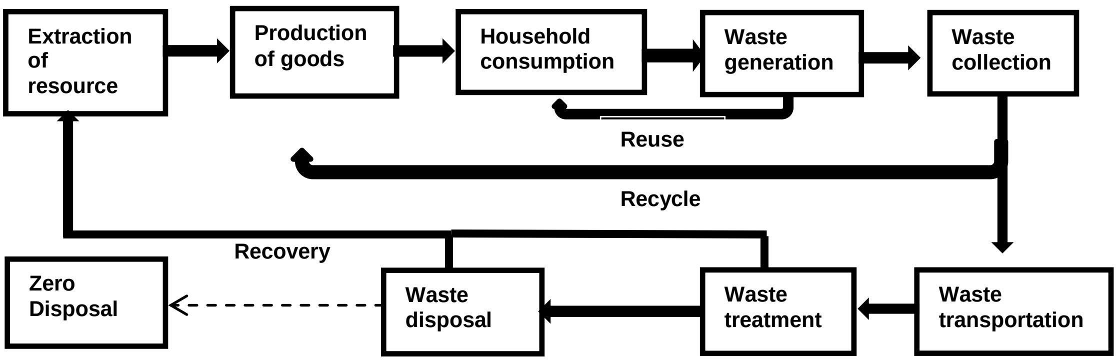
The hydraulic models used to size infrastructure for precincts require both domestic and commercial demands to be forecast. Commercial demands are currently forecast using data from NSW Burea of Transport Statistics (BTS). Commercial demands have generally remained more stable and are usually a smaller component of total demand so do not pose as big an issue as residential.

Mr John Devlin: Waste Demand Forecasting

Questions that arise for the waste demand forecasting task include 'what is zero waste?', 'where do we measure waste?' 'is waste avoidable?' and 'what about embedded waste?'. The average waste production for persons in Adelaide is 2.5kg per day, but what is used to estimate this figure and is this value useful? Defining waste by its weight is useful, but only to a certain degree for relevance to our ETWW project. With embedded waste, little changes in supply changes can have a significant influence.

Detailed classifications of waste types exist and the waste stream can be expressed as a hierarchy such as: avoid – reduce – reuse – recycle – recover – treat – collect – discard – pollute. Dr D. Halperin provides a definition of waste as 'waste is... the absence of value' but waste definitions can be subjective and contextual. Zero waste in the waste stream hierarchy, is to aim for 'avoid', 'reduce' and 'reuse' but it is important to note that there can be great differences between hierarchy levels, ie. reduce is 1000x better than recycle in terms of waste reduction

Figure 8: A conceptual model of zero-waste management chain for residential precinct [Source: Qian et al (2013)].



Approximately 70% diversion of waste from landfill in 2012 for SA but this figure can be misleading as questions can be raised about its accuracy and even its meaning. Is there a demand for waste? Professor S. Lehmann provides a definition for waste that 'waste is ... a misallocated resource'. Waste can be a combination of many resources such as time, material, effort, energy, space and capital, and so for this project it may be more appropriate to define the 'waste' component as a 'material ' component, changing our ETWW project to an ETWM (Material) project.

Resource demand is dependent upon design and behaviour and so barriers to long-term forecasting can be associated with mobility, the existence of borders and off shoring, timeframes, innovation, and value. Different ways can we use a waste demand forecasting tool can be as for tasks associated with prediction, exploration, prevention, speculation and for back-casting. Zero waste is a moving target which is influenced by real-time data, feedback investment strategies, governance, adaptation and innovation. In this context it may be better suited to perform waste demand forecasting for short-term time horizons.

Discussion

No one tool for the forecasting of waste demand has been developed as yet however regression and other methods can be drawn on for the waste demand forecasting tasks. It is not certain if the scope of the forecasting task is not only focus on waste but also the resource that it potentially provides. Uncertainty is also associated with the tracking the full life cycle and associated waste productions? Precinct waste production should be looked at from an activity perspective rather than just a categorisation of different waste types.

It is expected that difficulties may also be associated with forecast for recycling needs due to changing nature of waste and the influence of technology and time frames for forecasting. An example of this is the surge in waste televisions associated with recent advances in television technologies.

Associate Professor Tommy Wiedmann: Economy-Wide Carbon Accounting

Top-down approach for carbon accounting which utilises a database has 1284 products and 1248 industries. This develops a matrix containing approximately 1.6 million 'carbon cells' representing the carbon inputs to industry and the carbon production of products. Different emission sources are identified and the descriptives contain 120 building material types. Model integration into Mutopia and UrbanSim.

All Workshop Participants:General Discussion Session

In response to the presentations and to address the aims of the project, there is a need for the workshop participants to help in the development of workshop outcomes associated with:

the development of a framework that may be used by or developed for use by other models,
identify/discuss interactions,
possibility of ABS data use,
investigate behaviour and behaviour change – models use observed behaviour, so how do we accommodate behaviour change,
possibility of using stereotypes households,
inclusion of mixed land use developments and low carbon impacts – optimised
accommodating technological change in our forecast horizons
a report from this workshop and beyond

The following sections summarise the discussions that were held (in addition to those generated from individual presentations) on these and other issues of relevance.

Scenarios

The development and testing of future forecasting scenarios is an important stage for a number of reasons, largely associated with the investigation of behaviour and behaviour change impacts. Policy makers need to know the result of behaviour changes and hence this can be a political issue. In this respect, it may be best to use model to identify the best scenario for low-carbon outcomes. In terms of behaviour change, should this project identify the key behavioural changes that could occur that would give the greatest 'bang for buck' across all domains? Once these are identified, their impact could be projected into future year scenarios and hence provide an empirical estimate for the policy maker. There is a need to consider the key variables, inputs logical combinations of assumptions that may be utilised to develop scenarios which would be dependant on the precinct under consideration.

Developing this type of 'best case' scenario modelling would make pragmatic sense, but what then about other cases. Best/worst case scenarios are important, but cases that consider what is happening in between these extremes are also important. The question of how to identify a 'best case' scenario also arises which may depend on the work conducted and concluded from other CRC-LCL work packages. The CRC-LCL project on 'Vision 2050' will produce outcomes that should be useful to for scenario development, but whether this will occur in a timely manner to mesh with our project is not clear. The ETWW project research group definitely has some responsibility to generate its own scenarios, but can look to others in existence for our use.

Model Framework Development

A framework developed from this project should exist as a set of guidelines for model development in any precinct modelling tool. The scoping study on the "Performance Assessment of Urban Precinct Design" (Newton et al, 2013) contains and evaluation of precinct assessment tools, identifying some of these models. The models will need to differentiate between options, consider uncertainty and the integration between domains is essential to consider the equilibrium state between models.

This project should provide information for and connect with other packages in the CRC program by ultimately providing a means to efficiently and in an integrated manner forecast ETWW demands. The 'bigger picture' objectives of the CRC-LCL will need to be considered when developing this research.

Forecasting and Resolution

An appropriate level of resolution for modelling forecasts is an important consideration to provide results that are useful to the project team and also to the industry partner organisations that will be using the model in practice. Determining industry wants and needs for this model dimension is relevant. Consideration should also be given to available precinct-level descriptive datasets that will be utilised in the modelling routines when considering operational resolution.

This characteristic of the ETWW model should also be influenced by the common levels of resolution in use and it may be necessary to come up with a few levels of data resolution that would be used across the ETWW fields. Operation may depend on the data resolution needed in each of the fields to model human behaviour.

Data

In terms of data collection, this project does not have the scope or resources to collect new datasets, beyond those which may be collected as part of the PhD research. Rather the emphasis will be on the identification and collation of existing data that is appropriate for use in the model development, tapping into CRC data resources. Data should be able to identify components of behaviour with the mindset of the persons being important, especially in relation to behavioural aspects.

Discovering the categories and common elements that influence the four domain demands will help to discover the data, scale and resolution required and express the precinct development and scenario developments. Identifying these should therefore be an action for the group.

Common-ground across the domains should be realised by the datasets with the possibility of 'stereotyped' household definitions as a way of determining common ground for ETWW domains.
Common elements are important for such a household definition structure with elements such as income being an important factor for household transport and water and possibly others. How such characteristics change through time is important especially in relation to household/family changes.

What type of data is currently being used by the domains for demand forecasting? Are ABS, and Mosaic datasets used? Mosaic data is very detailed socio-economic profiles used by business and has been used for research. Mix of real surveys and imputation is very useful.

From a transport perspective ABS data is useful but moreso Household Travel Survey data reporting on a sample (1-2% of households) of very detailed household attributes and travel behaviour.

In relation to waste-demand forecasting, data is available at the council-level with some additional one-off type datasets. The problem here is the level of resolution. Many waste forecasting models operate at a council-region scale, so is this useful for the household or precinct scale? From a water perspective, the data can exist but in many cases the data sets can be restricted eg. small sample sizes and self-selecting sample bias.

Defining carbon production from waste generation processes including recycling has many influencing factors especially when considering the full life cycle. This project will need to decide on where to draw the line in terms of waste forecasting inclusions which depends on the overall purpose of the ETWW model. Waste forecasting framework may change depending on the project objectives.

Wastewater

Forecasting of precinct wastewater production is a topic which can belong to the domains of water or waste, and this needs to be clarified. Water recycling at the precinct scale depends on technologies in use and the nature of the scenario under scrutiny. Many of these issues associated with wastewater production are new issues, which provides policy and guideline barriers in itself and is an interesting challenge.

SA Water is involved in integrated water research projects for which results are scalable and therefore applicable to a precinct. The Goyder research which would be appropriate for consideration in this research will be available by the end of next year.

Conclusions and Synthesis

Within the energy domain, demand forecasting approaches exist, but there are questions over the incorporation of behavioural elements. Longer term forecasting may be problematic, especially with the impacts of new technolgies (ie. solar PV, electric vehciles) and potential policies associated with them. Relevant datasets such ad the Low Income Energy Efficiency program and Residential Building Energy Efficiency Standards Repository are established with some detailed sets with small geographic coverage. Thre is good potential to look to smart meters and living laboratories as a source of model development data. Robust modelling software platforms such as GridLAB-D and Accu-rate offer potential to handle the forecasting task.

The transport domain has well established base forecasting approaches, based largely on household-level datasets. ABS data especially at the CCD level along with transport-specific surveys and existing maro-scale model outputs can offer significant data sources. A range of behaviour-inclusive forecasting approches with differeing resolutions can be applied through various software platforms with invstigations into nano-scle softare such as Commuter underway. TAZ definitions offer a useful approach to precinctscale forecasting with approches now suggested for this process.

Top-down forcasting approaches are preferred for the water domain, based on population and demographic datasets. Forecasting methodology similar to that suggested by Polebitski and Palmer (2010) based on census tracts is suggested and a range of software packages are available. Representing behaviour changes pose a challenge for water demand forecasting particularly as it has been proven that water-usage behavoiurs are elastic and can be influenced.

Modelling approaches for the waste domain are not well developed, with the need to consider the scope for inclusions and the degree to which waste is considered as a resource. Limitations on datasets for base forecasting and software pose challenges for the waste production forecasting task along with long-term policy and technology uncertainties.

The need to integrate forecasting tasks for the domains introduces a range of challenges for the successful development of a modelling framework. This is emphasised by the differing nature and maturity of the forecasting approached described herein. All domains should consider potential interaction opportuntities within their respective model frameworks and seek a cohesive integration approach. Utilising data through a format of 'representative' or 'steroetyped' housholds and land uses may offer one approach to successful scenario development. Scenarios should consider time frames with the consideration that short-term forecasting of behaviour change will provide results with greater confidence when compared to longer term. The forecast resolution should be guided by the available data used in describing the precinct and in particular the nature and behaviour of the precinct in relation to household behaviour, adoption of techologies and land use mixes. In these cases, industry can offer guidance in terms of what is expected from the forecasting routines and potential policy inclusions.

Other data-handling opportunities exist with the application of GIS-based software that can represent inputs such as ABSdata, Mosaic data, domain-specific spatial land-use/sociodemographic data, networks for transport, electricity, water and waste infrastructure. In addition a GIS could offer a useful meand of representing carbon outcomes from demand and behaviour change.

For each domain it is essentail to realise the impact of acitivity happening inside the precinct on what happens outside and vice wersa. The question of 'where to draw the line?' arises is present in all domains, especially highlighted for the waste domain regarding material lifecycle and embedded waste. It may be impossible to accurately account for complete carbon impacts based on the precinct forecasts however, limitations need to be noted.

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Appendix A

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Energy Demand Forecasting

Modelling, Simulation and Projection of Energy Technologies for Green Precincts

Adam Berry and Steven Percy

Draft only; not for distribution

Contents

Figures

Part I Introduction

Placing energy demand forecasting in context

1 Introduction

Forecasting and analysing energy demand for a given residential precinct requires not just an understanding of the likely demand-side energy technologies that will be adopted by householders within that precinct, but also the likely behaviour of end-users with respect to that technology. This is obviously a complex task. The uptake of small-scale renewable technologies, the adoption and use of electric vehicles, the passive design of the home, the timing of energy use, remote demand management interventions and the ultimate flow of power around the electrical network of the residential precinct are governed by end-user attitudes, electricity tariffs, technology costs, convenience, government incentives, climatic conditions, central generation sources, network construction and the socio-economic status of residents (amongst many others). This report looks to illuminate the data sources, modelling approaches and tool-sets available for capturing the key factors driving new energy technology uptake, understanding end-use behaviour, estimating greenhouse gas emissions and simulating the low-level characteristics of power moving around a precinct electrical network. Effective collation, fusion and extension of these components and/or their outputs will ultimately form the heart of a unified tool for modelling, analysing and forecasting energy use in future residential green precincts. Given that no equivalent tool exists in the public domain, this work represents an exciting opportunity to both extend science and produce a practical output that is of relevance to both industry and policy makers.

It is worth noting that while this draft report provides a very light review of the nexus between transport and energy (emerging from electric vehicle uptake and usage), it does not touch upon the interaction that exists with water and waste streams. It is expected that the September Energy Transport Water & Waste (ETWW) Workshop will begin to explore and articulate these interactions, with a view towards identifying optimal paths towards integration into a unified tool chain.

Part II Data Sets

A review of data sets that will inform modelling of residential precincts

2 Residential Energy Use

There has been a paucity of data regarding the energy usage behaviour of Australian residential customers. Though interesting studies, such as the Commonwealth Government's analysis of residential energy use [1], endeavour to address this by exploring high-level trends (see Figure 1 and Figure 2), there has been little data available on what those trends mean for the fine-grained consumption behaviour of individual homes. In particular, conventional metering systems and billing methodologies have meant that where significant volumes of data are available, they seldom move beyond aggregate monthly energy use. The impact is that such data fails to reveal the time-sensitive trends in residential energy use, obscuring the nature of daily load profiles. Given the intermittent and time-bound behaviour of renewable generation systems and the growing import of high-peak loads (such as air-conditioning) to the design and operation of Australia's electrical networks, a lack of insight into the hourly behaviour of residential customers severely limits the capacity to deliver meaningful models and simulations of residential precincts. For effective green precinct design, the devil is in the details: it is the interaction between load and generation across a day (at customer and aggregate level) that really matters.

At least partly in response to such issues, CSIRO has been actively collating data sets that begin to shed some light on the daily load profiles of Australian residential customers. Taken together with more detailed modelling of specific housing stock (see Chapter 9) and forecasts on future energy use trends (see Chapter 8), this data can be used to develop realistic models of energy use for customers living in future residential precincts.

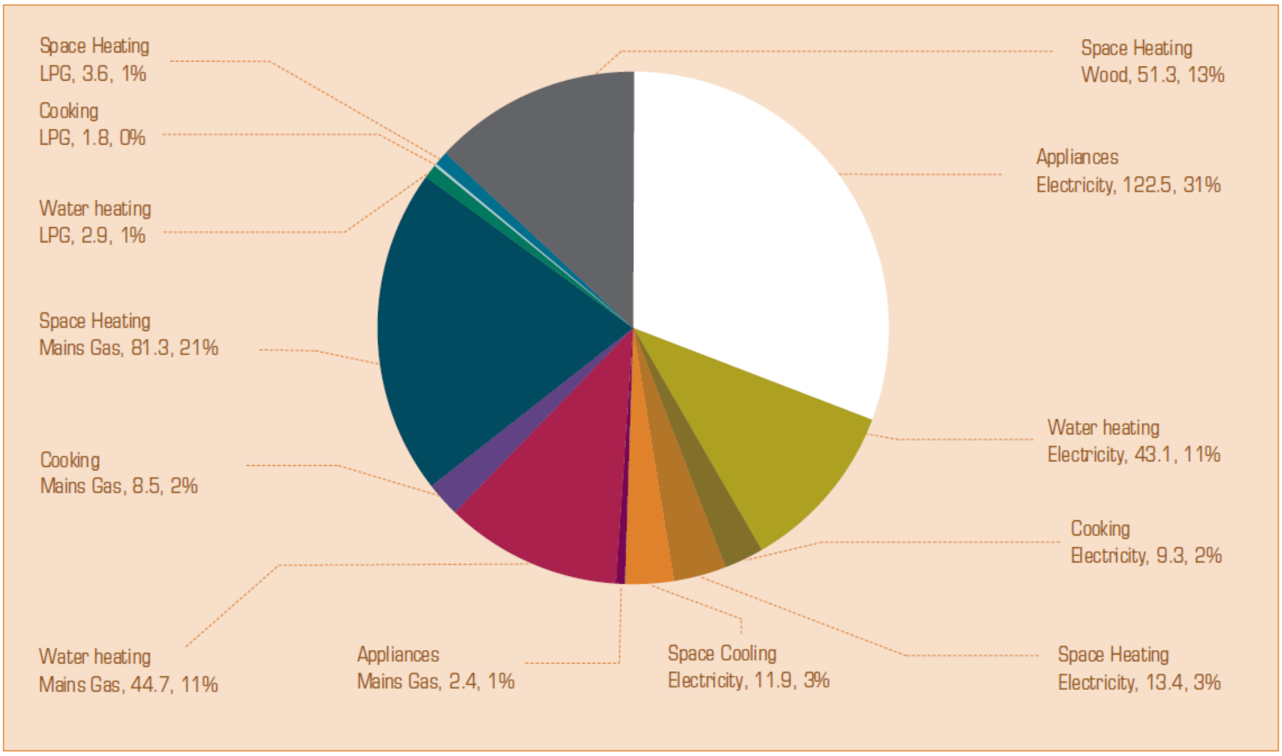

Figure 1. Residential appliance usage estimates for 2007 (source: [1])

Numerical values *represent total peta-joules (PJ) per year of consumption by households and the percentage share of total energy consumption for the particular end-use. All values based on modelling*.

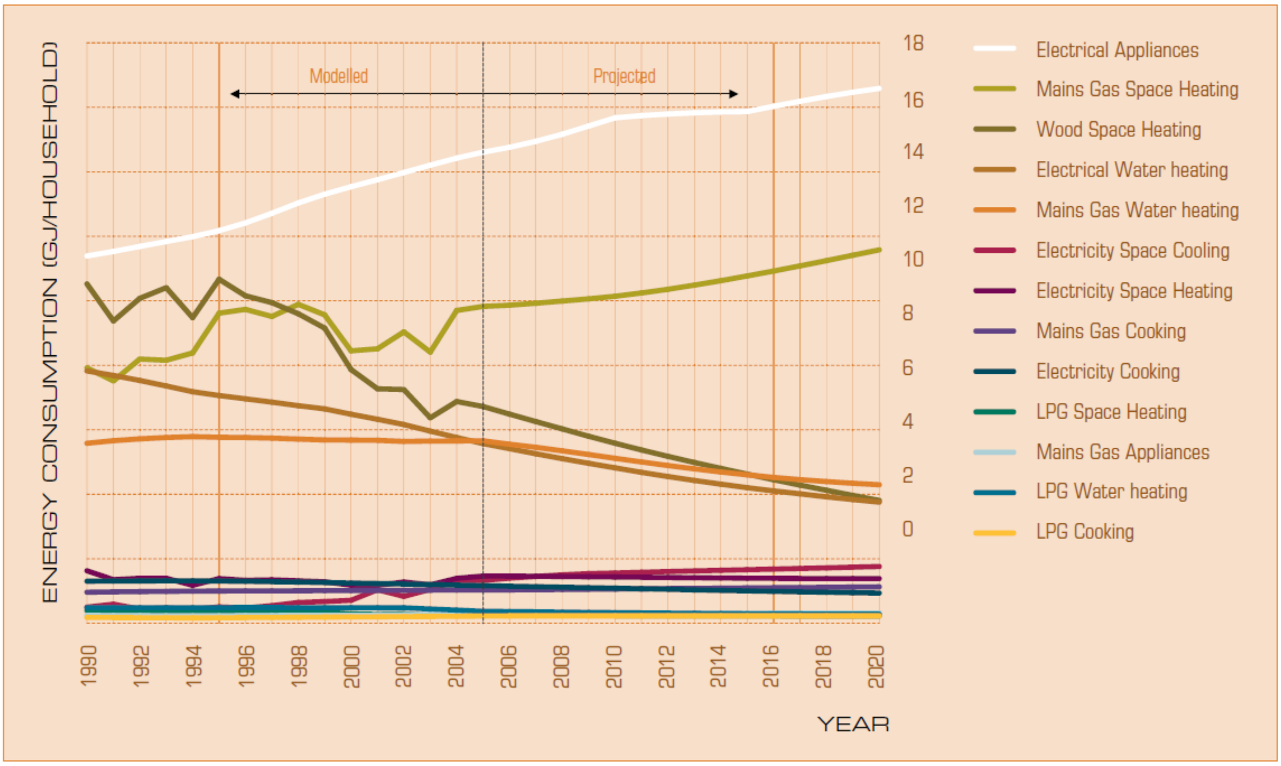

Figure 2. Residential energy consumption trends and forecast (estimated; source: [1])

2.1 Solar Cities

The $94 million Australian Government Solar Cities program~~me~~ to evaluate the effect of various energy efficiency measures, solar uptake and tariff models on residential energy consumption has recently come to a close. Amongst the many outputs from the program is a rich data collection that includes anonymous half-hourly load data for residential participants. CSIRO has reviewed, cleaned and collated this data into a store that contains load profiles for thousands of end-users across multiple years. The data is often married to high-level demographic information, may capture solar PV performance (where installed) and often captures loading across circuits (which can be used to disaggregate loads into particular categories). The store is the largest collection of detailed residential load data that the authors are aware of and will an excellent base for producing load profile taxonomies that describe representative residential energy use behaviour for Australian households. For precinct design, the availability of such load data will be essential for realistic estimation and simulation of residential developments.

As an indication of the type of load data available within the Solar Cities store, Figure 3 shows a representative load curve based on half-hourly median load recordings taken across multiple sites. Methods for mitigating the peaks seen in such residential curves will be explored in Chapter 5.

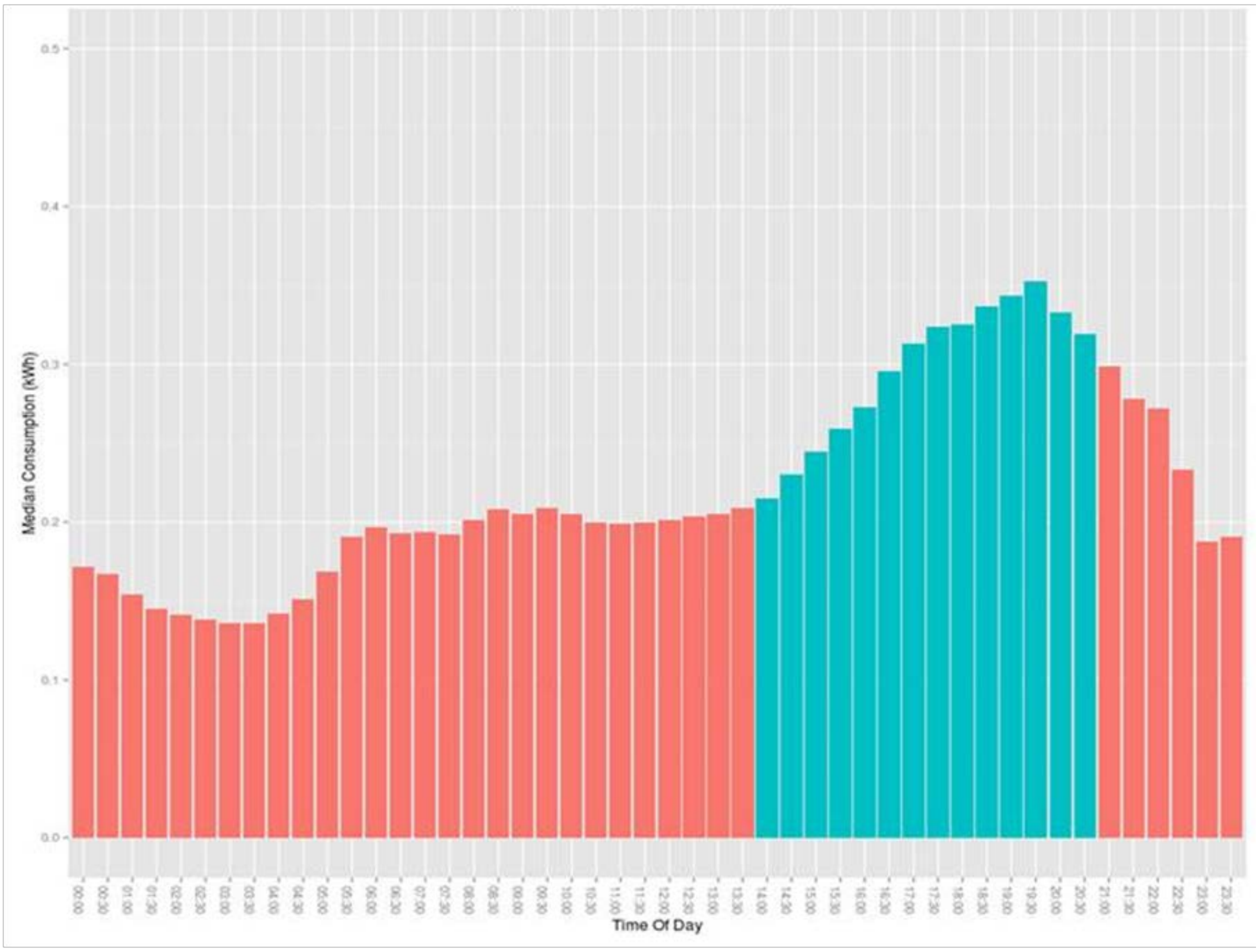

Figure 3. Illustrative load profile from the Solar Cities store

The cyan region indicates the peak tariff period for homes in the corresponding data set.

2.2 Low Income Energy Efficiency Program

The Low Income Energy Efficiency Program (LIEEP) is, in many ways, the successor of the Solar Cities program of activities. LIEEP focuses on the execution and assessment of trials targeting energy efficiency initiatives that are specifically designed for low income residential households. Though the LIEEP trials are at a fledgling stage and little data has been collected, CSIRO is again engaged in the management and collation of anonymous residential load data sets. In general, the data is expected to be less granular, though it will almost certainly include half-hourly load data for hundreds of homes, recorded across multiple years. The data is expected to supplement existent load data for the ETWW project.

2.3 Residential Building Energy Efficiency Standards Repository

CSIRO's Residential Building Energy Efficiency Standards (RBEES) repository houses energy use and temperature data for approximately 200 homes across Adelaide, Melbourne and Brisbane. This data is fused with socio-demographic data and home energy rating evaluations (as-per the Building Code of Australia) to explore the real impact of building energy efficiency standards on actual energy consumption. Energy data for each home is measured at half-hourly intervals and captures per-circuit use (which can facilitate direct identification of air-conditioner use for some residential users). Socio-demographic data is captured through surveying and provides insight into appliance types and use, building construction, energy use attitudes and customer type. An anonymised for of this data set, together with the Solar Cities and LIEEP sets, can be used to build-up a representative set of base energy use profiles for precinct modelling.

3 Distribution Network Construction

Though individual distribution network service providers are intimately aware of the construction and operation of their own electricity networks, competing proprietary software systems and models, concerns around privacy and security, and the complexity of the data itself has largely prevented collation and presentation of a nationally representative feeder set. In response, working cooperatively with 11 distribution network service providers from across Australia as part of the *Smart Grid, Smart City* programme, CSIRO and Ausgrid produced a succinct set of network models that effectively capture the diversity of Australia's electricity distribution networks. The representative set is formed through an iterative data mining process that identifies statistical trends and similarities present in a rich feeder data set, resulting in clusters of feeders that are similarly constructed. These clusters reveal the fundamental characteristics of feeders deployed in Australia, from modern urban underground systems through to the remote single-wire earth-return networks of rural Australia (see Table 1, for a summary). The resultant data set includes a collection of power-flow models and load profiles from which detailed assessments of network-level energy and voltage behaviour can be estimated for particular deployment and customer-mix scenarios.

Table 1. Representative distribution feeders extracted from National Feeder Taxonomy clusters

Cluster	Reliability Classification	Voltage (kV)	Description
1	Long Rural	33	33kV remote area feeder
2	Long Rural	11	11kV long rural with low SWER levels
3	Long Rural	22	22kV long rural feeder with high SWER levels
4	Short Rural	11	11kV short rural, moderate length, low load density
5	Short Rural	22	22kV rural with low SWER
6	Short Rural	33	Agricultural/small mining (agricultural loads such as irrigation pumps or dairies)
7	Short Rural	11	11kV short rural, short length, low load density
8	Short Rural	11	11kV suburban fringe feeder, principally residential
9	Urban	22	22kV suburban fringe feeder, principally residential
10	Urban	11	11kV medium density residential, majority overhead
11	Urban	11	11kV medium density residential, majority underground
12	Urban	22	22kV medium density residential
13	Urban	22	22kV industrial
14	Urban	11	11kV medium/high density residential, majority overhead
15	Urban	11	11kV industrial
16	Urban	11	11kV mixed industrial/commercial
17	CBD	11	Brisbane CBD
18	CBD	11	Sydney CBD
19	CBD	11	Melbourne CBD

In the context of modelling and simulation appropriate to ETWW, the representative networks will allow planners to explore the impact of high-level precinct design practices on wider distribution network performance (including voltage rise, the operation of transformers and transmission line capacity). This will be of particular import for planners looking to expand the integration of renewable energy into their precincts, where reverse power-flow and erratic aggregate load profiles are most likely.

4 Renewable Energy Data

The behaviour of distributed renewable energy technologies will obviously play an important part in the operation and design of residential precincts into the future. Of particular note is the rapid growth and size of Australia's rooftop PV sector, with estimated installed capacity rising from 23MW in 2008 to approximately 1.45GW by the end of February 2012 [2]. Even under moderate growth scenarios, the Australian Energy Market Operator anticipates that installed capacity will reach 5.1GW by 2020 and almost 12GW by 2031 [2] (see Figure 4). Moreover, recent reports suggest that there are now more than one million installed solar PV rooftop systems in Australia and that approximately 2.5 million Australians live in homes with solar panels installed [3]. Given both the prevalence and increasing uptake of PV, it is appropriate therefore to focus modelling and simulation efforts in this space. Other renewable technologies (such as small-scale wind) and alternative distributed generation systems (such as fuel-cells, battery storage and micro-turbines) may be addressed in future work.

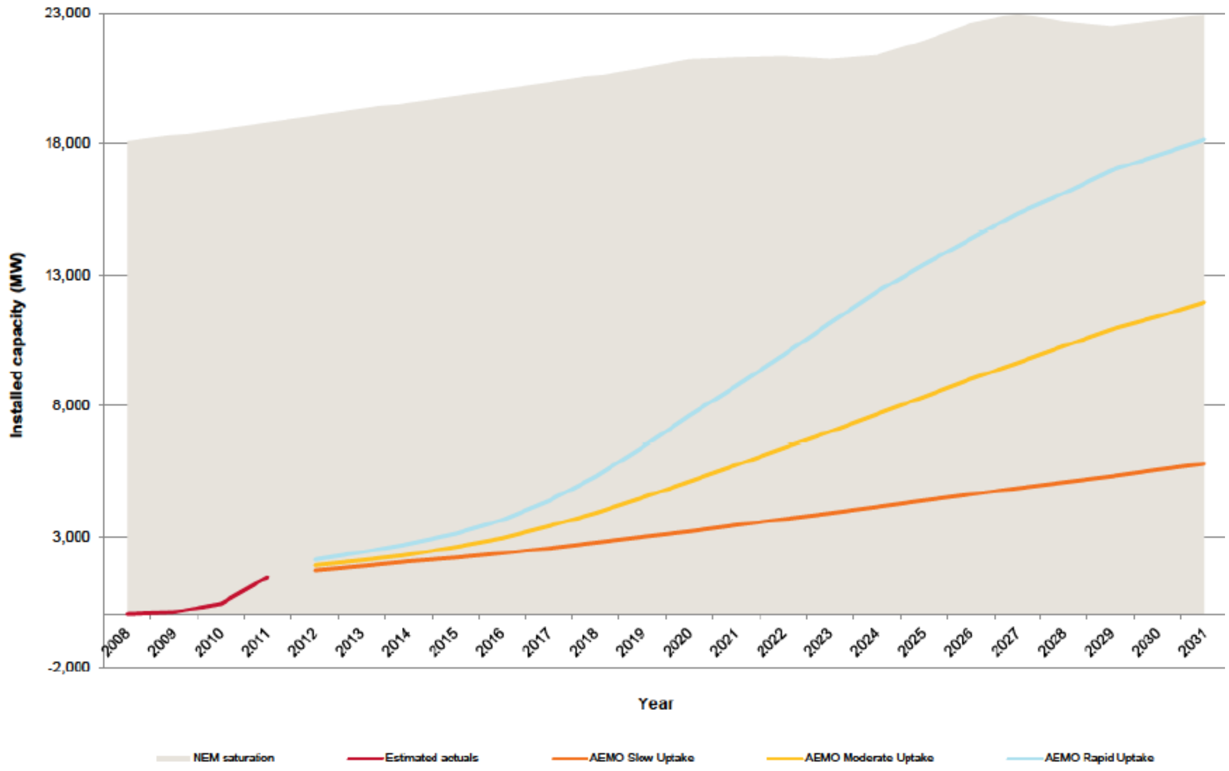

Figure 4. Rooftop PV installed capacity forecast for NEM (source: [2])

There are numerous data resources available that describe various aspects of both solar irradiance behaviour and solar system performance. The excellent PVWatts website (http://www.nrel.gov/rredc/pvwatts/) houses hourly performance estimates for PV systems deployed at multiple sites within Australia (and globally), based on irradiance data from a typical meteorological year and the high-level configuration of the particular PV system (including orientation, sizing and de-rating factors). Though the outputs provide an excellent first-cut insight into the behaviour of deployed solar systems and the impact of system configuration on performance, they lack insight into the short-term transient effects of intermittent clouding that may cause network stability issues for real-world precincts (see [4] for a discussion on the importance of short-term transients in solar power systems).

Fine-grained (one-minute) solar irradiance and weather data has recently been made available by the Bureau of Meteorology (BOM) for multiple sites within Australia (see [5]). This comprehensive data set captures multiple years of data and, as such, analysis of intra-hour irradiance variability may provide an appropriate avenue for translating from coarse outputs of the type seen in PV Watts to more meaningful (and statistically representative) per-minute solar power profiles suitable for detailed modelling and simulation.

Data from deployed residential solar systems may provide interesting baselines against which the modelled solar performance can be compared and tuned. To this end, anonymous real-world solar system output data collected as part of the CSIRO Virtual Power Station (VPS) project in Lake Macquarie [6] may be leveraged. Though the set comprises only a small number of homes (fewer than 20), the data captures per-minute output profiles across multiple months. The Solar Cities database (see Section 2.1) also provides solar system performance data in the form of half-hourly measurements. Though this data is more coarse than the VPS set, it examines performance in multiple Australian regions and includes anonymous data from hundreds of Australian homes. Together, these sets could provide important analytic power for model validation.

5 Demand Management

Demand management as an approach to mitigating peaks has been gaining increasing traction in the Australian residential space. At this stage, most of the work has taken place in the form of residential load control and critical peak pricing trials:

- ETSA Utilities in South Australia conducted a collection of air-conditioner load-control trials with approximately 1,000 volunteers from 2006 until 2009;
- The Adelaide Solar City programme of activities included a critical peak pricing trial with more than 1,000 participants and up to 10 critical peak pricing events per year (designed principally to reduce load during particularly hot summer days);
- Energy Australia is trialing a critical peak pricing scheme that charges households more than 12 times the normal price of power for up to 14 critical pricing events per year (scheduled to run for two hours at a time and again targeting air-conditioner use on hot days);
- Energex's Cool Change programme, which has over 1,800 residential participants, has been trialling remote load control of air-conditioners, hot water systems and, more recently, pool pumps since 2007;
- Wester Power registered over 1,000 residents for the 2007 Cool Community Trial, which examined remotely controlled air-conditioners for peak management in Nedlands, Claremont and Dalkeith; and
- Synergy's Air-Conditioning Trial (ACT), which forms part of the Perth Solar City initiative, is a two year peak demand response programme that commenced in the summer of 2010 and ran until Spring 2011.

Though outputs from such trials claim peak reductions of between 13% [7] and 35% [8] for remote-operated air-conditioner control, there is generally a lack of high-quality data which provides insight into the impact of remote demand management on total energy consumption or end-user behaviour (though the Solar Cities programme touches upon these). With the solidification of remote demand response system standards (such as AS4755) and the continuing deployment of residential smart meters, however, it is expected that both the breadth and depth of knowledge in this area will grow.

6 Greenhouse Gas Emissions Data

To assess the impact of residential electricity consumption on greenhouse gas emissions, it is necessary to both model the source of electricity generation and the carbon intensity of those sources. The National Greenhouse Accounts Factors [9] provide approximate emissions intensities for a variety of fuel types and provides state-based assessments of emissions factors for electricity purchased from the grid. The 2013 estimates are provided in Figure 5 and give a sense of how electricity imported into contemporary residential precincts is produced. To enable forecasting of emissions intensities for future precincts, however, estimates of future centralised generation mix must be known. This is an incredibly difficult task, complicated by changing carbon policies in Australia. Still, multiple reports provide some measure of insight into the coarse electricity generation trends expected across the medium-term horizon.

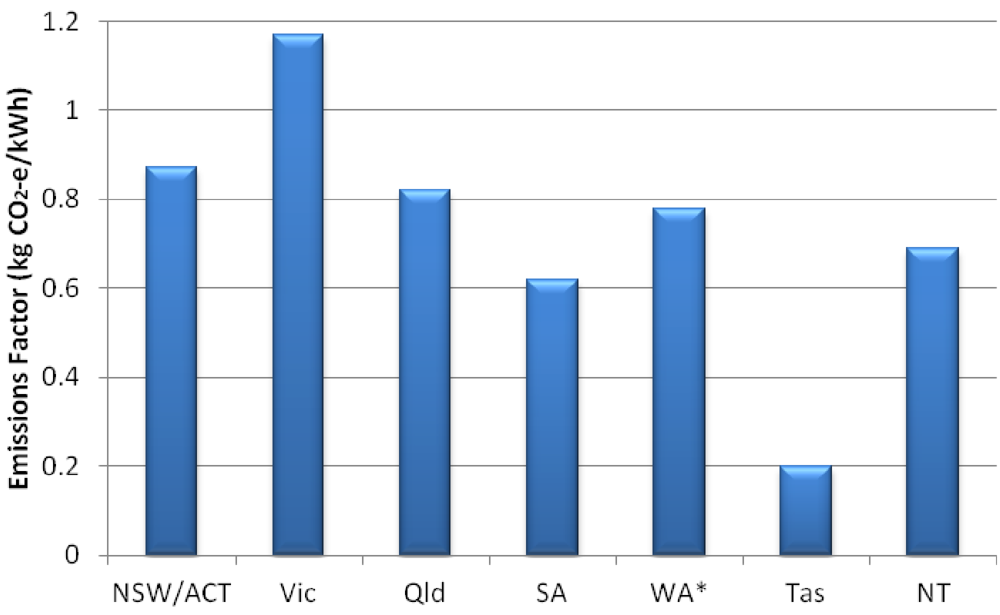

Figure 5. Greenhouse gas emissions factors for consumption of electricity purchased from the grid (source: [9])

***WA* refers to the South-West Interconnect System (SWIS) only.**

The Bureau of Resources and Energy Economics (BREE) project significant changes in the make-up of electricity generation by 2034-35 (their target horizon) [10]. Looking at changes from 2008-09, the share of coal-fired generation is projected to decline from 74% to 38%, the share of gas-fired generation is projected to increase from 16% to 36% and the renewable share is projected to grow from 7% to 24%. CSIRO also anticipates sharp changes in both Australian and global electricity generation technology mixes [11], as shown in the example electricity generation technology mix projection provided in Figure 6. Such projections may be used to provide indicative carbon intensities for energy consumed from the grid for future residential precincts.

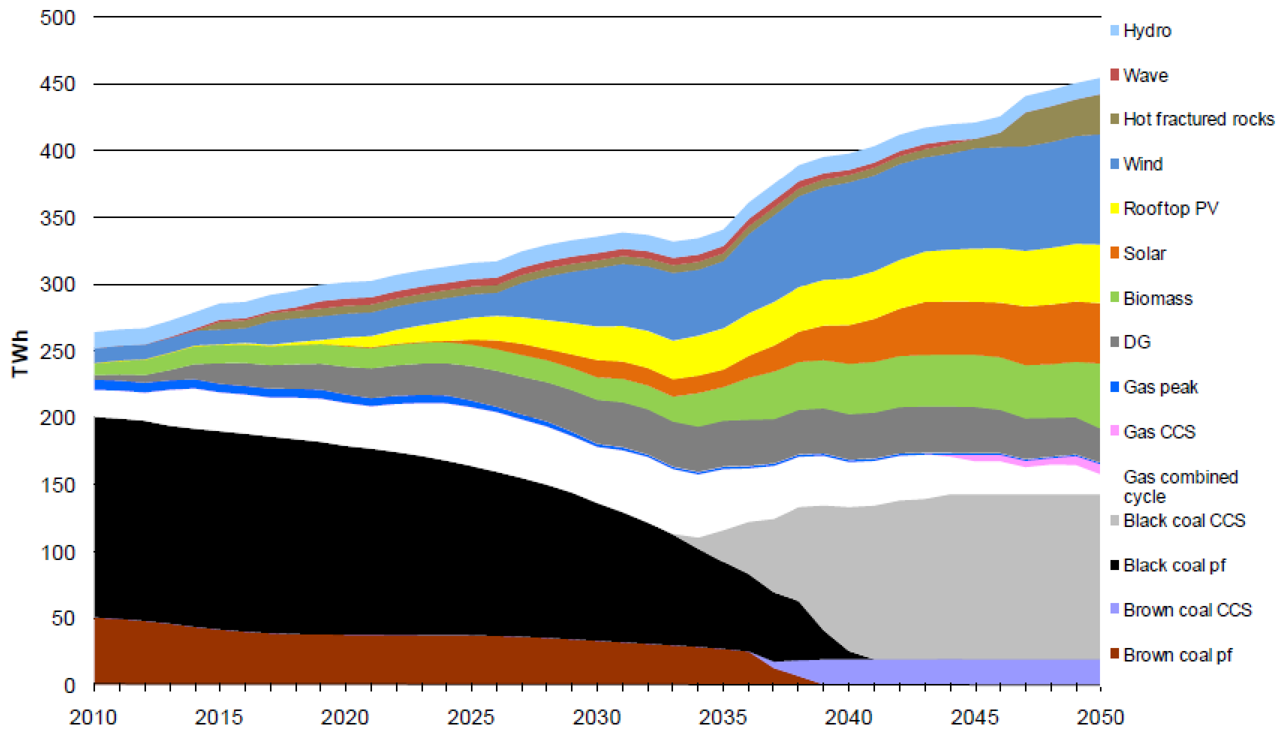

Figure 6. Projected Australian electricity generation mix under the CPRS-5 carbon price scenario (source: [11])

***DG* refers to distributed generation.**

Part III Modelling and Simulation

Methods to estimate the electrical behaviour of future residential precincts

7 Modelling of Precinct Power Flows

The likely growth in uptake of distributed generation and storage technologies in residential precincts means that any detailed energy forecasting and analysis should include at least some measure of power flow modelling at the level of the low voltage network. Detailed modelling here will identify voltage rise issues, line capacity problems and capture the power requirements of the precinct at points of connection to the distribution network. These factors are fundamental to estimating the energy infrastructure costs borne by the precinct and to understanding how effectively distributed renewable systems will function in the context of the network (voltage rise, for instance, may lead to generation curtailment or inverter shut-down for solar system inverters).

Though there are a host of power flow simulation and modelling applications available (including PowerFactory, SINCAL and ASPEN), it is likely that energy modelling for the ETWW project will leverage the emerging GridLAB-D software environment (http://www.gridlabd.org/) developed by Pacific Northwest National Laboratories (PNNL) for the US Department of Energy. GridLAB-D provides a robust modelling system, features a permissive open source licence and has been used extensively within Australia as part of the multi-million dollar Smart Grid, Smart City project. Since the representative distribution networks captured in the National Feeder Taxonomy Study (see Chapter 3) are modelled in GridLAB-D, it will also accelerate modelling and testing of test precincts.

8 Load Forecasting

The time horizon for load forecasting is ultimately contingent upon its end-use. Shorter forecasts, which focus on the near-term future from minutes to days, are relevant to systems control, economic dispatch and identification of peak load events. Longer-term forecasts, which may look at load trends out to years in the future, are central to planning infrastructure investment decisions. The number and extent of demand forecasting methodologies and models developed is large, however, and there exists no novel technique that can serve all situations [12]. The time frame of the forecast, data availability, the accuracy and cost of the forecast, the application and purpose of the forecast are some of the important parameters in the selection process.

Traditional load forecast models use statistically based historical data such as seasonal temperature and day type. Examples of these models include Box–Jenkins autoregressive integrated moving average method [13][14], exponential smoothing by Fourier series transformation forecasting method [15], temperature forecast uncertainty on Bayesian load forecasting method . Newer techniques employ knowledge-based expert systems, artificial neural networks and support vector machines [12]. Despite relatively accurate predictions being produced by the Australian Energy Market Operator (AEMO) using such methods, the state-of-the-art in load forecasting do not integrate the complex aspects of social uptake of renewables, electric vehicle uptake, distribution network construction, demand management and intermittent generation in estimating precinct-level loading.

9 Modelling of Individual Buildings

If sufficient information about residence construction is known for a given precinct, reliance on de-facto load data (as-per Chapter 2) and trend forecasting (as-per Chapter 8) may be reduced by the application of detailed building energy modelling systems to generate realistic load profiles. For instance, considering building construction materials, building orientation and local climate, the commercial AccuRate simulation engine develops realistic home-specific space heating and cooling loads based on occupant thermal comfort levels and available natural ventilation air flows. Merging such outputs with detailed appliance usage modelling, as-per the work of Ren [16], can produce detailed residential energy use models that are specific to home designs for a given residential precinct.

Though powerful, the complexity and commercial nature of AccuRate limits the potential for direct integration into a unified Energy, Transport, Water and Waste tool. Should such a bottom-up modelling approach be pursued for this project, the most likely avenue would be to use AccuRate or equivalent tooling to construct a collection of representative homes that align with trends seen in Australian residential precincts. The outputs from these models, likely fused with the type of real-world data seen in Chapter 2, would define realistic base energy profiles that could easily be integrated into demand forecasting tools, so long as the general categories of housing stock are known in advance (such as approximate size, building materials, appliance types and occupancy).

Part IV Residential Technology Trends

Methods and data for understanding consumer response to new and emerging technologies

10 Solar PV Uptake Behaviour

A key component of longer-term energy modelling of residential precincts is forming an understanding of how on-site generation may be adopted or deployed by end-users over time. Since distributed solar, in particular, may seriously affect the power quality of small-scale networks or impact the operation of up-stream voltage regulation devices, estimating the uptake of solar systems over time is likely to be key to designing robust residential energy networks.

To this end – and as discussed in Chapter 4 – the Australian Energy Market Operator (AEMO) has released a report discussing past and future rooftop solar PV uptake within Australia. The report notes that uptake rates for 2010 and 2011 were 28 MW and 74 MW per month respectively and that future economic payback is expected to improve strongly, with innovative financing reducing up-front payment costs.

Still, while the AEMO report provides context for wider PV market conditions and suggests general trends in PV uptake, it is likely too coarse to provide sufficient insight for detailed residential precinct forecasting and modelling. CSIRO provides a more granular analysis by forecasting uptake of solar PV and water heaters for household types across New South Wales [17]. The forecasting approach draws on multi-criteria analysis, diffusion models and a host of variables that likely influence proclivity to purchase solar technologies, from household income and projected savings in energy costs to dwelling density and the percentage of Greens voters in the region. The resultant forecasts, validated against historical uptake data, provide detailed insight into how solar PV is likely to be adopted over time, how policy initiatives may affect uptake and in which specific post-codes that uptake is likely to be the strongest (see Figure 7 for an example).

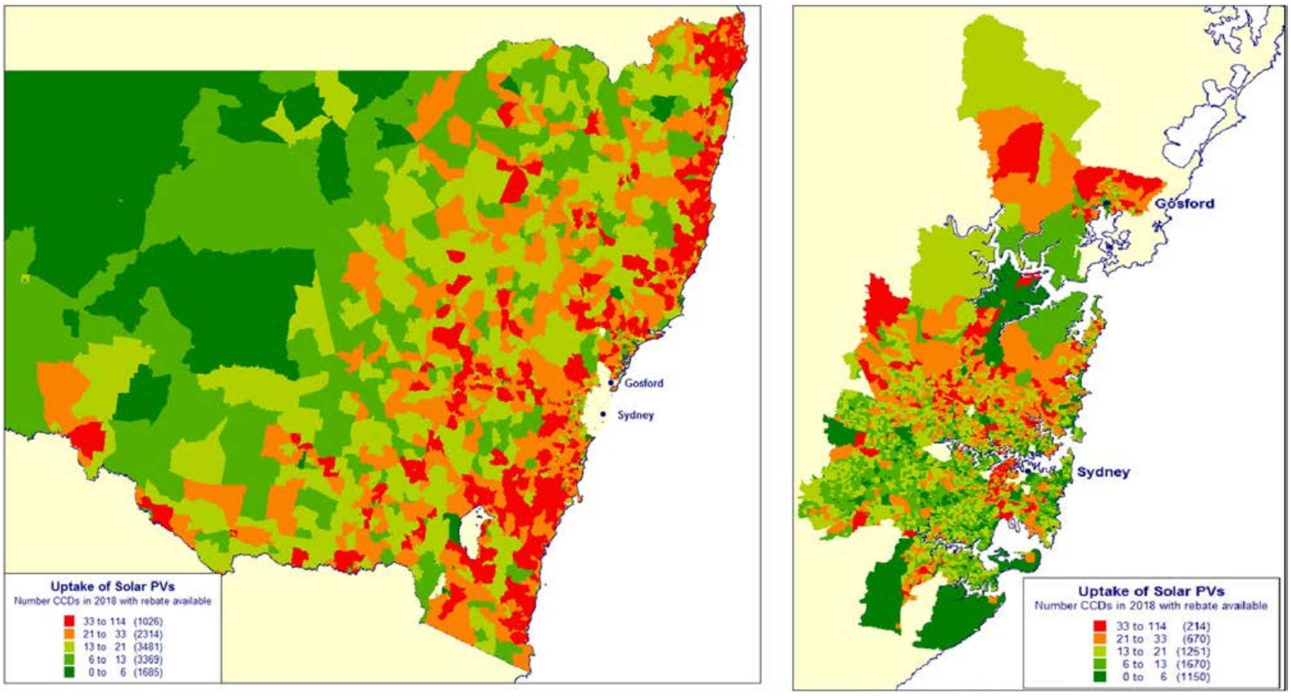

Figure 7. Forecast uptake of solar PV systems in NSW in 2018 (assumes small-scale technology certificates are maintained; source: [17])

11 Electric Vehicle Uptake Behaviour

Electric vehicle (EV) uptake and use represents a nexus point between transport and energy behaviour in future green precincts. EV driving patterns, recharge cycles and discharge algorithms will all have a fundamental impact on the shape and degree of residential load curves for many future Australian residences.

EV uptake has been forecast by CSIRO for Victoria out to 2030, drawing on multi-criteria analysis, choice modelling and technology diffusion theory to capture how annual costs, purchase costs, household income, driving distances, demographic characteristics and vehicle performance (amongst other factors) will likely affect purchase of battery, plug-in and hybrid electric vehicles. Reporting here underlines key drivers for electric vehicle uptake, the impact of rebate schemes and also underlines which regions (and thus, residential precincts) within Victoria are most likely to be impacted by charging schedules and attitudes [18]. Integration of these types of findings into future green precinct planning will be key for the accurate modelling of future residential energy use.

With uptake models in place, CSIRO has fused multiple models and data streams to obtain spatial and temporal projections of the electrical load impacts of plug-in electric vehicles in Victoria. The results, which are based on the existing EV uptake models, household travel trends, estimated residential load profiles and likely charging regimes (on-demand, off-peak and off-peak with discharge capacity), provide hourly charge/discharge estimates for fine-grained Census Collector Districts (equivalent to approximately 250 homes) across a full year and for all of Victoria. Figure 8 and Figure 9 provide an illustration of the findings seen in the corresponding report [19], highlighting both the types of charging profiles expected and the impact that charging regimes would have on regional peak load. Noting the impact that electric vehicles will have at both the household and regional levels, it is clear that any future residential energy precinct model must carefully consider the type of charge/discharge curves that will be seen across households.

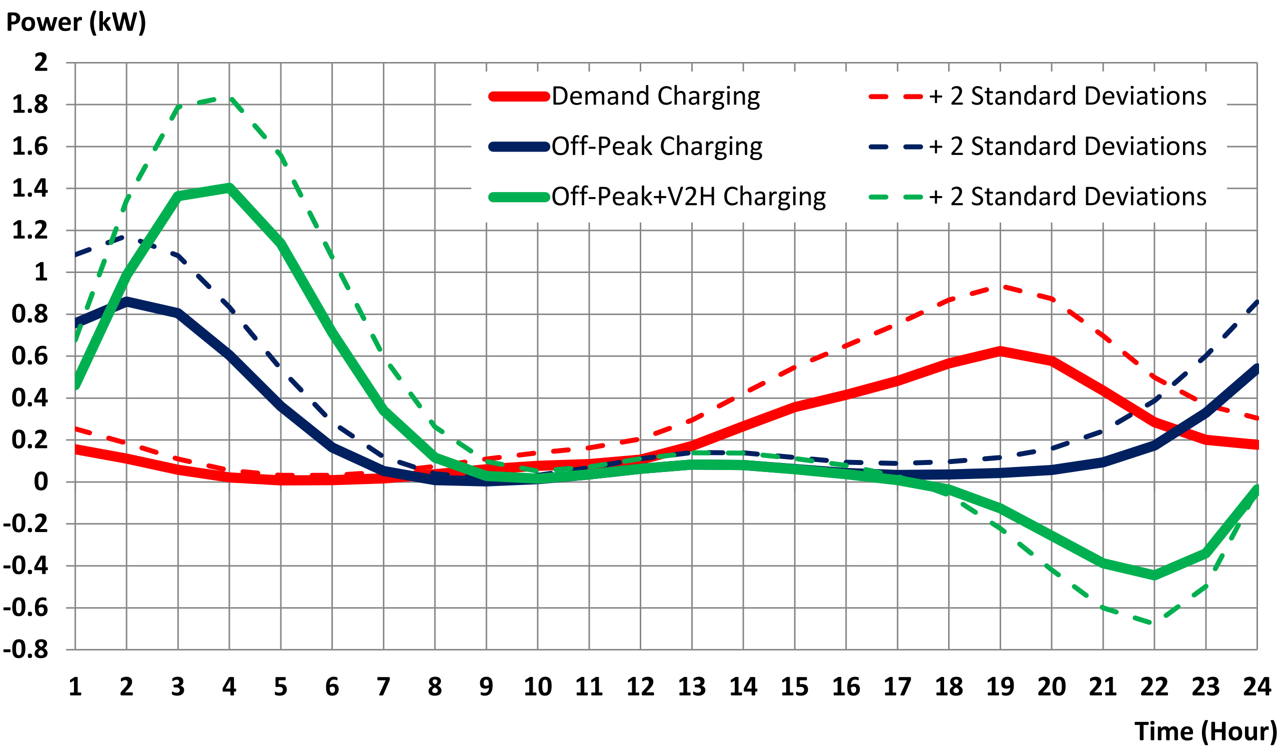

Figure 8. Projected daily charging load profiles per vehicle for Victoria (source: [19])

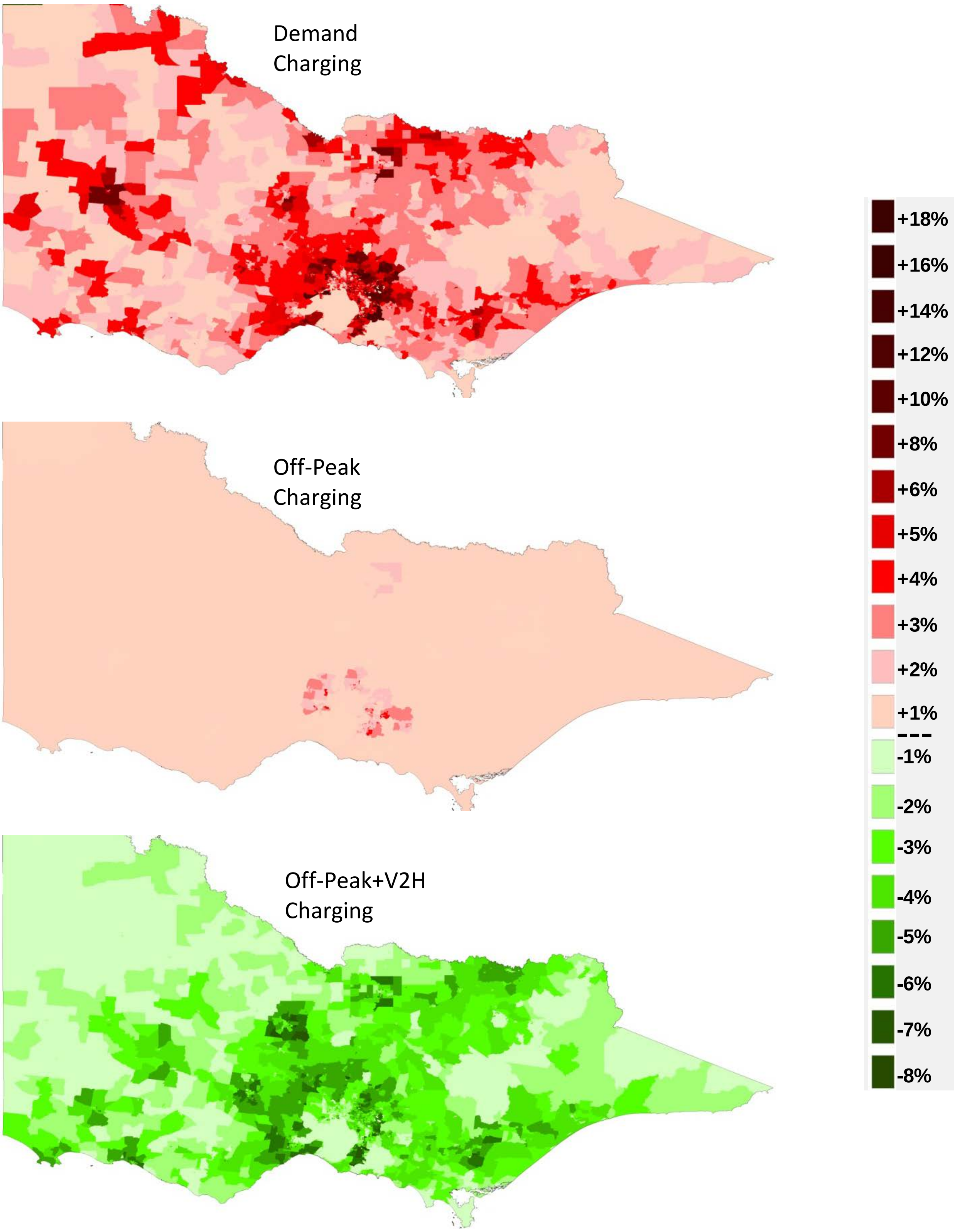

Figure 9. Spatially projected normalised peak load increase on hot summer day (base case uptake – Victoria; source: [19])

Part V A Possible Path Forward

Sketching how methods and data may be fused to provide a useful framework for green precinct energy forecasting, analysis and planning

12 Data and Model Fusion

An effective energy forecasting and analysis tool for residential precincts will ultimately require the:

- application of modelling packages to produce generic and representative residential load profiles based on typical Australian housing stock and climatic conditions;
- fusion of the many existing disparate data sources discussed across this report to capture realistic residential energy behaviour, technology uptake trends and the CO_2 cost of energy sources; and
- integration of existing open source tooling for high-performance power-flow simulation to estimate infrastructure requirements and stress points for residential precinct electricity networks.

Figure 10 provides a brief summary of the likely key inputs and outputs required for the energy component of the ETWW demand forecasting tool.

Note that though it is clear that transport behaviour will impact the use of electric vehicles and this must be effectively integrated into energy modelling, it is much less obvious how best to integrate water and waste streams. Exploring this nexus will be a key next step in developing a unified energy tool.

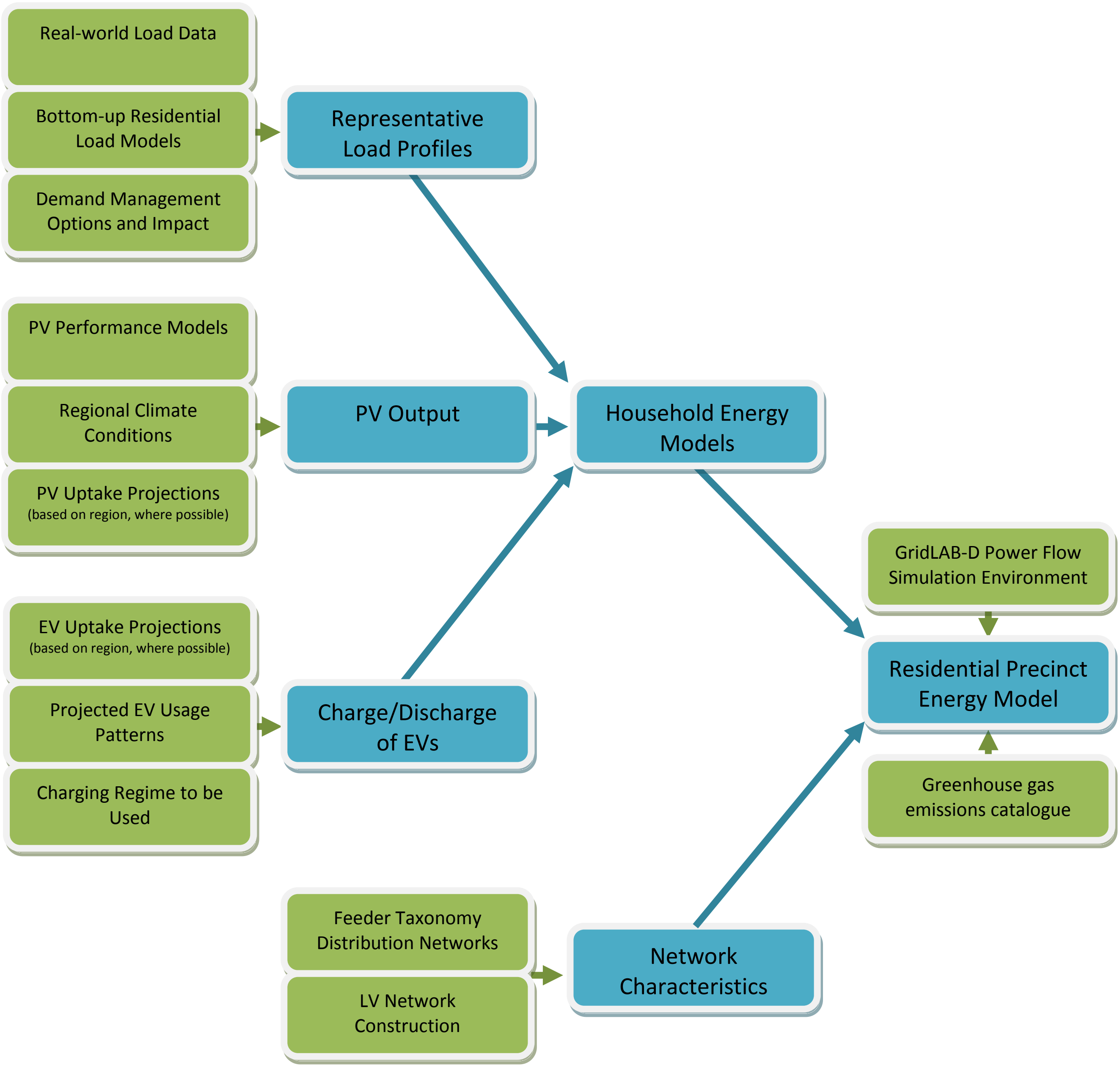

Figure 10. Dependency map for the posited residential precinct energy model

Green **shows inputs drawn from pre-existing data, tools or models.** ***Blue*** **shows outputs delivered through data, tool and model fusion.**

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CONTACT US

t 1300 363 400
+61 3 9545 2176
e enquiries@csiro.au
w www.csiro.au

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FOR FURTHER INFORMATION

Energy Technology
Adam Berry
t +61 2 4960 6123
e adam.berry@csiro.au

Appendix B

Transport Demand Forecasting.

A paper for researchers involved in the Low Carbon Living CRC's project on integrated ETWW demand forecasting and scenario planning for precincts (ETWW: energy, transport, waste and water).

Introduction

Transport forecasting involves the estimation of present and future year transport behavior patterns across a region where the community utilises transport networks to achieve daily activities. This process is assisted by the use of computer-based modeling packages which estimate travel demands for a population based on socio-demographic and land use data and assigned to the transport network supply. For the transport planner, motorised modes of travel such as cars, trucks, buses and trains on the urban networks are often given the most consideration but non-motorised travel is also of great importance.

Forecasting tools are used by government planning authorities (such as Departments of Transport), transport network owners, administrators and managers (in general) to development of policy and planning strategies. Future year transport forecasting methods may be integrated with energy, water and waste forecasting tools to assess overall carbon impacts of urban developments or redevelopments effectively and efficiently.

Transport Forecasting Model Types

A range of transport forecasting approaches have been adopted in practice, many with a long history of research and development. The choice of model type often depends on the geographical scale, analysis detail required and the resources and data available to develop and operate them. Aspects of some of the more common approaches are detailed in the following

Inter-City or Nation-wide Transport Forecasting Models (National Models)

Operating at a national or state-wide network level such as depicted in Figure 1, these models represent travel demands between urban locations (such as capital cities) and aggregate flows within them. They are often applied to freight demand estimation and inter-city passenger demand and account for road, rail, and sometimes air and sea-based transport routes. Policy and planning objectives associated with these models are highly strategic in nature and temporally they are aggregate with representation of long time periods such as annual patterns and longer forecast horizons.

Data requirements are also aggregate as models encompass large regions such as a state or a whole nation travel demand between urban areas and bulk commodity flows across large regions. Representations of travel demand are static, such as a single output result of total flow over a given time period.

Figure 1: Indicative map of a national land freight network (source: Infrastructure Australia, 2011)

Such models have been applied to transport networks across Australia (Infrastructure Australia, 2011) as well as internationally within countries such as the USA (Battelle, 2011), the UK, Sweden, Germany and Italy (Gunn, 2001).

Urban Area/ Metropolitan Strategic Transport Forecasting Models (Macro Models)

Metropolitan area transport forecast models operate over an entire or sub-region of an urban area such as a city. They represent multimodal travel demands within urban areas with a focus on road traffic and including public transport, non-motorised modes (walk, bicycles) and freight. Such models distinguish between classes of private-vehicle users and recognise travel aspects such as trip purpose.

Strategic in nature with respect to policy and planning, data requirements are low in detail over a large region with land use and socio-demographic data utilised to derive demand with strategic transport network and operations represented. Traffic Analysis Zones (TAZ) are defined to simplify the data requirements and modeling complexity and are necessarily related to the Australian Bureau of Statistics (ABS) zoning systems, with a tendency for modern models to equate TAZ to Statistical Areas Level 1 (SA1) zoning definitions (ABS, 2011). Over time these models represent flows over a typical day with, peak and inter-peak periods often represented with static travel demand estimations. In Australia, metropolitan macro models exist for the capital cities of Canberra (CSTM), Sydney (STM), Brisbane (BSTM-MM), Adelaide (MASTEM), Melbourne (MITM) and Perth (STEM). More detail on this type of model is to follow. The strategic network included in MASTEM is illustrated in Figure 2.

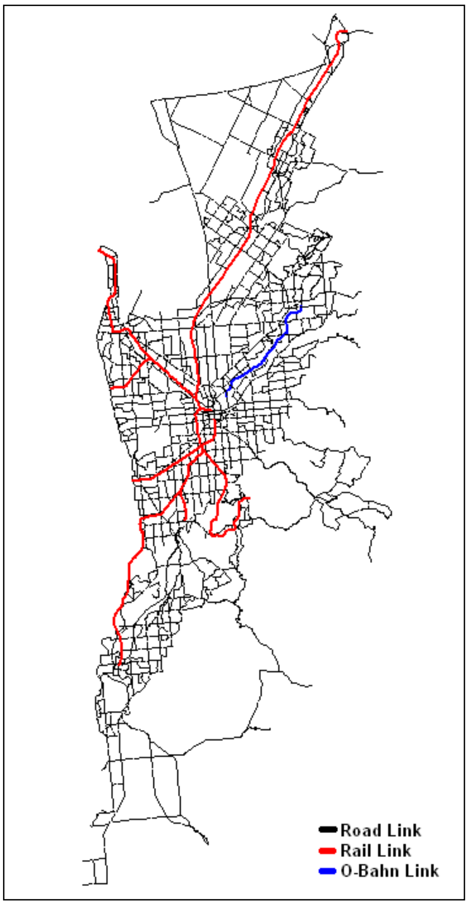

Figure 2: MASTEM strategic model network for Metropolitan Adelaide

Sub-metropolitan/local area Transport Forecasting Models (Micro Models)

Micro scale travel simulations are appropriate for smaller sub-regions of a metropolitan area such as an intersection (as depicted in Figure 3) or collection of intersections along a transport corridor. They can represent multimodal travel demands with detailed interactions between pedestrians and motorized modes but are often developed for vehicular travel only. Strategic modeling applications but can also represent the localised effects of changes to operational parameters eg. road geometry, traffic signal changes, bus timetable changes and the influence of ITS. Due to the detailed nature of the modelling, data requirements are high as much descriptive information is required on the demand and the network layout and operations. Software also has many parameters that need defining such as vehicle/flow characteristics and lane changing behavior.

Figure 3: Screen capture example of a dynamic microsimulation model result.

Data specification assumptions/simplifications still occur such as the presence of TAZ definitions however these can represent the end of road links or carparking locations rather than a cluster of land uses. Time periods are finely disaggregated with demand profiles such broken down into 10 minute (or similar periods) required for operation. Models represent the dynamic nature of transport interactions with continuous transport operations that are visually impressive. Calibration and validation of these models is a resource intensive task, especially when larger areas are to be modeled. Activity based microsimulation models estimate personal activity and travel over the period of an entire day and them represent this on a detailed multimodal network (eg. TRANSIMS)

Urban Area/ Metropolitan Strategic Transport Forecasting Models (Macro Models)

Strategic traffic modelling approaches are based on the concept of providing forecasted travel patterns on the road traffic network with long time ranges (often around 10 to 20 years). They are used in the testing of policies that relate to the traffic network, estimating the impacts of changes in the network operation. For this reason strategic models are extremely useful in assisting the decision-making processes of the traffic planner and policy maker in the testing of new and revised strategies.

Data requirements for such models include data sets for estimation of included parameters, ie. calibration and validation tasks during model development and operational data requirements when running the model on a day to day basis. Typically these models are developed as four step models with four key stages in demand estimation, with support from additional stages to supplement this process. The fundamentals of this were developed in the 1950's and 1960's and apply to transport forecasting for urban areas, such as the Metropolitan Adelaide Strategic Transport Evaluation Model (MASTEM) model developed for the Adelaide urban region (Holyoak et al, 2005)

The classic four stage planning model, as depicted in
Figure 4 with the addition of land use and trip timing components, has the ability to predict the levels of demand for the transport network through the sequential execution of the algorithm. Initially, demographic data relating to the population and economic activity is used to predict the transport demands created throughout the network in terms of trip numbers. The mode by which these trips are made is determined and then the trips are allocated to the transport network itself, completing the modelling process with the possibility for feedback loops and iterations to improve travel estimates.

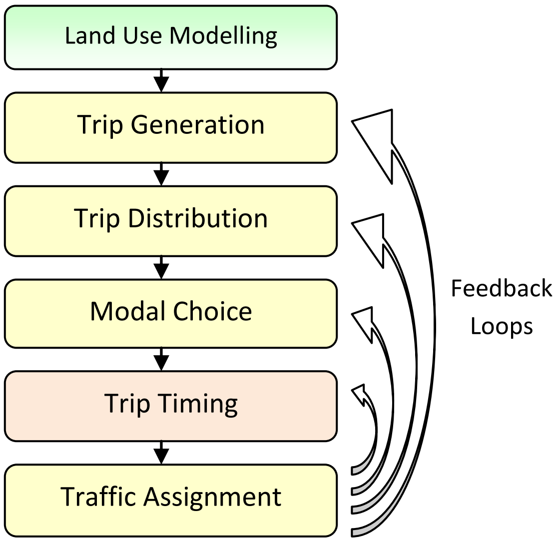

Figure 4: Conceptual four-stage modelling process with the traditional four stages in yellow.

The detail or disaggregation achieved in the modelling process is directly dependent upon the definition of the Traffic Analysis Zones, or TAZs, for the network. A large number of TAZs defined for the study area will mean smaller zones and therefore a higher disaggregation. The TAZ allows for the simplification of the modelling process as household and individual attributes are considered homogenous throughout the zone. The purpose of the TAZ definition is to simplify data requirements and computation required. Within MASTEM, the Adelaide metropolitan region is represented by 606 TAZ.

Land Use

Land use plans and population distributions are the main inputs into the travel demand models. However, the shape, form and technology of the transport system in a region influence its land use development. Thus there has been development of land use-transport interaction (LUTI) models which attempt to model the development of the land use system in parallel with the development of the transport system. A review of LUTI model concepts may be found in Roy et al (1996). The basic conceptual approach to LUTI Modelling is by considering the notion of accessibility in a region, being the ability of a population to access services and facilities and the ability of the service and facility providers to reach that population. 'Wegener's Wagon Wheel' (Wegener, 1996) provides a good pictorial representation of the chain of considerations that form the interactions between a land use system and a transport system.

Figure **5** shows this arrangement.

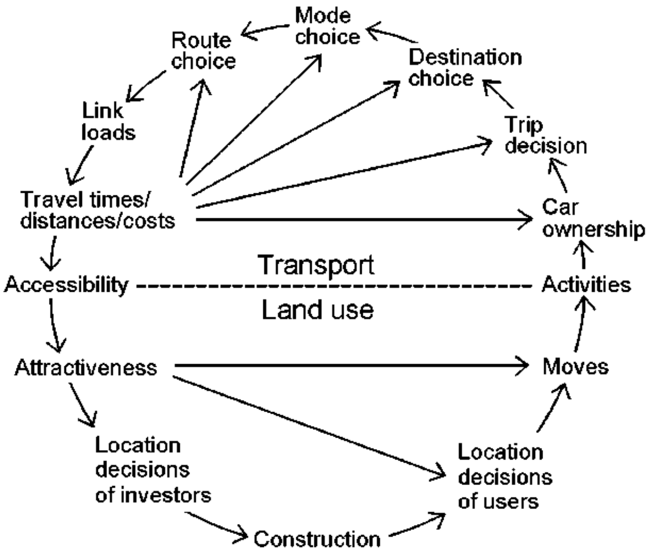

Figure 5: Wegener's wagon wheel representation of the land use-transport interaction, indicating the central role of accessibility in determining location decisions and its influence by traffic congestion

The key land use decision of individuals is where to locate their homes or enterprises. Their decisions translate into travel and communications activity, which results in the levels of congestion experienced on the transport system, which in turn affects the accessibility of different locations in the region.

There has been considerable research since the 1960s on LUTI Models, but until recently these models have not found much use in planning practice. As indicated by Tillema and Van Maarseveen (2005), LUTI models can help to improve forecasting of land-use transport developments, by extending traditional transport planning with a land-use component. Internalising these land use transport interactions in traditional transport planning makes planning consistent; land use interacts with transport and vice versa. Most contemporary transport planning tools only consider a oneway relationship between land use and transport and therefore lack this consistency. The dynamic interaction between land use and transport determines on a strategic level the autonomous development of transport and land use systems. However, while the interaction between land use and transport is widely accepted, there is little understanding of the required theory.

One exception of an operation LUTI model is the Cube Land model (Citilabs, 2013 website) which forecasts land use and land price by simulating the real estate market under different economic conditions. For a user-defined scenario, Cube Land forecasts the supply and the demand for different types of properties, and estimates the location of households and non-residential activities. It can estimate the impacts of:

- economic growth and decline
- changes in population, employment, and wealth
- urban management policies
- specific real estate projects
- transport infrastructure projects

- changes in consumer behaviour.

This model is based on the MUSSA model developed at the University of Chile by Francisco Martinez (Martinez, 1992).It uses a microeconomic approach to determine an economic equilibrium between land supply and demand. The process also considers perceptions of the real estate market, market restrictions, and regulations. This is done using a 'bid function' for each consumer. The bid function estimates property values in the market and sets rents and the location patterns for activities. The bid function considers consumer preferences, perceptions of parcel attributes, and budget restrictions. Model input variables represent the characteristics of consumers, properties and neighbourhoods. Such variables might include indices that represent accessibility to the transportation system, environmental quality, and location.

Generation

This initial step addresses the question of 'shall I travel?' posed by a given traveller. Trip generation is employed to establish the total number of out of home journeys produced from and attracted to each of the TAZ's within the study area, or otherwise stated, the magnitude of the total daily travel demands. Socio-economic and demographic data used in producing the number of trip productions may include household income, vehicle ownership and structure of the household unit. Trip attraction is dependent on the land uses within the zone and can be based on the number of persons employed or the square metre-age assigned to particular land uses. As a result of the trip generation stage, the model is supplied with the number of trip productions and attractions or trip ends which can be further disaggregated by trip purpose. Generated trip productions and attractions can be disaggregated by:

- Purposes such as work, shopping, education, recreation, employer's business, other…
- Time of day including entire day, peaks or inter/post peak times
- Traveller types, for example classified by household car ownership or income group

To estimate the numbers of trips, the trip generation process is commonly achieved with the application of category analysis or regression models. Category analysis is a simplistic tabular formula when correctly applied to zonal attributes generates total zonal productions and attractions. Although this is an uncomplicated and relatively quick technique, it lacks flexibility in dealing with the introduction of new household structures and determining the best categorisation can prove to be a resource intensive process.

Regression equations offer flexibility and the ability to provide greater accuracy in trip generation. The objective is to find a relationship between the number of trips produced or attracted by the zone, using characteristics of the zone as independent variables. It is also possible to gauge the accuracy of the regression equations with the use of associated statistical methods (eg. the determination of the R-squared statistic). An example of a generalized regression equation is:

$$TP_i = b_0 + b_1 X_1 + \ldots + b_n X_n$$

where TP_i are the trip productions from zone *i*, b_0 is a constant, b_1 to b_n are coefficients to be estimated and X_1 to X_n are zonal descriptive.

Distribution

Step two of the process addresses the traveller's question of 'where shall I travel to?' It is necessary to establish a picture of the pattern of trip making behaviour by distributing the trip productions amongst the available destination or attraction points in the study area. This leads to the construction of a trip matrix (
Figure **6**), a two-dimensional array with entries representing the total number of trips T_{ij} from each production zone *i* to all attraction zones *j*.

Attractions

		1	2	3	.... j
Productions	1	T_{11}	T_{12}	T_{13}	T_{1j}
	2	T_{21}	T_{22}	T_{23}	T_{2j}
	3	T_{31}	T_{32}	T_{33}	T_{3j}
	⋮				
	i	T_{i1}	T_{i2}	T_{i3}	T_{ij}

Figure 6: Conceptual trip matrix structure.

To assist in this estimation procedure, further inputs relating to transport network attributes including in-vehicle travel times, waiting and transfer times and fares or tolls incurred by the traveller during the journey. The gravity model is a common technique employed at this stage. A generalised form of the gravity model equation is presented as follows:

$$T_{ij} = A_i O_i B_j D_j f(c_{ij})$$

Here, the total trips *T* between two zones *i* and *j* is calculated based on A_i and B_j which are balancing factors applied to O_i the trips origins from zone *i* and D_j the trip destinations to zone *j*. The cost function $f(c_{ij})$ defines some impedance between zones *i* and *j*, which is often represented by an exponential function, and usually includes travel time and/or distance. The gravity model as defined here has been present in one form or another for over 100 years and was first utilised in the transport planning process when the analogy between the spatial interaction of trip making and the gravitational interaction of physical bodies distributed over space was developed.

Modal Choice

At this stage the traveler now has the question of 'how shall I travel?' The modal choice process represents the traveller's discrete choice decision on which mode to select for the journey. It is at this point that a travel mode is allocated for the journey between the origin and destination established in the previous stages. The trip matrix used as input in this stage is disaggregated into trip matrices for each of the modes. Attributes of the mode, traveller and the journey are involved in the mutually exclusive decision represented here. Modes represented in the MASTEM tool include walk, bicycle, public transport and car with the motorised modes, and especially the car journeys are of particular importance for strategic planning purposes.

The discrete choice process is achieved with the use of a calibrated estimation tool such as a discrete choice model. One example of a discrete choice model formulation widely applied in practice is the multinomial logit model, with a generalised formulation as follows:

$$P_{mi} = \frac{e^{\beta U_{mi}}}{\sum_m e^{\beta U_{mi}}}$$

In this model, P_{mi} represents the probability of an individual *i* selecting choice *m* from all mode choice alternatives. The the β parameter is related to the common standard deviation of the Gumbel (or extreme value type one) distribution and the utility of *m* is component U_{mi}, an additive linear function of measured attributes such as:

$$U_{ri} = \alpha_r + \sum_j \beta_{rj} X_{ji} + \sum_k \gamma_{rk} Y_{ki}$$

In the utility function that here for alternative *r*, α *is an alternative-specific constant, the* X_j's are the mode specific variables and the Y_k's are person-specific variables with β and γ calibrated coefficients. Discrete choice models have many applications both within and outside of the transport forecasting field. More information on these models can be gained from literature such as Hensher, Rose and Greene (2005).

Trip Timing

With the development of interest in time dependent travel demand analysis, for instance for phenomena such as 'peak spreading' as part of travel demand management, shorter time intervals (peak period vs off-peak, length of a peak demand period, etc) became of interest. A new (fifth) question can be added to the traveller decisions incumbent in the earlier 'four-step' process – 'when shall I travel?', which may be described as 'trip timing'. The traveller's decision based on this question could well depend on the differences in traffic congestion (delays, queues, seat availability, parking availability, etc) occurring at different times of day. Timing choice can be achieved by mean of applying a discrete choice model such as demonstrated by Holyoak, (2002).

Assignment

The final question in the sequence is 'which route shall I take?' In the final stage of the four stage modelling process, all desired road-based journeys are assigned to the transportation network, essentially completing the algorithm by matching network supply and travel demands. There are several techniques used to achieve this and all result in establishing a pattern of traveller demands within the prevailing conditions of the road network. Again, the private vehicles (including freight) are the focus of this process with some models including a separate assignment routine for and public transport trips representing persons travelling on multimodal services.

Willumsen (2000) reports that most traffic assignment methods employ three basic steps, repeating some if they require an iterative process, until they reach stable, convergent solutions. In outline, these steps are:

1. To identify a set of routes attractive to drivers; these routes are identified and stored in a structure called a tree, and therefore this task is often called the tree building stage.
2. To assign suitable proportions of the trip matrix to these routes or trees; this results in flows on the links in the network.
3. To check for convergence. Many techniques follow an iterative pattern of successive approximations to lead to an ideal solution, eg. Wardrop's equilibrium (Wardrop, 1952); convergence to this solution must be monitored in order to decide when to stop the iterative process.

Techniques used to find appropriate paths through the road network from origin to destination can be grouped into those that do and do not include stochastic effects and others that do or do not consider the influence of traffic congestion.

The all or nothing approach is the most simple traffic assignment technique ignoring both the congestion and stochastic effects and therefore assuming that the penalty for using a link, or the link cost, is fixed regardless of traffic volumes. It also assumes that all travellers consider the same attributes in the same way with the same relative importance given to them. The modelled effect of this is that all drivers wishing to travel between zones i and j will take the same route, that being the most attractive (e.g. least cost incurred).

Stochastic effects introduce variability in the travellers' perceptions of the network attributes and the objectives that they seek to attain (e.g. minimal cost incurred). The logit assignment, or *route-splitting technique*, is a method of improving the simple all or nothing technique, with the Dial (1971) approach probably the most widely used incarnation. It involves the use of a logit model to disperse proportions of the trips to different routes. The most common approach to the *probit*-based stochastic assignment is based on Monte Carlo simulation where link costs are randomised before a deterministic user equilibrium is sought, simulating an error between individuals' perception of costs.

Road links with a network possess a finite capacity. Associated with a limited capacity are restrictions on the amount of traffic to flow through a road link segment over a period of time. Between the traffic flow extremes of "free-flowing" (low traffic demand) and "crawling" (very high traffic demand) are degrees of congestion, best described in the modelling process with the use of a congestion function. The widely applied Akçelik (1991) time dependent travel time function is:

$$c = c_0 \left\{ 1 + \frac{r_f}{4} \left[(x-1) + \sqrt{\left(\frac{(x-1)^2 + 8J_D x}{Cc_0 r_f} \right)} \right] \right\}$$

Within the travel time function, c represents congested travel time on the road link, c_0 represents free-flow travel time, r_f is the ratio of the flow (analysis) period to free-flow travel time, x is the volume-capacity ratio, C is the link capacity and J_D is a delay parameter.

In traffic assignment procedure, trips from the appropriate origin-destination matrix are allocated to the traffic network, subject to its constraints. The traffic network is represented in the model by individual links with associated attributes, meeting at nodal points and often intersecting with other links. The continuity of flow equations provide a generic solution to the traffic assignment problem and ensure that demands represented by the origin-destination matrix are satisfied. Wardrop (1952) postulated two principles for reaching equilibrium between traffic demands and the supply of the network itself. The first and most widely applied of Wardrop's principles can be stated as '*Under equilibrium conditions traffic arranges itself in a congested network such that all used routes between an OD pair have equal and minimum costs while all unused routes have greater or equal costs'.*

That is, when equilibrium is reached, journey times on all routes between an origin and a destination are equal and shall be less than times experienced on any other route. This is a result of individual drivers seeking to optimise their own travel time, independent of the behaviour of all other drivers. Mathematically, this can be represented as the following constrained optimisation problem:

$$Z = \min \left\{ \sum_e \int_0^{q(e)} c_e(x)dx \right\}$$

subject to the continuity of flow constraints

$$T_{ij} = \sum_r X_{rij} \qquad \text{for all } i, j$$

$$q(e) = \sum_{ijr} \delta_{eijr} X_{rij} \qquad \text{for all } i, j$$

and the non-negativity constraints

$$q(e) \geq 0 \qquad \text{for all } e$$

$$X_{rij} \geq 0 \qquad \text{for all } r, i, j$$

where

$\delta_{eijr} = 1$ if e is on path *r* from *i* to *j*
$= 0$ otherwise

In this optimisation model, the objective function is *Z*, $c_e(q)$ represents the link travel cost (travel time), and *q(e)* represents the traffic flow rate on the link. This model is known as the user-equilibrium traffic assignment problem for fixed travel demand (because it assumes that all T_{ij} are held constant). Replacing the objective function *Z* by

$$Z' = \min\left\{\sum_e \int_0^{q(e)} c_e(x)dx + \frac{1}{\alpha}\sum_{ij} T_{ij}(\ln T_{ij} - 1)\right\}$$

with the same constraints yields an elastic demand user equilibrium in which the zone to zone trip numbers T_{ij} (i.e. the O-D matrix) can also vary in response to congestion on the transport network. In the formulation of this elastic demand user equilibrium problem α is the decay constant in the specific form of the trip distribution gravity model with a negative exponential deterrence function, i.e.

$$T_{ij} = a_i O_i b_j D_j \exp(-\alpha c_{ij})$$

Feedback Processes

Iterative feedback loops involve traffic condition information resulting from the route assignment returned to previous stages as the model is re-estimated in successive runs. Calculations of the generation, distribution trip timing and modal split of trips are based on better estimates of travel costs and times and this process is repeated until an acceptable balance is achieved between the travel costs and times used in estimation and those output by the route assignment model.

Practical Aspects of Modelling

Today, there exists a range of available software packages to assist in the development of these models, each with it's own particular strengths. Some of these software packages are Cube (Citilabs), TransCAD (Caliper) and SATURN (Atkins, 2013). Irrespective of which package is adopted, all strategic transport forecast models require data to operate.
Figure **7** illustrates the MASTEM modelling processes with the types of data required for operation and outputs that are possible.

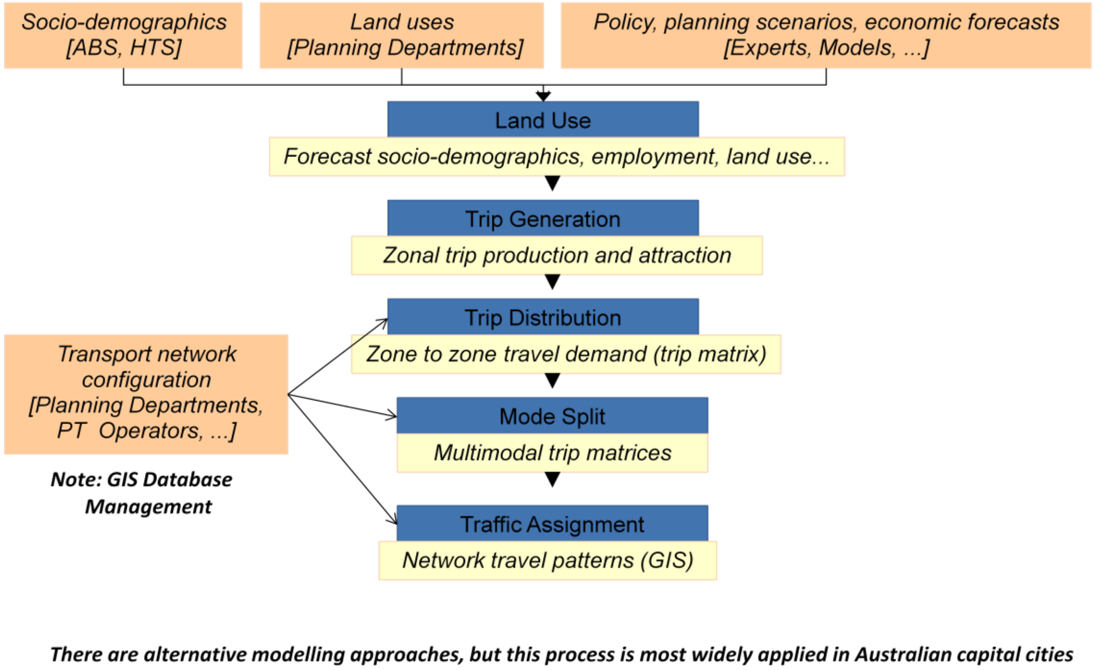

Figure 7: Strategic modelling processes and data elements.

Data requirements can vary somewhat from model to model and are heavily dependent on the model configuration, availability and local area suitability. Those provided here are with reference to Adelaide metropolitan transport forecasting.

Modelling Inputs

Broadly in terms of information input, the data describe the nature of the transport system and the people and activity opportunities around it.

Zoning Definition

Traffic Analysis Zone (TAZ) representation through centroids connected to the strategic network. Connectors are a representation of the local street network. TAZ are defined by planning authorities and often will take into consideration population densities, location of transport provisions and concentrations of land-use development with connections to ABS census zoning definitions important for compatibility of data.

Road Networks

Geo-spatial representation of the strategic road network, often assembled in GIS with link and intersection data attached. Critical links attributes include speed and/or travel time, capacity, and length. Speed-flow relationships for each link type also define how the link performs under congested conditions. The strategic road network is defined by planning authorities will take into account major and strategic transport routes, public transport facilities and network connectivity.

Public Transport Network

The Public transport networks are primarily based on road network with additional links for non-road modes such as rail, bus-only etc. Service routes require definition in terms of the path taken, headway/frequency, stops, direction and mode. Operational service information such as ticketing and transfer costs, wait times and modes (vehicle types, capacities). Connectivity is completed with the inclusion of walking links connecting zone centroids to the PT network. A range of data sources may be used to define these databases, the majority of which will be from the service providers and planning authorities with service routes, timetables and costs often freely available to the public.

Intersections

Intersections of strategic importance are described in more detail, particularly if they are signallised. Intersection layout, and type are required and for signallised - cycle and green times, phases, capacity, lane geometry (turn lanes etc), banned turns whereas unsignallised intersections are simply represented with a delay turn penalty. Planning and network operation authorities are the suppliers of this information.

Socio-Demographics

Population and household attributes for each TAZ are included in the model estimation routines, including the total population and households, numbers of residents, workers, dependants and cars or income per household. This data is estimated by planning authorities and based on census information with consideration given to forecast housing and related developments, planning policies as well as historical trends.

Land Use

For each zone descriptive information relating to the total jobs in industries including services, manufacturing, technical, trade, retail, education, entertainment and other. Also included are total enrolments for primary, secondary and tertiary education institutions. This data is estimated by planning authorities and based on existing land use with consideration given to forecast land use developments, planning policies as well as historical trends.

Freight

Total vehicle or commodity flows between TAZ's are included and a range of sources are utilised for the estimation of freight demand. In some models, limited networks for freight vehicles apply. By and large, freight demand estimation models are less well developed than the passenger models.

Modelling Output Types

Forecast data outputs describe the nature for the travel demand and resulting travel behavior for the metropolitan region as a whole.

Travel Demand

For each TAZ, the total number of trip productions and attractions which may be disaggregated by trip purpose, household type, car ownership, time of day or other classification. Following on from this the model routines can also provide trip matrices that summarise total trips between origin and destination pairs such as depicted in
Figure 8, again disaggregated by the same classifications as trip productions and attractions.

1 CAR_HBW | 2 CAR_HBE | 3 CAR_HBS | 4 CAR_HBR | 5 CAR_HBPB | 6 CAR_HBO | 7 CAR_NHBEB | 8 CAR_NHBPB

	Sum	12	13	14	15	16	17	18	19	20
	2302544.83	6721.53	8788.56	389.21	11629.75	10756.24	10150.36	5539.83	5570.61	11959.89
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	3077.23	0.00	52.57	3.09	71.34	58.86	41.13	19.89	17.55	61.79
3	1692.82	26.36	28.24	1.23	37.36	30.94	28.29	11.60	10.73	38.76
4	4055.65	71.01	74.40	3.45	95.55	86.28	82.12	36.02	30.33	113.57
5	17273.43	194.51	176.72	10.35	222.03	213.10	422.30	216.85	167.00	545.34
6	1425.76	27.94	31.73	1.20	41.87	45.52	40.47	19.27	14.03	44.90
7	3961.30	78.05	93.34	3.27	121.14	124.66	108.55	50.18	35.89	113.24
8	8014.58	131.12	0.00	5.69	264.49	227.25	153.71	68.40	54.96	171.85
9	4961.59	41.09	96.26	2.44	119.82	121.91	117.51	62.54	44.38	135.95
10	1375.72	17.15	29.88	0.76	38.36	39.03	34.83	19.77	15.33	41.62
11	1152.56	13.69	27.53	0.62	34.44	37.96	0.00	0.00	10.69	32.91
12	2559.57	51.09	0.00	3.66	92.81	47.80	24.22	11.33	10.83	29.96
13	2714.25	0.00	77.51	3.16	0.00	89.23	36.59	17.78	15.46	42.58
14	139.39	2.68	2.82	0.34	3.64	1.85	1.13	0.55	0.47	1.31
15	4735.90	102.36	0.00	5.11	219.85	0.00	56.54	27.48	23.87	66.33
16	3953.09	52.38	103.32	2.25	0.00	177.50	0.00	39.70	21.80	56.80
17	3591.67	22.90	48.03	1.37	50.77	0.00	129.62	0.00	27.36	95.91
18	3403.60	19.09	35.83	1.00	44.58	69.53	0.00	83.64	0.00	128.39
19	3943.74	21.57	37.34	0.92	48.04	43.94	64.12	0.00	121.19	173.61
20	3768.88	23.61	39.05	1.41	47.37	45.74	87.47	52.87	55.88	109.98
21	2988.52	24.14	26.96	1.45	35.21	34.80	57.49	48.17	47.90	0.00
22	383.38	1.76	1.64	0.12	2.35	2.39	3.11	2.31	3.11	4.92

Figure 8: Example of a trip matrix representing travel demands.

Network Travel Patterns

Patterns of travel are represented in macro models as total vehicular or passenger flows on network links and at intersections, supplementary representations including select link analysis. This is assisted with the use of a GIS environment and analysis assisted with the use of GIS tools and additional information layers as depicted in the following figure.

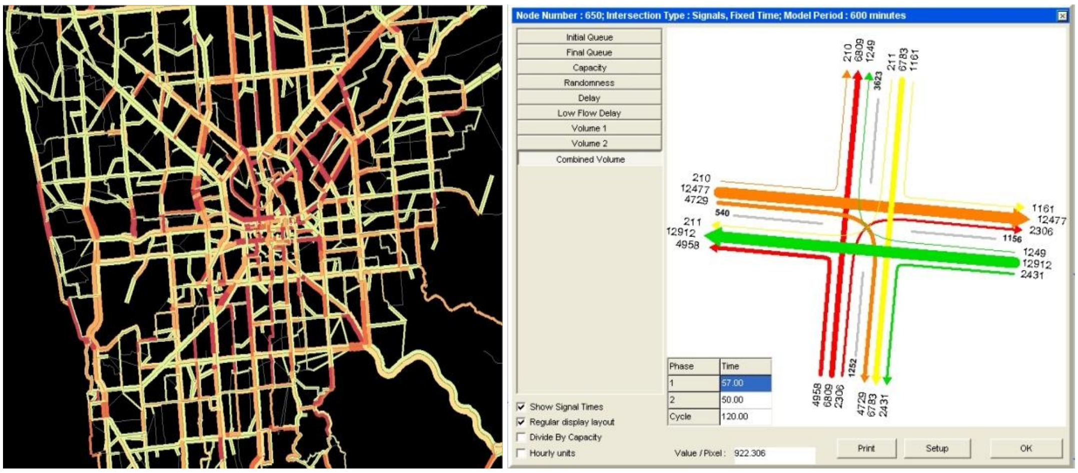

Figure 9: Examples of network traffic volumes and congestion (left) and intersection flow (right) outputs.

From the model outputs it is also possible to estimate network environmental impacts such as emission production, noise production and energy consumption estimates based on link (eg. speed, level of congestion) and vehicular flow characteristics. An example of emission output representation is provided in Figure 10.

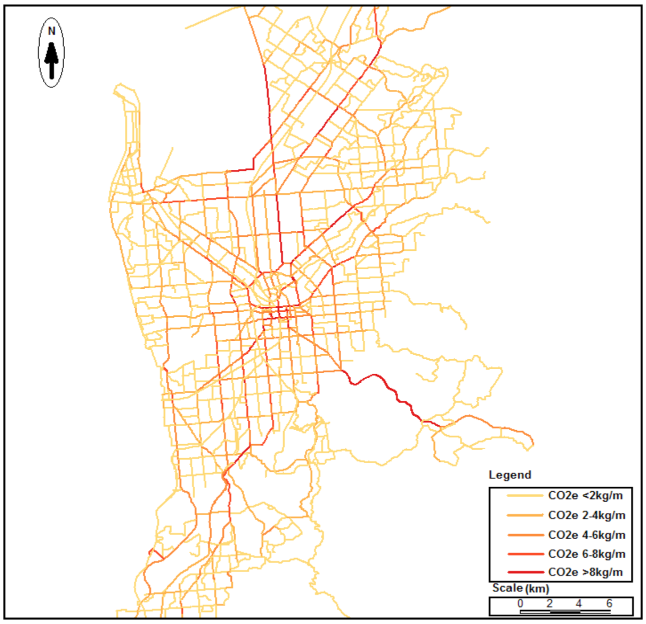

Figure 10: Example of network emissions output.

Emission estimates can also be reported at the zonal level as emissions resulting from travel generated by the zone, a useful approach when considering precinct-based analysis.

Activity Based Modelling

Approaches described so far have focused on estimating travel demand forecasts purely in terms of trip estimation. Currently, this is by far the most popular method applied throughout Australia and Internationally. An alternative approach which has received growing attention in past decades is the activity-based forecasting approach.

Activity based modelling focuses on the estimation of individuals' activity locations in time and space. Travel is therefore a derived demand that gives recognition to complex interactions, including those at the household and related to travel. The organization (scheduling) of trips is considered as part of pursuing multiple stops in a single journey from home, necessary to complete the desired activities.

The activity-based approach requires time-use survey data for analysis and estimation and can offer models that are more complex in nature than traditional four-stage approaches. In turn, greater effort and resources may be required to accurately calibrate such models that operate at a finer data resolution. Resulting tour-based travel structures on activity-based platforms (scheduling) offer forecasts at a microsimulation level.

One foundation approach to activity based models involves a heavy reliance on discrete choice model applications. These techniques have been discussed in previous sections of this paper.

GIS Data Management

Transport planning data such as socio-demographic and land use inputs and network-based outputs have a common spatial element such as network link location and zone location. A GIS is therefore well suited for the management and interpretation of such databases with visual display possibilities when mapped. GIS can add to the analysis of transport forecasting outputs with additional mapping and data layers including energy use, waste production, water use as well as other resources such as census and planning data.

Behaviour Change

In essence, transport forecasting models strive to replicate the decision-making process associated with people's need to travel. In many ways they therefore have the ability to forecast different aspect of behaviour change in response to policy levers (eg. Holyoak, 2002), provided that the model contains calibrated parameters that reflect the policy aims. Subsequently these models are used in to forecast the potential impact of policy strategies and this gives them potential to forecast travel decisions such as whether to travel or not, destination choice, time of travel and mode of travel and their impact of low-carbon technologies, policies and strategies.

It also also possible to apply manipulation functions to post-model run outputs that reflect behavioural responses to policy (Taylor, 1999). One example of this would be the application of elasticity functions to travel demand matrices. Potential to represent the influence of many low-carbon living policies on travel behaviour provided there is sufficient accurate information available to allow for these calculations.

The Precinct

Metropolitan-wide models described here estimate the travel made to and from destinations within the metropolitan region as a whole. In terms of transport forecasting, a precinct is a sub-region of the network with:

(1) some travel occurring completely internally,
(2) some will travel to/from destination/origin outside,
(3) some travel will pass completely through with both the origin and destination completely outside,

The existing modelling routines can account for (1) with existing however some other estimation technique will be required for (2) and (3). Travel that has either an origin or destination or both will require further estimation calculations, assisted by the data for the metropolitan region.

Transport Interactions with Energy, Waste and Water

From a transport perspective, possible areas of interaction with water, waste and energy demand forecasting that may occur in an integrated ETWW modeling approach may occur as:

- Transport demand and the use of 'traditional' liquefied fuel energy sources,
- Electric vehicle transport demand and the use of electricity,
- Telecommuting and increased household-based activity, impacting on energy, water and waste,
- The physical transport of household, industrial and other waste to processing locations,

The list of possible interactions is not exhaustive and other significant and non-significant interactions are possible.

Conclusions

This research focuses on developing a tool that forecasts low carbon impacts for a precinct, therefore the definition of that precinct is critical. This definition is not only the geographical extent but also the components contained within as well as time-span and forecasting horizons. It is necessary to forecast the low-carbon potential asiciated with activity contained completely within the precinct and also necessary to provide estimates that include selected activity and impact beyond the precinct boundary.

Integration between energy, transport, waste and water requires the identification and modelling ability to forecast interactions between these domains. This will be assisted through a common modelling platform with base operational data elements and data management and integration with GIS. It is recommended that the adequate identification and description of the household unit will play a key role in this process.

As this project aims to allow for scenario planning for ETWW under low carbon futures, transport as well as all other fields needs carbon estimation routines. For the transport sector this largely relates to to vehicular emissions for which there are modelling approaches available and widely applied in practice. The focus of this research will also identify and present planning scenarios and alternatives for low carbon strategies.

Key Literature and Resources

Over the past years, the transport modeling/forecasting area has been well researched and documented. Much literature on forecasting including revised approaches, applications, additions and critiques. Examples of some of key literature that expands on topics raised herein including modelling, applications and sustainability include:

- Ortuzar and Willumsen (2010),
- Hensher and Button (eds, 1994),
- Bhat and Koppelman (2003),
- Holyoak *et al* (2005),
- Ryley and Chapman (eds, 2012).

In addition, the following websites describe particular software suites as well as provide links to further information sources:

- Cube software website (Citilabs, 2013),
- EMME software (Inro, 2013)
- TransCAD software website (Caliper, 2013),
- The US Travel Model Improvement Program website (TMIP, 2013).

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Appendix C

Modelling and representing precinct-level travel demand – a discussion note

M A P Taylor, Emeritus Professor, School of Natural and Built Environments, University of South Australia, and Program Leader 'Low Carbon Precincts', CRC for Low Carbon Living

Introduction

The Low Carbon Living CRC includes a major research program on low carbon precincts, and is funding an initial major research project on the simultaneous and integrated estimation of demands for energy, transport, waste and water (ETWW).

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 will be required.

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

[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 a CCD (or its equivalent). Historically, due to computational and computer memory and storage constraints, TAZ would have been composed of 2-4 contiguous CCDs, but the advances in computer technology now mean that a TAZ can often and reasonably be taken as an individual 'CCD'.

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 1, which is a schematic representation of the precinct and the (urban) region in which it is situated.

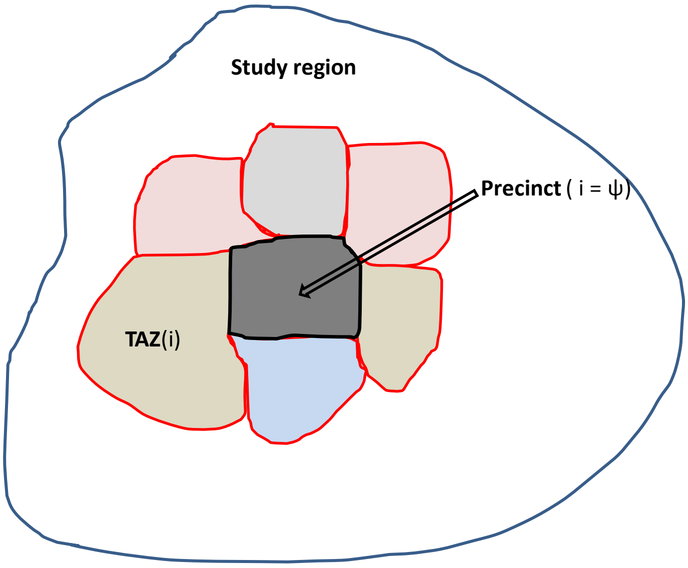

Figure 1: The precinct as TAZ ψ in the study region

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

$$\mathbf{T}^{kmt} = \begin{bmatrix} T_{11}^{kmt} & \dots & \dots & T_{1n}^{kmt} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & T_{ij}^{kmt} & \dots \\ T_{n1}^{kmt} & \dots & \dots & T_{nn}^{kmt} \end{bmatrix} \tag{1}$$

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

$$\mathbf{T} = \begin{bmatrix} T_{11} & \dots & \dots & T_{1n} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & T_{ij} & \dots \\ T_{n1} & \dots & \dots & T_{nn} \end{bmatrix} \tag{2}$$

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.

$$\mathbf{C} = \begin{bmatrix} c_{11} & \dots & \dots & c_{1n} \\ \dots & \dots & \dots & \dots \\ \dots & \dots & c_{ij} & \dots \\ c_{n1} & \dots & \dots & c_{nn} \end{bmatrix} \tag{3}$$

which also forms part of the output of the regional travel demand model (c_{ij} 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 $\mathbf{r}_{\boldsymbol{\psi}}$

$$\mathbf{r}_{\boldsymbol{\psi}} = \begin{bmatrix} T_{\psi 1} & \dots & T_{\psi n} \end{bmatrix} \tag{4}$$

and

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

$$\mathbf{s}_{\boldsymbol{\psi}} = \begin{bmatrix} T_{1\psi} \\ \dots \\ T_{n\psi} \end{bmatrix} \tag{5}$$

These two vectors are the row and the column for ψ in the O-D matrix of equation (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 ($\mathbf{u}_\psi$) and (2) extra-precinct travel demand with destinations in the precinct ($\mathbf{v}_\psi$). These two vectors are:

$$\mathbf{u}_\psi = [u_1 \quad \ldots \quad u_n] \tag{6}$$

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

$$\mathbf{v}_\psi = [v_1 \quad \ldots \quad v_n] \tag{7}$$

in which $v_i = T_{i\psi}$ for $i \neq \psi$ and $v_i = 0$ for $i = \psi$. The intra-precinct travel demand $T_{\psi\psi}$ 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 $N(\psi)$, which is

$$N(\psi) = \sum_{j=1}^{n} u_j + \sum_{i=1}^{n} v_i + T_{\psi\psi} \tag{8}$$

noting that $N(\psi)$ 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 $Z(\psi)$ of precinct-generated travel is

$$Z(\psi) = \sum_{j=1}^{n} c_{\psi j} u_j + \sum_{i=1}^{n} c_{i\psi} v_i + c_{\psi\psi} T_{\psi\psi} \tag{9}$$

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. Our 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.

Estimation of energy, pollutant and carbon for precinct travel

Equation (9) 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 2), which can be derived from the available trip numbers and travel costs (see equations (3) – (8)). 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 frequency distributions.

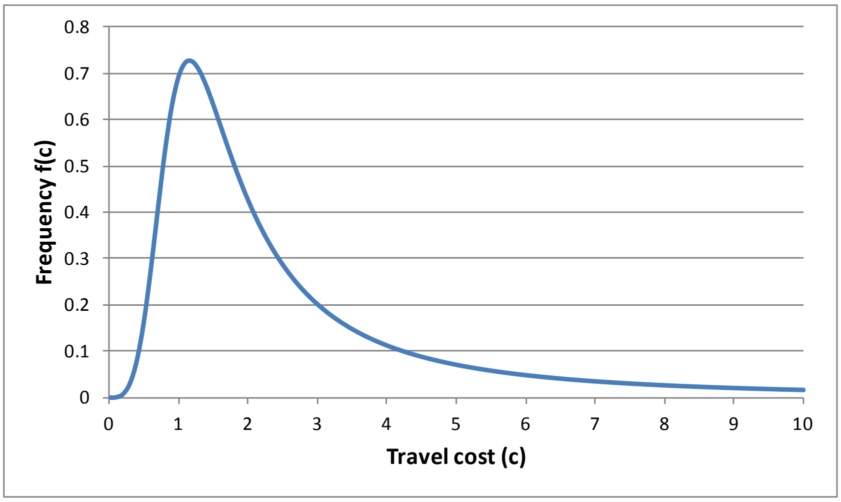

Figure 2: Example trip length frequency distribution for a precinct

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. Appendix A describes a generic model for energy and emissions estimation. This model 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.

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).

We have 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.

Intra-precinct travel demand analysis

Given the energy/carbon focus of Low Carbon Precincts research, further consideration should also be given to intra-precinct travel, as low carbon options may seek to maximise this, e.g. through mixed land use development. This will also give 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 will be defined in some detail and that a comprehensive data description of the precinct will 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 for physical movement, so that the precinct contains its own transport network(s). 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 3 provides a schematic representation of a precinct suitable for the purposes of travel demand estimation.

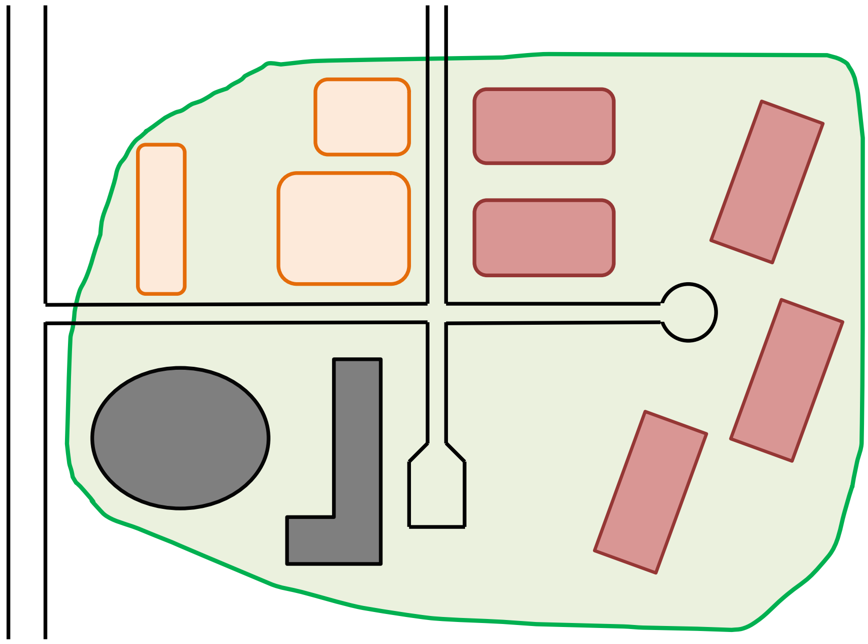

Figure 3: Representation of a precinct as a connected set of buildings and facilities (which can be represented as 'micro-zones')

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,

$$\boldsymbol{\tau}^{\Psi} = \left[\tau_{hd}^{\psi}\right] \qquad (10)$$

with

$$T_{\psi\psi} = \sum_{hd} \tau_{hd} \tag{11}$$

Precinct-level travel demand analysis will require knowledge of both ex-precinct travel $\mathbf{u}^{\psi}$ and $\mathbf{v}^{\psi}$, together with $\boldsymbol{\tau}^{\psi}$. 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 would be the household for home-based travel and the enterprise (office, shop, etc) for non-home-based travel. This suggests the use of 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 household. 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) *Commuter*) 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.

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Appendix A: A generic transport network model for energy, fuel and emissions analysis

A generic model of energy and emissions performance of transport networks can be defined which uses the outputs of a regional travel demand model and which is responsive to different transport and vehicle technologies, variations in travel demand and levels of congestion on the network. This model may be applied at different levels of aggregation, including:

- a 'simple' model of travel between origins and destinations, requiring information on trip movements between O-D pairs and the distances between them and average energy consumption and emission generation rates per unit distance for different vehicle and energy types
- a congestion-responsive model of travel between O-D pairs, using the average speed of travel (and hence consumption and emission rates dependent on macro-level congestion)
- a link-based model which allows maximum flexibility and detail for the analysis of where and when fuel consumption and emission generation occurs, and which allows fully for interactions between vehicle flows and resulting traffic congestion across the network.

Further, the generic model may be used for all modes of urban transport.

The generic model is defined by the following system of equations. The equations are described at the network link level in the first instance, but simplified versions of the model may also be applied to flows between O-D pairs, for which the link representation is replaced either by the spatial separation distance between origin and destination or the network path(s) between them. At the link level, the generic model can calculate the total amounts of fuels and energy consumed and emissions produced by all traffic on each link in a network. The system is such that it enables the energy and emissions results to be sensitive to parameters such as increasing load factors, changing proportions of vehicle and fuel types in the vehicle fleet, different road types and different congestion levels. This is important because many transport-land use policy options and transport system management schemes may vary these and other parameters in different ways on a link-by-link basis.

The basic input to the fuel and emissions modelling system is the result of a multi-class user equilibrium traffic assignment for the network. This model will provide data not just on total flows on the network links and paths but also on the flows of individual vehicle types. The average traffic volume (veh/unit time) on link (or path) *a* in time period *t* is $q_t(a)$, given by

$$q_t(a) = \frac{1}{U_t} \sum_r Q_{rt}(a)$$

where U_t is the duration of time period *t* and $Q_{rt}(a)$ is the total number of type *r* vehicles assigned to link *a* in *t*. [The total time period (e.g. one day) for the analysis is given by $U = \sum_t U_t$.]

The average link speed v_{at} in time period *t*, which reflects the level of congestion on the link in the period, is also an output from the assignment model, is

$$v_{at} = v(q_t(a), L_a)$$

where L_a is the link class for *a*. Let:

$E_X(a,t)$ = emission rate per unit distance for pollutant type *X* emission on link *a* in time period *t* (g/km)

$G_X^t(a)$ = total mass of pollutant type *X* emitted on link *a* in time period *t* (g)

$G_X(a)$ = total mass of pollutant type *X* emitted on link *a* per day (g)

$f_s(a,t)$ = energy/fuel consumption rate per unit distance for energy/fuel type *s* on link *a* in time period *t* (e.g. L/100km)

$F_s^t(a)$ = total volume of energy/fuel type *s* consumed on link *a* in time period *t* (e.g. L)

$F_s(a)$ = total volume of energy/fuel type *s* consumed on link *a* per day (e.g. L)

p_{rs} = proportion of class *r* vehicles in fleet using energy/fuel type *s*

g_{rsX} = base type pollutant *X* emission rate per unit distance for vehicle class *r* and energy/fuel type *j* (g/km)

h_{rs} = base energy/fuel consumption rate per unit distance for a class *r* vehicle using energy/fuel type *s* (e.g. L/100km)

$v_{at}(q_t(a), L_a)$ = average travel speed on link *a* in time period *t*

$\mu_{rsX}(v_a)$ = speed correction function for type *X* pollutant emission from vehicle class *r* and energy/fuel type *s* on link *a* with average speed v_a

$\rho_{rs}(v_a)$ = speed correction function for type *s* energy/fuel consumed by vehicle class *r* on link *a* with average speed v_a

λ_{rsX} = load correction factor for type *X* pollutant from vehicle class *r* and fuel type *s*

ω_{rs} = load correction factor for energy/fuel type *s* consumed by a class *r* vehicle

d_a = length of link *a* (km)

The energy/fuel consumption rate for fuel type *s* per unit length on link *a* in time period *t* is then given by

$$f_s(a,t) = \sum_r p_{rs} Q_{rt}(a) h_{rs} \rho_{rs}(v_{at}(q_t(a), L_a))\omega_{rs} \qquad \text{(A1)}$$

so that total quantity of energy/fuel type *s* consumed on link *a* in time period *t* is

$$F_s^t(a) = d_a f_s(a,t) \qquad \text{(A2)}$$

and the total quantity of energy/fuel of type *s* consumed on the link per day is

$$F_s(a) = \sum_t F_s^t(a) \qquad \text{(A3)}$$

For pollutant emissions, the emission rate per unit distance for pollutant *X* on link *a* in time period *t* is given by

$$E_X(a,t) = \sum_r Q_{rs}(a) \sum_s p_{rs} g_{rsX} \mu_{rs}(X, v_{at}(q_t(a), L_a))\lambda_{rsX} \qquad \text{(A4)}$$

so that the total quantity of *X* emitted from the link in time period *k* is

$$G_X^t(a) = d_a E_X(a,t) \qquad \text{(A5)}$$

and the total quantity of *X* emitted per day on the link is

$$G_X(a) = \sum_t G_X^t(a) \tag{A6}$$

The speed correction functions are used to incorporate the impacts of travel demand and traffic congestion (as well as road design standards) into transport energy and emissions analysis. Higher levels of demand and congestion generally imply lower average travel speeds. Road design standards also affect travel speeds. In previous research we have established a suitable family of models covering wide ranges of vehicle and fuel types, and including many emissions of interest (Taylor et al 2005). The basic forms for the family of models were taken from the European emissions inventory guidebook (EEA 2002) then modified for Australian conditions using the available local databases. The guidebook also suggested a model for the effects of varying vehicle loading levels on fuel and emissions performance, which is useful for considerations of the performance of goods vehicles and transport and logistics policies that encourage load consolidation. The models relate energy/fuel consumption and emissions generation rates to average travel speeds, using piecewise functions to cover the possible range of speeds. The chosen functions are either power functions or polynomials. The generic form of the speed correction function is, for the energy/fuel consumption factor ρ_{rs} for fuel type *s* for a given vehicle class/subclass *r*,

$$\rho_{rs}(v) = \begin{cases} z_{1rs}(v) & v_0 \le v < v_1 \\ z_{2rs}(v) & v_1 \le v \le v_2 \end{cases}$$

where

$$z_{\alpha rs}(v) = Kv^{-n} \quad \text{or} \quad z_{\alpha rs}(v) = A + Bv + Cv^2$$

where v is the average travel speed and K, n, A, B and C are constants. In the generic model presented in this appendix, v is taken to be the average link travel speed. Similar models are also available for the pollutant emissions of interest.

References

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Appendix D

Review of Water Demand Forecasting

Jeffrey Cooke

UNSW – CIVIL & ENVIRONMENTAL ENGINEERING

Review of Water Demand Forecasting

by

Jeffrey Cooke

2013

A report for researches involved in the Low Carbon Living CRC's project on integrated Energy, Transport, Waste & Water (ETWW) demand forecasting and scenario planning for city precincts.

University of New South Wales

[1]ACKNOWLEDGEMENTS

The Author would like to acknowledge the help of the following people:

Tommy Wiedmann - UNSW

Ross Henderson – WDF modeller at Thames Water (London)

Katherine Beatty – Senior Demand Analyst at Sydney Water

Fernando Gamboa - Strategist, Servicing and Asset Strategy, Livable City Solutions at Sydney Water

Adrian Miller - Manager, Urban growth at Sydney Water

The author would also like to acknowledge the use of the tabulated review of papers published in the report by Donkor et al as a basis for the literature review matrix and figure 4 in this paper (Donkor, Mazzuchi, Soyer, & Roberson, 2012, pp. 35-39).

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SUMMARY & RECOMMENDATIONS

In this paper the author undertook a review of papers published over the last six years to understand and summarise the current focus of research in water demand forecasting (WDF). The author also conducted a survey and a number of interviews with water utility companies to understand current practice in industry. From this research it is recommended:

1. Research is undertaken to model changing human behaviour
2. A method of quantifying uncertainty is included in WDF models.

INTRODUCTION

Water, water, every where, nor any drop to drink"

(from the 'Rime of the Ancyent Marinere', Samuel Taylor Coleridge)

The RP2002 ETWW (Energy, Transport, Waste & Water) projects aim is to develop tools for the integrated demand forecasting of energy, transport, waste & water of city precincts. This paper provides a contemporary summary of the methods and models used for modelling WDF. It focuses primarily on current models & methods used in Australia for domestic WDF in urban areas with additional information on modelling being used abroad.

1.0 COMPLEXITY IN DEMAND FORECASTING

Water demand forecasting for domestic use in urban areas is complex because of the high degree of uncertainty around the variables that are the basis for the demand analysis. These variables include:

- Human Behaviour
- Demographics/Land-use Change
- Water supply system
- Source substitution
- Legislation

1.1 HUMAN BEHAVIOUR

In interviews with representatives of major urban water utility companies (Sydney Water & Thames Water, London) both interviewees concluded that the need for a greater understanding of human behaviour and decision making to be incorporated into water demand forecasting models. There are models available that simulate human behaviour however these all rely on relevant accurate data as an input to get any meaningful output and there are a limited number of years of relevant data for the Sydney Water region. Systems like that used by Melbourne Water use agent based ANN models to attempt to simulate human behaviour. However using techniques that are meant for manufacturing to predict human behaviour ultimately cannot be that accurate because of the uncertainty of human behaviour.

Many of the most recent publications are into Artificial Neural Networks, some using a learning algorithm and agent based micro-simulation models Figure 4 suggesting that current research is attempting to address this issue.

In an interview with Fernando Gamboa of Sydney Water he pointed out that the most uncertain variable in water demand forecasting is human behaviour (Gamboa, 2013). He noted that because the Sydney Water region was in a drought, for approximately 6 years, the data from this period is not usable given the influence of restrictions on people's water use related behaviour. Mr. Gamboa stated that Sydney Water effectively only have about 3-4 years of representative consumption data that can be used for forecasting purposes and that demand has changed significantly noting that demand has not returned to pre-drought levels. There has been an approximate 30%-40% reduction in maximum day demand (used for sizing bulk water infrastructure). A combination of factors including; efficient appliances, people not watering gardens, people not washing their cars and a decline in demand from heavy industry, likely cause this reduction. Concluding that overall the change in human behaviour was the primary contributing factor in the reduction of domestic demand. He noted that currently Sydney Water is monitoring for the potential bounce back to pre-drought levels.

Peak-hour forecast has changed and varies in each reservoir zone. Historically during summer the peak hour was in the afternoon but now the peak has changed to the morning probably because people are not watering their gardens as much. There has been evidence that customers are also looking at the weather forecast and are spreading the demand load over more than one day consequently reducing the maximum day and maximum hour demand. Examples include the hot days experienced in January 2013. A change in people's behaviour resulted in a huge change in water demand simply because of the education of users and the response to the supply shortage. This highlights that it is quite possible that this level of demand might be maintained and spending money on education could be far more cost effective than increasing spending on infrastructure.

There is an important role for education of water users to understand the consequences of their water use practices. Sydney Water has analysed average day demands using end-use data and has estimated how much that change is due to changing water use practices and the increases in the efficiency of water using appliances. They do not yet have the requisite detail to do this for the changes in peak demand. Before the last drought, peak day demand was usually around double average day demand so predicting the maximum day demand could be reasonably predicted using this assumption. The reliance on this simple estimation however is no longer valid. Peak day used to be calculated by doubling the average day demand but now it has changed significantly and can be as low as 1.4 to 1.6 depending on the location (reservoir zone).

Even areas serviced by both recycled and drinking water are showing a drop even though restrictions did not apply to on recycled water use. This may be because they would have been affected by the broader water education campaigns and/or they have responded to the pricing change for recycled water.

It was suggested that surveys of water use of household typologies and demographic typologies as 'focus groups' might help understand changing behaviour. Kate Beatty of Sydney Water said that better understanding of customers was a focus of the newly developed Customer Value and Research Strategies in the Business Strategy & Resilience (BSR) division at Sydney Water but it may be some years before meaningful results were available in this area.

1.2 DEMOGRAPHICS & LAND USE CHANGE

In an interview with Fernando Gamboa he stated that water demand forecasts at Sydney Water use the population forecasts prepared by the Department of Planning in the form of the Metropolitan Development Plan (MDP). They receive almost monthly updates that can make developing a water demand forecast more complex because changes in planning policy have a major effect on water demand forecasting for individual supply (distribution) systems.

Population growth has a very large influence on water demand but is also one of the more certain influences. For network system planning, Sydney Water is now looking at the past 3 years of water demand data for an area and if that area is likely to have a 10% increase in population then water demand should increase by 10%. But changing human behaviour could have an effect on this calculation as described in the previous section.

Preliminary high-level data on BASIX[2] houses showed that on average they were using the same as non-BASIX houses, however if you took a snapshot of houses before the introduction of BASIX and those after, BASIX houses were using less water. But the reduction could be to do with lot sizes becoming smaller and increasing density. Relatively recent changes by the Department of Planning to allow Complying Development Certificates in lieu of a Development Approval could be increasing the density of city area, reducing lot sizes and decreasing demand[3]. Therefore changes in planning policy can potentially have a significant effect on water demand, and the area where water demand originates. The new focus on precinct planning is driving the need for better precinct planning tools. (Miller, 2013).

1.3 WATER SUPPLY SYSTEM - SYDNEY

As stated by Fernando Gamboa of Sydney Water if we can achieve a better water demand forecasting model and have increased certainty as to where they have to supply water there are potentially large saving on infrastructure costs (Gamboa, 2013).

As one example Sydney Water supply water to and area of approximately 12,700sq km and it is critical that they know where housing and industry will be located to be able to build the infrastructure to meet demand (Miller, 2013).

Changes in planning policy[4] can have a major effect on infrastructure planning by changing the location of planned new housing and therefore moving demand. The change in location of demand and subsequently infrastructure is driven by a number of factors other than planning policy; changing consumer preference and consumer demand drive it. Throughout the 1970's and 1980's the model for urban development was lateral expansion of the city building more housing on greenfield sites on the periphery of the city. The land costs are cheaper but the infrastructure cost to supply amenity are very large. Since the 1990's there has been a change in consumer preference with people preferring to live closer to the inner city rather than incur a long commute to work. This has led to a greater amount of urban infill on brownfield sites linking into existing infrastructure; reducing infrastructure costs. Changing taxation policy has also contributed creating a new investor market driving demand for denser apartment precincts. These changes in policy and taxation cause subsequent change in where infrastructure needs to be provided. One strategy for dealing with change is to use more decentralised systems, allowing for storm water to be re-used within a precinct, similarly power generation can be decentralised to a precinct scale moving the cost for infrastructure provision from the public utility to the private developer.

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[2] Basix is a NSW Government initiative that sets minimum standards for reducing energy and water use in houses www.basix.nsw.gov.au.

[3] In NSW if your site area and proposed development are with a template size a shape one can opt for a Complying Development Certificate (CDC) rather than seek approval from council with a Development Approval (DA). The approval takes 10 days. http://housingcode.planning.nsw.gov.au/

[4] On March 16 2013 Urban Activation Precincts were legislated as a method of housing delivery and stimulating employment, focusing on 8 key locations close to public transport nodes www.planning.nsw.gov.au

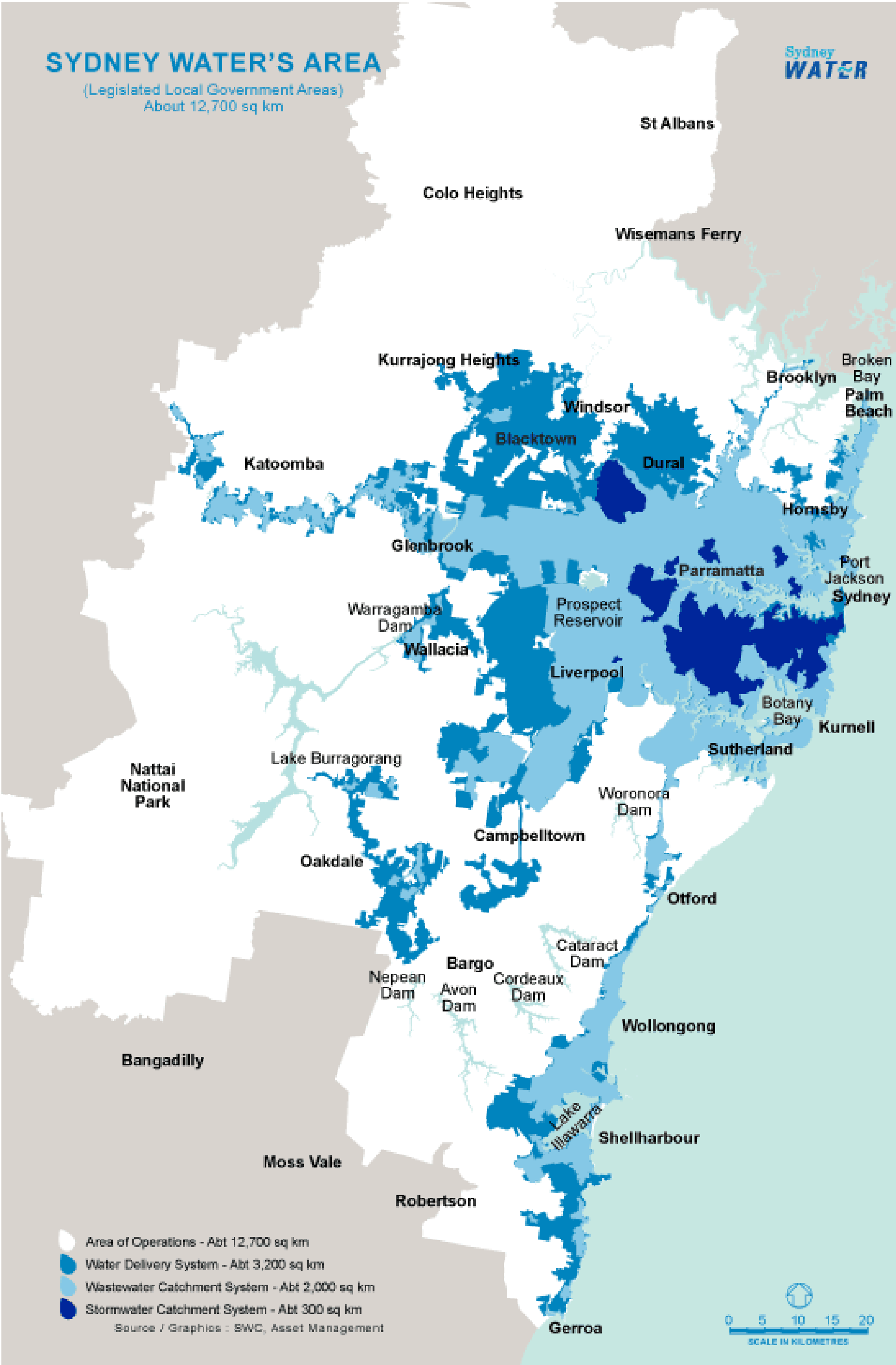

Figure 1 Sydney Water Area of Responsibility from Sydney Water website www.sydneywater.com.au

Adrian Miller stated that Sydney water are currently planning infrastructure so that it can adapt to change, this adds some cost but means that a failure of supply and risk of over-investment is less likely.

Local councils own the majority of the storm water system, which adds an additional level of complexity for integration with the overall water system (Gamboa, 2013). There are a number of cases in Sydney where stormwater has been used and recycled. This is now happening in most major development s with the collection of rainwater before it is lost down the drain.

1.4 SOURCE SUBSTITUTION

As mentioned in the previous section one potential method of addressing water supply is to use a decentralised supply and source substitution. This has the potential to delay the need for single major infrastructure investments and somewhat reduce the need for de-salination plants.

The introduction of rainwater tanks particularly with the advent of BASIX in NSW has been a major driver for the inclusion of source substitution in housing. The resulting impact on demand is variable. As previously mentioned, data on BASIX houses showed that on average they were using around the same as non-BASIX houses, however if you take a snapshot of houses just before the introduction of BASIX and those after, BASIX houses are using less water (Gamboa, 2013).

Precincts can be planned with two systems of supply, potable and a non-potable recycled water system. This has already been done in some new precinct developments, usually for landscape irrigation, reducing the demand on potable water. Wastewater Treatment Plants (WWTP) produced by companies such as Eloy water [5] are being used for small homes and residential precincts to treat wastewater (blackwater) in a de-centralised way closer to the source of the wastewater. The treated wastewater can be used for toilet flushing or irrigation and with further treatment can be 'Class A' (under AS 1546.1) potable water. These systems will increasingly reduce water demand (Printant, 2013).

[5] Eloy water are a Belgian company specialising in water treatment and make water treatment products for smaller scale treatment plants http://eloywater-au.cd.epic.net/

2.0 LITERATURE REVIEW OF MODEL TYPES

A literature review matrix of papers published from 2007 to 2013 was created to analyse the current research in water demand modelling see Appendix.

2.1 MODEL & METHOD TYPES OVERVIEW

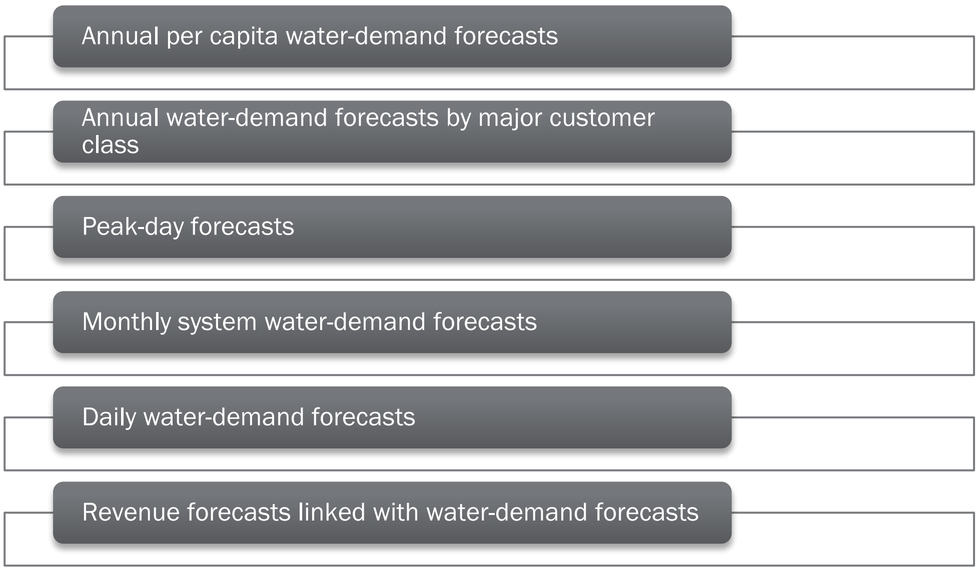

Figure 2 Model Types (Billings & Jones, 2008, pp. 31-32)

Water demand forecasting model methods can be broadly categorised in two main groups:

1. Bottom up (End user data)
2. Top Down (Statistical analysis)

Within these broad groupings these can be further dis-aggregated into various end-user models and statistical models and combinations of both.

The complexity of the model or the requirement for a complex model is based on need; for example Tasmanian Water has an adequate supply of water and very slowly growing population so there is no pressure on water supply and therefore a simple projection of historic water demand data is all that is required. The usual water demand-forecasting models undertaken by water utility companies are listed in Figure 2 and various methods are used to create the most accurate model to predict demand.

One such model currently being used by Melbourne Water and developed by ISD Analytics software incorporates micro simulation of human behaviour, incorporating appliances and products used, demographic typology, household typology etc. The model uses a bottom up approach combined with a top down approach. This software will be discussed in more detail later in this paper. The majority of water utility companies currently use a top down approach using statistical projections of historical data to identify trends and project future demands Figure 4. However use of historical data alone does not account for more sudden changes, including changes in human behaviour.

There are numerous forecasting methods and some of the most common methods can be seen in Figure 3. Qi & Chang (2011) categorised six approaches that include:

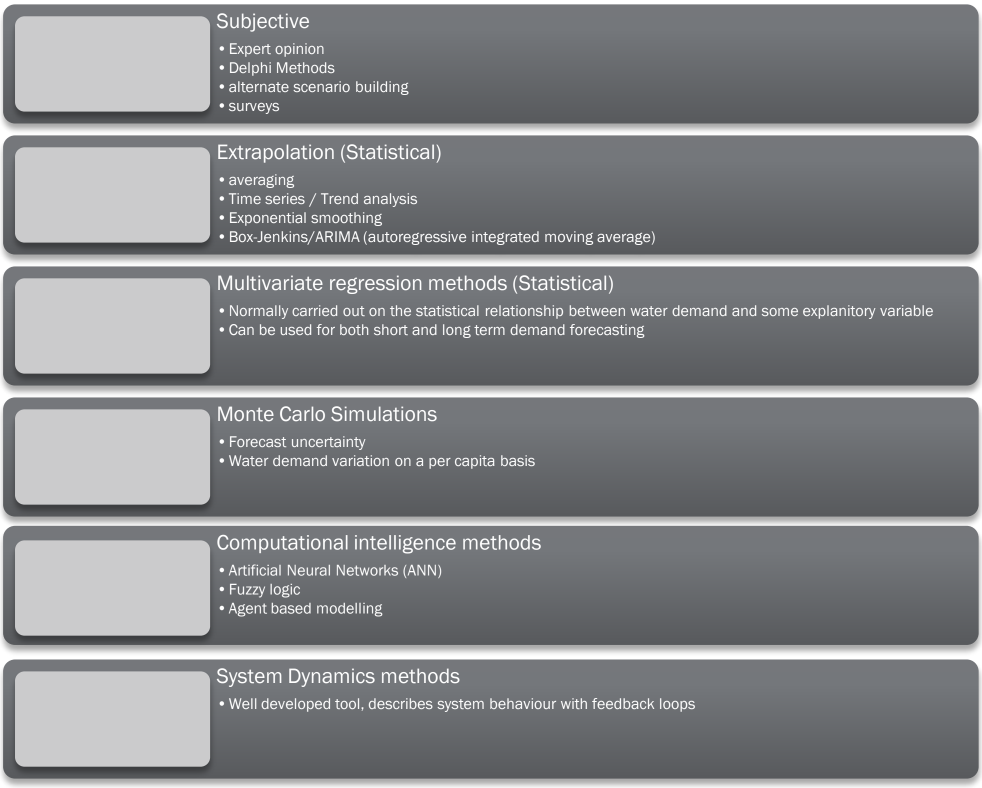

Figure 3 Forecasting Methods amalgamation of (Billings & Jones, 2008, p. 34) & (Qi & Chang, 2011, pp. 1629-1634)

Multivariate regression analyses (statistical)

This is a more traditional approach and can be used for short and long term projections. Long-term forecasts are primarily based on population growth as a variable and shorter term forecasts can be corrected by the introduction of other variables, such as temperature or precipitation (Qi & Chang, 2011, pp. 1629 -1634).

Time series analyses

Uses the statistical abstraction of trends that contribute to water demand and may include analyses of long, short and cyclical trends. It has been widely used for short-term water demand forecasts (Qi & Chang, 2011, p. 1629).

Computer intelligence models

This is a broad heading that covers a number of methods including: Artificial Neural Networks (often in combination with another method), fuzzy logic and agent based models. These methods are useful for simulating complex systems and historical data are used to train a learning algorithm until it reaches acceptable accuracy.

Hybrid approaches

This approach integrates a number of models to attain a greater accuracy than one model alone(Qi & Chang, 2011, p. 1629).

Monte Carlo Simulations

Using Monte Carlo Algorithms allows modellers to quantify forecast uncertainty. This is the approach recommended by Ross Henderson of Thames Water (Henderson, 2013). This method can be used in conjunction with other modelling methods to give an understanding of the uncertainty attached to any forecast.

System dynamics models

These models describe systems behaviours including feedback loops to gain accurate forecasts because it incorporates the complex interactions between systems. It is a method that has been supported by Qi & Chang (2011).

2.2 CURRENT RESEARCH

A review of papers published on the topic of water demand forecasting between 2007 and 2013 was conducted and the results are in the Appendices. As can be seen from Figure 4 between the years 2007 to 2013 the greatest amount of research has been into regression based methods and neural network based methods. There has been less research conducted into methods incorporating Monte Carlo analyses, system dynamics models or scenario based modelling where there is a greater gap in current research.

Of the current research reviewed a number of papers are of interest for potential application to water modelling at a precinct level. In their review of current research Donkor et al. emphasis the importance of including quantifying uncertainty in any model, this is corroborated by Ross Henderson of Thames Water who also emphasised the importance of quantifying uncertainty through the use of Monte Carlo Algorithms (Henderson, 2013) (Donkor, et al., 2012, p. 25). Cutore et al. use a ANN and Neuro Fuzzy logic to quantify uncertainty in their study at city scale and found similar performance between Bayesian ANN, Regression & Adaptive Neuro-fuzzy models (Cutore, Campisano, Kapelan, Modica, & Savic, 2008). Recent regression methods used by Lee et al. also included a probability density function of water consumption (Lee, Wentz, & Gober, 2010).

A large number of papers surveyed researched Artificial Neural Networks (ANN) models but the results of their effectiveness are mixed. Research conducted by Bennett et al. in South East Queensland used end use data to predict water demand finding an ANN with Hidden Layer Sigmoid Activation Linearly Activation Output most accurate. However Herrera, Manuel et al. concluded that ANN models performed poorly and that support vector regression models were more reliable (Herrera, Torgo, Izquierdo, & Pérez-García, 2010). The primary issue when using ANN model is the large historic data set they require for validation. To be useful for precinct modelling data sets would be required for each region the tool was to be used in order to validate its output. This would be complex to apply to different precincts.

Time Series Regression & Regression	*Scenario-based*	*Decision Support Systems (DSS)*	*Neural Networks - Time Series & Regression*	*Neural Networks & Fuzzy Logic approach*	*End use*	*Hybrid Approach*	*Monte Carlo Simulations*	*System Dynamics Models*
Hejazi, Mohamad et al (2013)	Hejazi, Mohamad et al (2013)	Feng, S., Li, L., Duan, Z., & Zhang, J. (2007)	Bennett, Christopher et al (2013)	Yurdusev et al., (2009)	Carragher, Byron et al (2010)	S.L. Zhou et al (2000)	Khatri and Vairavamoorthy, (2009)	Qi, Cheng et al (2011)
Lee, Mengshan et al (2011)		Mohamed, M., & Al-Mualla, A. (2010)	Herrera, Manuel et al (2010)	Wu and Zhou, (2009)	Rozos, Evangelos et al (2013)	Shirley Gato et al (2007)		
Lee, S., Wentz, E., & Gober, P. (2010)			Adamowski, J., & Karapataki, C. (2010)					
Polebitski & Palmer (2010)			Ghiassi, M., Zimbra, D., & Saidane, H. (2008)					
Caiado, J. (2010)								

Figure 4: Research papers on water demand forecasting by method, published 2007 - 2013

One model research by Adamowski et al. used an ANN model in combination with a regression model to forecast short-term water demands in the city gardens in Nicosia, Cyprus. They found that ANN models could be more accurate that regression models alone in predicting peak water demand (Adamowski & Karapataki, 2010). Andrew Bovis at Sydney Water is currently researching peak hour demand looking at climate change and other variables.. Ghassi et al used a combination of time series data and Neural Networks for daily water demand forecasting and reported a 99% accuracy (Ghiassi, Zimbra, & Saidane, 2008).

Qi et al. attempted to include for externalities in water demand forecasting including economic impacts on long term water demand using a System Dynamics Model (Qi & Chang, 2011) . This could be of interest to the ETWW project as one method of integrating water forecasting models with other variables from external models.

The primary issue with these more complex modelling methods is that they require specialist personnel to input and interpret the data and in the case of ANN methods they require a good historic data set to validate and calibrate the ANN algorithm. The majority of utility companies in Australia surveyed used far simpler statistical methods (see Figure 5) like regression analysis because there is no need for a complex method or to invest in specialist software and staff.

One interesting study conducted by Polebitski et al. used three regression methods to improve water demand forecasts at the census area scale allowing for the spatially distributed demands within a system. This could be used for long or short term forecasts and may be a more suitable model for precinct level modelling but it does require more disaggregated data than is usually available (Polebitski & Palmer, 2010).

2.3 VIEW FROM THE COAL FACE

The author conducted a number of interviews with the water demand forecast modellers for Sydney Water and Thames Water (London) to get an understanding of what water utility companies require.

A Questionnaire (see Appendix A) was sent to a number of water utility companies to ascertain the current state of water demand forecasting in Australia

State and organisation	WDF under-taken?	Basis of model or data	Mathematical Basis	Time Horizon	References & Comments
New South Wales, Sydney Water	Yes	Top-down & bottom up, Panel data econometric models 1-5 years. Beyond 5 years, end use modelling and trend analysis (see appendix)	Econometric and end use forecasting (appliance stock models use various mathematical methods).	5 – 10 – 50 years	Beatty 2013, Gamboa, 2013), (Miller, 2013), see appendix
South Australia, SA Water	Yes. 2 models long & short term	Top-down, Historical data extrapolated based on population growth etc.	Statistical: non-linear regression model	short-term 7days, long-term 10-25 years	Currently developing a third stochastic demand forecasting tool using POAMA data to forecast 6month - 2years
Tasmania, TasWater	Partly for infrastructure	Top-down, Historic data			
Victoria, Melbourne Water	Yes	Top-down & bottom up	No response	No response	
Western Australia, Water Corporation	Yes.	Top-down, Approach 1 Identifying trends and extrapolate from data. Approach 2 Demand = Population x per capita consumption	Statistical	Short (1-2 years), Medium (up to 2030) Long term (50 years)	Trialling iSDP model developed by Institute of Sustainable Futures. But no advantage found.

Figure 5 Survey of current water demand forecasting[6]

From the sample of utility companies that responded to our survey questionnaire the specific model type varied due to geographical scale, local regulatory requirements, the available data and human resources available to undertake the analysis. Overall the majority of water utilities companies model at the Macro scale (top down). Ross Henderson of Thames Water in London stated, ‘econometric models alone are of little

[6] A number of utilities did not respond in time for inclusion in this report

use for domestic water demand forecasting and a micro-component model coupled with a probability density function is required to give results meaning' (Henderson, 2013).

Fernando Gamboa is a Strategist responsible for water demand forecasting for system planning at Sydney Water. In an interview with Fernando he stated that the water demands are an input to hydraulic models that are used for analysing servicing options (Gamboa, 2013). He stated that Sydney Water have experimented with a number of demand modelling techniques including using the results of smart metering and end-use modelling etc. and concluded that for network planning and infrastructure sizing at a delivery system level, the simpler the model the better. The Growth Servicing Strategies that Sydney Water creates are reviewed every 5 years so it allows for re-alignments to be made and infrastructure can be built with the caveat that it may be upgraded if required to meet demand and it can be re-aligned at a later date. Generally, Growth Servicing Strategies would be robust enough for 15 years into the future.

Thames Water do similar analysis but in an interview with Ross Henderson (the mathematical modeller for Thames Water) he felt that there were two main aspects needed to be added to water demand forecasting modelling methods (Henderson, 2013):

1. Inclusion of a method of quantifying uncertainty, a Monte Carlo Algorithm
2. As previously stated, a better model of changing human behaviour

A more accurate water demand model could help reduce infrastructure size, cost and carbon footprint. As precinct modelling is primarily about infrastructure investment and Sydney Water currently do a trade-off analysis to calculate risk and reward of infrastructure investment and as a part of that energy use is considered and carbon foot print could also be considered although currently usually it comes down to what it the cheapest option. However, with the advent of a price on CO2 it maybe that the CO2 cost of the infrastructure will be more important in the pricing.

2.4 WATER DEMAND FORECASTING SOFTWARE USED BY UTILITIES

A number of software packages are used currently by water utilities and these are summarised in Figure 6. Sydney Water currently uses Innovyze software for pressurised water hydraulic analysis that has a number of different sections dedicated to different hydraulic needs. The current software in use by Sydney Water has the capability to give a carbon footprint output but it is not currently being used, it could be used as part of the calculation when investigating different scenarios for water infrastructure.

Melbourne water use SimulAlt water forecasting software that uses both a top down and bottom up approach and a computer learning ANN component to simulate human behaviour using an agent-based model.

IWR-Main was developed by the US Dept. of Energy and is used by water utility companies in southern California.

DSS software developed by Maddeus Water Management is used by water utility companies in California as an end use based least cost planning tool for long term water demand forecasting for infrastructure.

Forecast Pro is generic software used in many areas of business and can be used to perform a number of statistical forecasts on any data.

Figure 6 – Examples of software that incorporate or provide water demand forecasts

2.5 MOST RELEVANT MODELS FOR PRECINCT MODELLING

The most relevant model & method for precinct modelling will be those used for sizing precinct infrastructure. Peak-day forecast is most important for infrastructure storing and transfer capacity (Gamboa, 2013). Models such as Polebitski et al. (2010) could be adapted for precinct modelling to capture both long term and short term forecasts while quantifying uncertainty (Polebitski & Palmer, 2010). A model that can be used for short-term peak-day forecasting is most appropriate for precinct modelling and could be a top down model capable of short & long term forecasts.

3.0 CONCLUSION

In conclusion, water demand forecasting is a complex subject and no singular methodology is currently used for all water demand forecasts. The challenges to developing an integrated model for water demand forecasting include:

1. A better model of changing human behaviour.
2. The inclusion of a method of quantifying uncertainty possibly by using Monte-Carlo Algorithms.

4.0 METHODOLOGY

The author undertook a survey of Australian utility companies and interviewed industry representatives in Sydney Water and Thames Water to ascertain the current state of WDF in industry (see Figure 5 & appendixes).

The survey questionnaire was sent to:

- ACTEW water (ACT)
- Sydney Water (NSW)
- Hunter Water (NSW)
- Sydney Catchment Authority (NSW)
- Power Water (NT)
- SEQ (Queensland)
- SA water (SA)
- TasWater (Tasmania)
- Melbourne Water (Vic)
- Water Corporation (WA)

Structured interviews were undertaken with members of industry and their responses recorded electronically and in writing.

A survey of current research was undertaken by searching all papers published on the topic of WDF and the results compiled in a literature review matrix (see appendix). These were then cross tabulated (Figure 4) by WDF model type to understand where most research is being done and identify gaps in current research.

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6.0 APPENDICES

APPENDIX A: Literature Review Matrix in Excel format

APPENDIX B: Questionnaires

SA Water

Models for Water Demand Forecasting Questionnaire

My research is initially in water demand forecasting and subsequently the carbon footprint of the provision of that water (including infrastructure). My study is part of a larger collaborative study involving a number of stakeholders including the Centre for Low Carbon Living CRC and the Water Research Centre at UNSW more information on the project is available here.

As an initial step I am trying to gather as much information as possible on the current state of water demand forecasting and the models used in Australia. If you would answer the following questions I would be very grateful.

1. Do you undertake any water demand forecasting? If so what models do you use? (e.g. System Dynamics Model, Simulation Model, Steady-state and dynamic model, Operational research models, Expert systems, Hybrid expert systems)

Yes, SA Water currently forecasts water demand for two main purposes. Each purpose has its own model, but both are operational research models. One model extrapolates historical demand by future population growth over the long term and the other is a non-linear regression model that tries to predict demand based on forecast climate information.

2. Briefly explain the water demand-forecasting model that you use and why you use this model?

The two models are used to forecast demand for different time periods and steps. The long-term demand forecasting model used by SA Water is an in-house model for likely future demand growth. The model looks at historical annual demands and extrapolates them based on projected growth in residential, commercial and other customers and incorporates pricing and weather factors.

The short-term demand forecast model uses climate data and historical demand to calibrate a model. Forecast climate data is then input into the model to produce a forecast of future demand

3. How do you undertake the modelling and what is the mathematical basis of the model (s)?

The Long-term model is contained within spreadsheets by users as required.

Short term modelling is conducted using an automated calculation engine to calculate the forecast demand on a daily basis. The short-term model is recalibrated as required using historical data sets.

4. What is the time horizon for the model and what is the regional coverage?

Long term demand models are used to forecast over a 10 to 25 year horizon across the breadth of South Australia. The short term demand model forecasts a period of up to 7 days over Metropolitan Adelaide.

5. If possible is there any information on your water demand forecasting that you can share for my research? (I/we are happy to sign a confidentiality agreement if required)

Subject to a confidentiality agreement, SA Water would consider providing information to support the research, particularly if research outcomes are able to provide insight or add value to SA Water's existing forecasting systems.

6. Do you have any suggestions of any current research/work I should be aware of?

SA Water is in the process of developing a third, stochastic demand forecasting tool utilising POAMA data to produce forecasts for a 6 month to 2 year horizon for the Metropolitan Adelaide region.

WA Water

Models for Water Demand Forecasting Questionnaire

My research is initially in water demand forecasting and subsequently the carbon footprint of the provision of that water (including infrastructure). My study is part of a larger collaborative study involving a number of stakeholders including the Centre for Low Carbon Living CRC and the Water Research Centre at UNSW more information on the project is available here.

As an initial step I am trying to gather as much information as possible on the current state of water demand forecasting and the models used in Australia. If you would answer the following questions I would be very grateful.

1. Do you undertake any water demand forecasting? If so what models do you use? (e.g. System Dynamics Model, Simulation Model, Steady-state and dynamic model, Operational research models, Expert systems, Hybrid expert systems)

Response from Water Corporation of WA: Yes we do undertake water demand forecasting

There are 3 Modes we consider: Short (1-2yrs), Medium (Up to 2030) and Long term (50yrs). But sometimes we do not distinguish between Medium and Long term.

We do not use any commercial or other so called mathematical models. We had been trialling the iSDP model by Institute of Sustainable Futures but did not see any big advantage of using it as we do not collect the data in the form that can be fed into the model. In essence we do not see the effort involved in keeping the model functional as it does not give us any better results than what we get by working out from basics. And we do not keep a dedicated trained person for the use of the models.

Our approach is from basics. The approach we use can be applied by an engineer easily. The methods we use had given successful forecasts in the past (within 3% of actuals). This suits our needs and we are not convinced that the computer models out there can predict better than 3%.

2. Briefly explain the water demand-forecasting model that you use and why you use this model?

Approach 1: Identify the recent trends and extrapolate with the information we gather from other departments, shires etc.

*Approach 2: Demand = Population * per capita consumption. (We forecast population and define the future per capita targets based on other proposed water efficiency programs, demand management strategies, Government requirements etc)*

We also analyze:

- *Daily water supply for Perth for tracking purposes*
- *Past supply data sector by sector to make a well informed forecasting.*

3. How do you undertake the modeling and what is the mathematical basis of the model (s)?

See the above answers

4. What is the time horizon for the model and what is the regional coverage?

We operate in many country towns, minor cities and Major cities in Western Australia. The Biggest one is the IWSS (Integrated Water Supply Scheme) supplying Perth, Mandurah and Goldfields and Agriculture.

Note: We do not use models

5. If possible is there any information on your water demand forecasting that you can share for my research? (I/we are happy to sign a confidentiality agreement if required)

If requested we could provide a technical note that has been prepared for the IWSS. But we would not wish for this to be published or disclosed without written permission from us first.

6. Do you have any suggestions of any current research/work I should be aware of?

The work by Institute of Sustainable Future CSIRO and Sydney Water

<u>Tas Water Response</u>

(note TasWater chose not to fill in the questionnaire but replied in an email)

Hi Jeff,

We don't do any special demand forecasting with fancy models etc. We base our assumptions on historical data, which has proved accurate enough for us.

Note that by and large, Tasmania and southern Tasmania in particular don't have an acute supply problem, i.e. a shortage of water unlike other parts of Australia, we have plenty of surface water, our supply issues are more infrastructure related. Therefore our modelling is much more hydraulic/engineering modelling that we use to determine how big do our pumps need to be, how much water can we squirt through a pipe etc.

So what we tend to do is to make some assumption about demand and then use these assumptions (backed up by historical data) to run our hydraulic models to inform our forward investment in pumps and pumps etc.

With that in mind, and looking at your questionnaire, I'm not sure if the questions are relevant to our activities.

I can advise you of a CO2e per ML of water once we run the carbon numbers for this year, which is in about 2 weeks time.
In terms of embodied carbon in our infrastructure e.g. the concrete, the steel, etc we haven't done much work on this and at present there is not a strong driver to do so. Suffice

to say that with the high percentage of renewable power available in Tassie, we have a pretty low carbon emissions regime relative to other water corporations and there's not a huge driver for us to reduce our emissions or measure them better without some sort of financial push such as a Carbon price that hurts. Currently it doesn't hurt at all.

In terms of carbon footprint for new precincts I'm guessing you'll be looking more at the embodied carbon of the infrastructure rather than the ongoing carbon required to push the water & sewage around. I cant offer you much in that space more than the commonly available literature.

Happy to discuss if you want to give me a call. See numbers below.

Cheers,

Lance

Lance Stapleton
Manager - Scientific Services (South)

TasWater

Tel *(03) 6237 8293*
Mobile *0408 175 522*
Fax *1300 862 066*
Post *GPO Box 1393, Hobart TAS 7001*
Street *169 Main Rd, Moonah, 7009*

Email *lance.stapleton@taswater.com.au*

7.0 GLOSSARY

WDF – Water demand forecasting

DSS – Decision support system

ANN – Artificial Neural Network

Appendix E

Water demand forecasting in practice

Fernando Gamboa

Project: Establishing a framework for integrated ETWW demand forecasting second workshop

24 September 2013

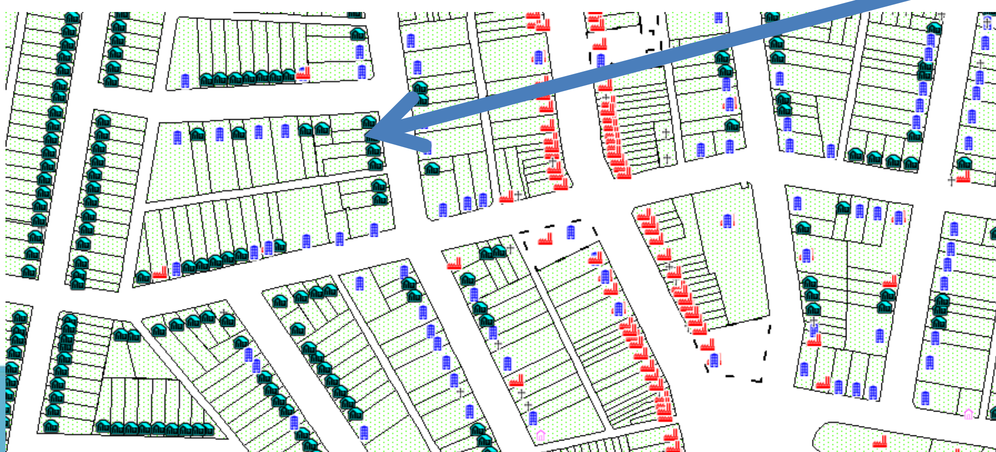
Overview

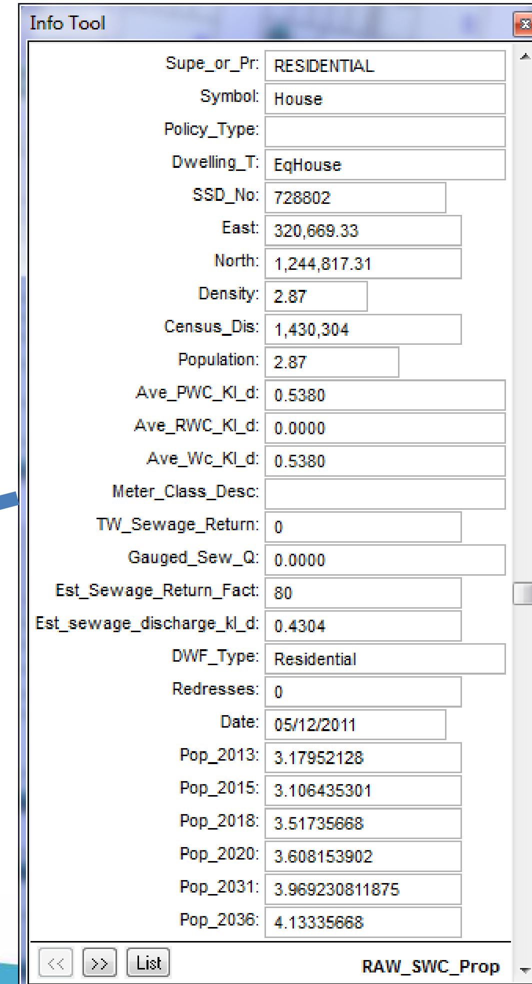
- Sources of data used as inputs in forecasting
- Demand forecasting
- Current challenges
- Planning approach
- Tools
- Future focus areas

Sydney WATER

Sources of data used as inputs in forecasting

- Population forecasts from the DoPI (lot level resolution)
- Historical consumption trends
- Census data
- Development applications





Sydney WATER

Demand Forecasting

Greenfield developments

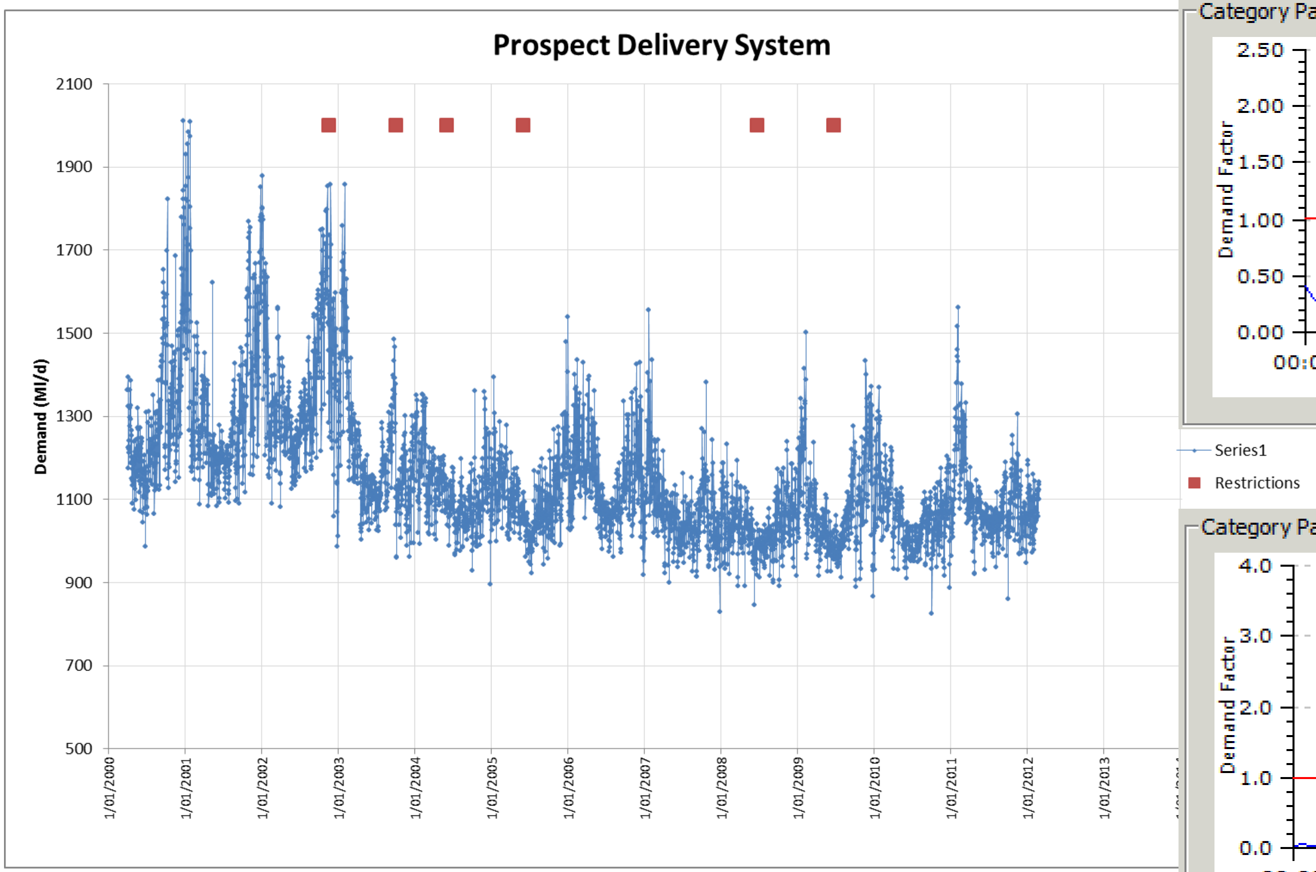
- Analyse and derive demand rates for zones in the vicinity
- Consider level of BASIX coverage and adjust as required
- Adopt demand rates and model
- Carry out sensitivity assessment to develop risk profile

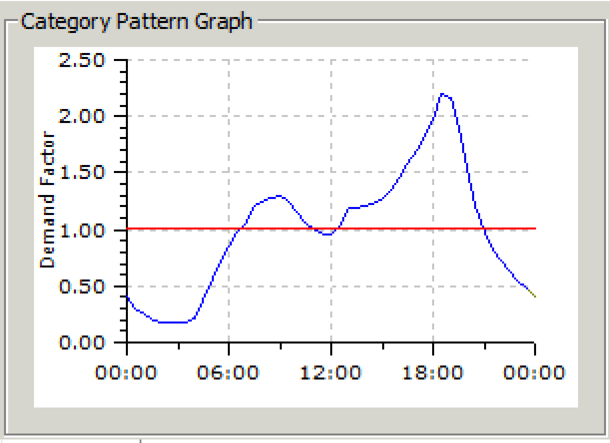
Infill developments

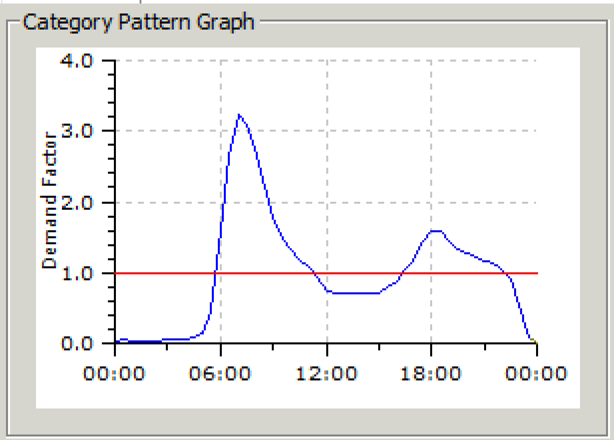
- Analyse and derive demand rates within the zone
- Adjust for BASIX
- Adopt demand rates and model
- Carry out sensitivity assessment to develop risk profile

Sydney WATER

Forecasting challenges







Planning

Phase 1
Define objectives

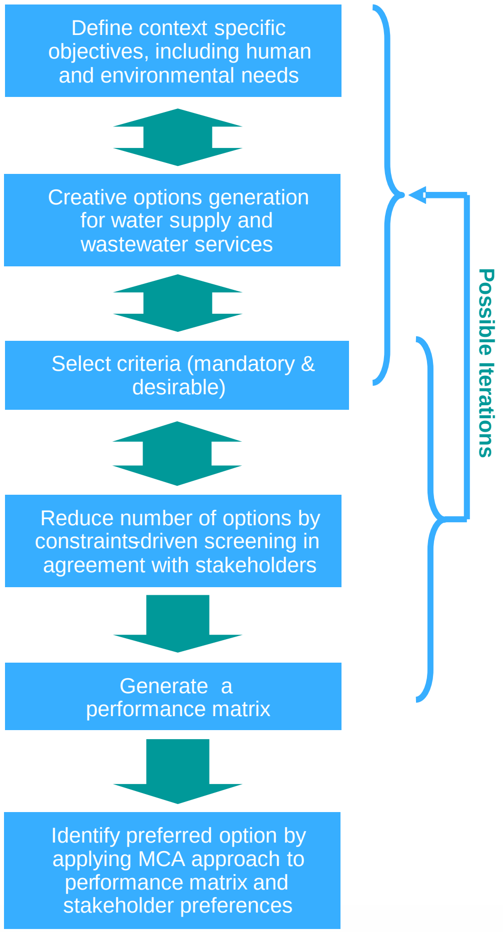
Phase 2
Generate options

Phase 3
Select sustainability criteria

Phase 4
Screen options

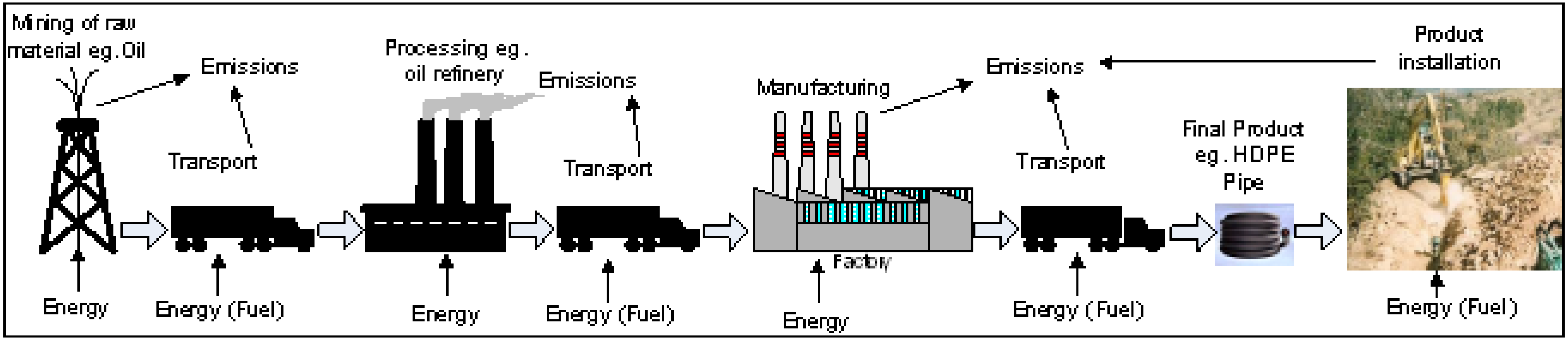
Phase 5
Perform detailed options assessment

Phase 6
Recommend preferred option



Tools - Energy and Carbon

- Energy and Carbon Estimator (ECE)
  - Estimates the life-cycle greenhouse gas emissions
  - Life-cycle energy costs for water and wastewater assets
    - Construction
    - Operations



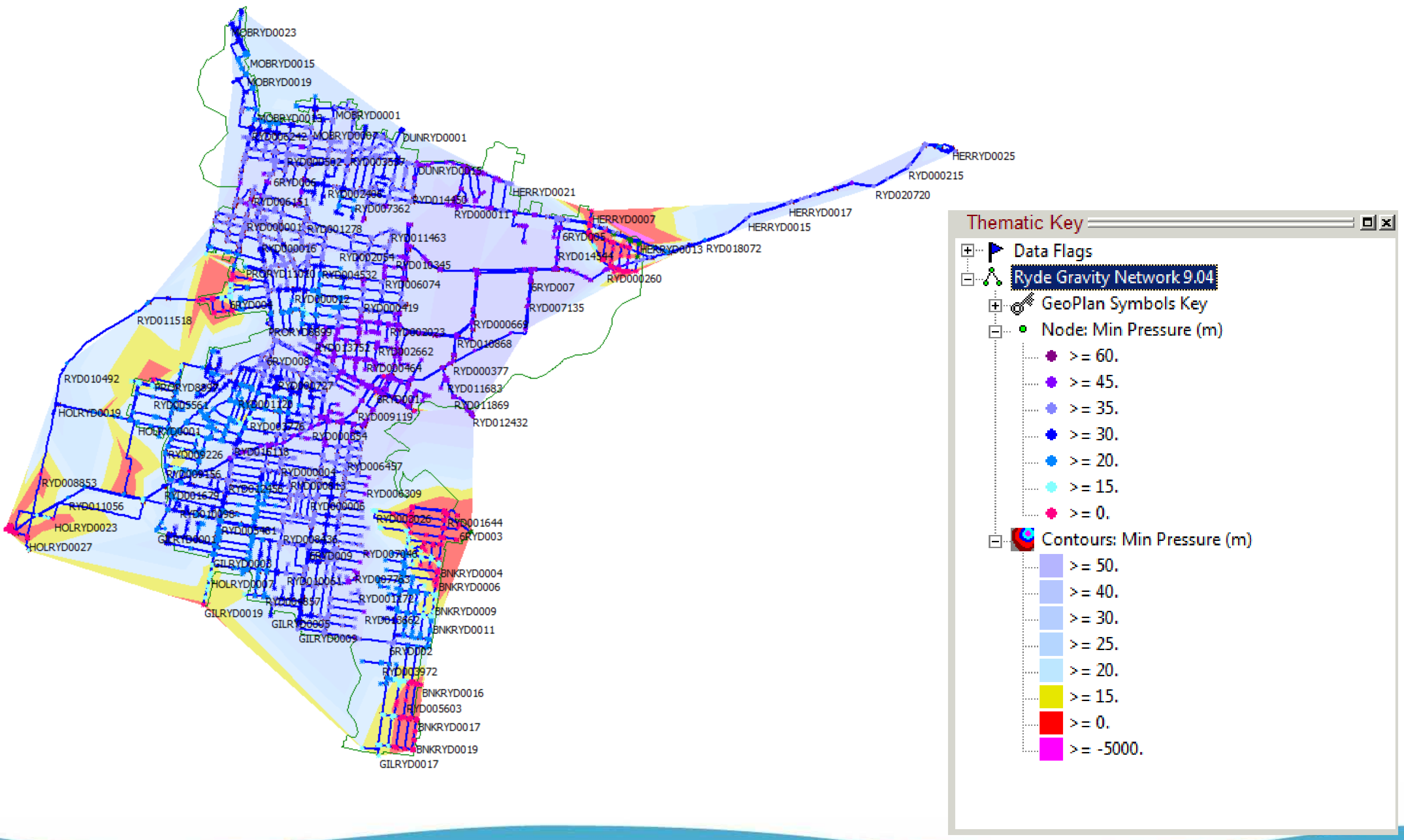
Sydney WATER

Tools – Construction/Operating Costing

- Capital costing tool
- Economic options evaluation
  - Costs and benefits of investment options, using discounted cash flow (DCF) techniques.
  - B/C

Sydney WATER

Hydraulic Modelling



Future focus areas

- Continue to refreshing the planning process
- Continue to monitor consumption trends
  - Improve resolution (smart metering)
- Improve understanding of the dynamics in changes in behaviour

Sydney WATER


Questions?

Appendix F

Waste Demand Forecasting

CRC for Low Carbon Living, Program 2: Low Carbon Precincts

24th September 2013

Steffen Lehmann, Atiq Zaman, He He, John Devlin

Presented by John Devlin

CSIRO

LOW CARBON LIVING CRC

RenewalSA people partnerships progress

中澳城市环境与可持续发展研究中心
China–Australia Centre for Sustainable Urban Development

University of South Australia

UNSW THE UNIVERSITY OF NEW SOUTH WALES

SA Water

Government of South Australia
Department of Planning, Transport and Infrastructure

UniSA Zero Waste SA Research Centre for Sustainable Design and Behaviour

Sydney WATER

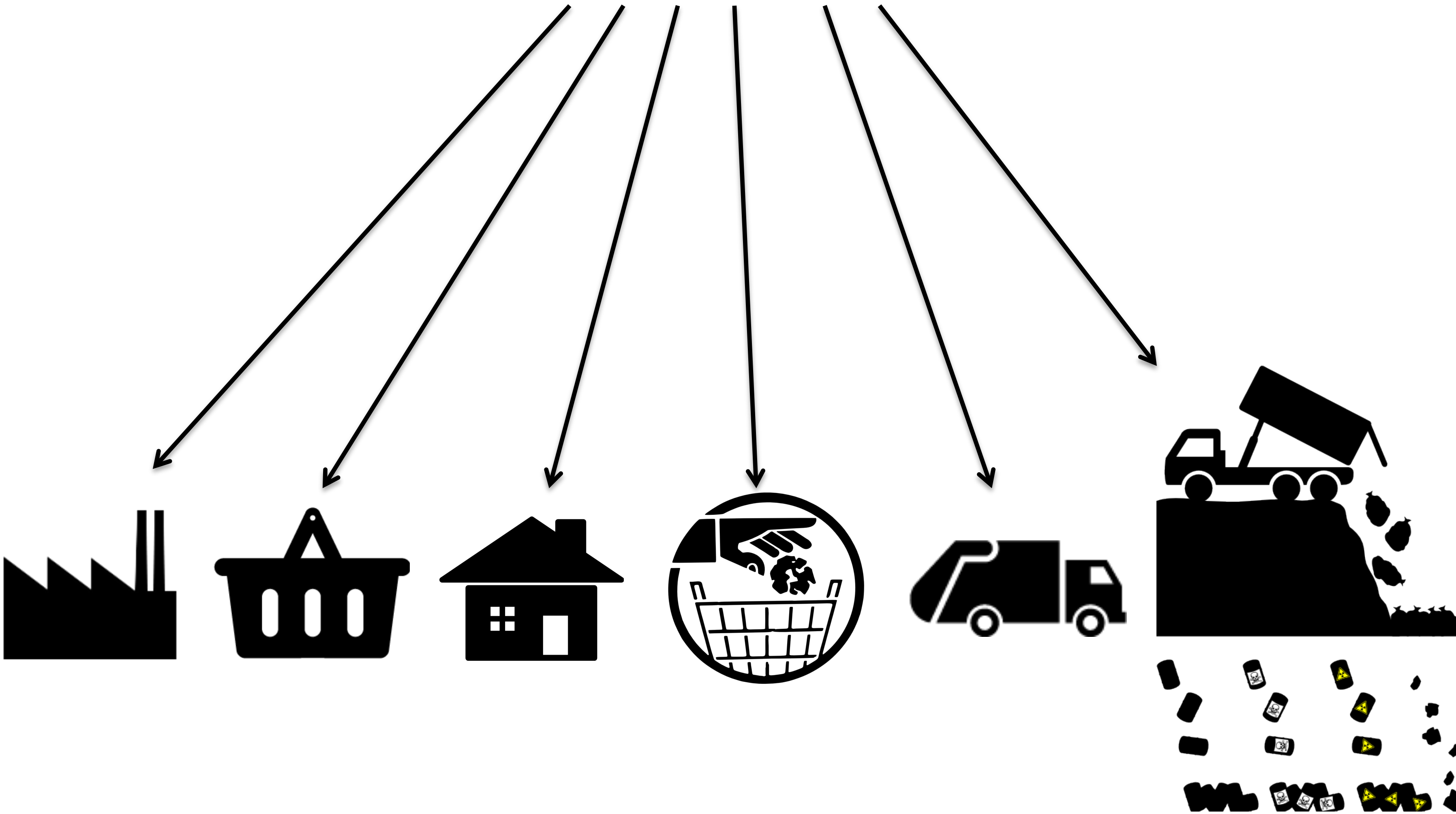
Government of South Australia

Department of Environment, Water and Natural Resources

AECOM

what is zero waste?

where do we measure waste?



2.5Kg

Amount of waste produced by average Adelaide-ian each day (2012)

Is this accurate?
What does it mean?

LOCAL

GLOBAL

Look up the item you need to recycle and check the coloured code next to that item. Match the code to the key list provided.

R	Recycling bin (yellow lid)	H	Hard waste collection	B	Beverley Waste Management Centre	Y	Yellow pages for specialised professionals
O	Organics bin (green lid)	L	Library	W	Wingfield waste and recycling centre	S	Local charity shops, op shop etc
G	Waste bin (blue lid)	P	Local pharmacies/chemists	Z	Zero waste hazardous waste depot	A	Australia post – Cartridges 4 Planet Ark program
C	Compost (Backyard)	C	Council Civic Centre	M	Mitre 10 stores	SM	Supermarkets

A			
Aerosol cans	R		
Aluminium foil (in a ball)	R		
Aluminium cans	R		
Asbestos	Y		
B			
Band-aids	G		
Batteries (mobile phone)	L		
Batteries (household)	G		
Batteries (car)	B		
Biscuit trays	R		
Bottles (plastic and glass)	R		
Bottle tops (plastic)	R		
Bottle tops (metal)	R		
Boxes (cardboard)	R	W	
Boxes (polystyrene foam)	G		
Branches	O	C	B
Bricks /rubble	B	W	
Building material	B	W	
C			
Cake trays (plastic)	R		
Car/auto parts	W		
Car tyres	B		
Cardboard	R	B	W
Carpet and underlay	H	B	W
Cartridges (printer/toner)	A		
Cassette tapes	G		
Cat litter	G		
Cat poo	O	G	
Cellophane	G		
Ceramics	S	G	
Chemicals	Z		
Chocolate wrappers	G		
Cigarette butts	G		
Cling wrap/plastic film	G		
Clothes	S	G	

Compact discs	G		
Computers	B		
Concrete	W		
Crockery	S	G	
Cutlery (metal)	S	G	
Cutlery (plastic)	G		
D			
Door mat	G		
Dog poo	O	G	
E			
Egg cartons	R		
E-waste (Computers and TV's)	B		
F			
Fluorescent tubes	B	M	
Foam boxes	G		
Foam cups/trays	G		
Foil and foil trays	R		
Food scraps	O	C	
Fruit and vegetable scraps	O	C	
Furniture	H	B	W
G			
Garden waste	O	C	
Gas bottles	Z		
Glad wrap	G		
Glass bottles and jars	R		
Glasses (drinking)	S		
Grass clippings	O	C	
H			
Hot water units	H	B	W
Household chemicals	Z		
I			
Ice cream containers	R		
J			
Jars (glass and plastic)	R		
Jar lids (metal and plastic)	R		
Junk mail	R		

L			
Leaves	O	C	
Light globes/bulbs	M	Z	
Linen/towels/sheets	S	G	
Lolly wrappers	G		
M			
Magazines	R		
Margarine containers	R		
Mattresses	H	B	W
Meat	O	G	
Meat tray (polystyrene foam)	G		
Meat tray (plastic)	R		
Medicines	P	Z	
Milk bottles	R		
Milk cartons	R		
Mobile phones	L	B	
N			
Nappies	G		
Newspaper	R		
O			
Oil - cooking	O	G	
Oil - motor	B		
P			
Paint	Z		
Paint tins (empty and dry)	R		
Paper	R	O	
Paper towel	R	O	
Pet food cans	R		
Pharmaceuticals/medicines	P	Z	
Phone books	R		
Pizza boxes	R	O	
Plant pots (plastic)	R		
Plastic bags	SM	G	
Plastic cups and plates	R		
Plastic wrappers	G		
Plasterboard	B	W	

Polystyrene	G		
Printer cartridges/toners	A		
Pyrex ovenware	S	G	
R			
Rags	G		
S			
Scrap metal	H	B	W
Shoes	S	G	
Smoke alarms	Z	G	
Shrink wrap	G		
Steel cans	R		
Syringes (must be in approved containers)	C		
T			
Take away containers (empty)	R		
Tea bags	O	C	
Televisions	B		
Timber	H	B	W
Tissues	O	C	
Toilet paper rolls	R	O	
Toner/printer cartridges	A		
Tools	H	B	W
Toothpaste tubes	G		
Toys	S	G	
Tyres	B		
V			
Vacuum cleaner dust	O		
W			
Weeds	O		
Whitegoods	H	B	W
Window glass	H	B	W
Wrapping paper	R		
X			
X-rays (Red Cross only)	S		
Y			
Yoghurt containers	R		

AVOID

REDUCE

REUSE

RECYCLE

RECOVER

TREAT

COLLECT

DISCARD

POLLUTE

“Waste is…

…the absence of value”

Dr. David Halperin

Waste is
subjective and contextual

>

What role does
information and infrastructure
play in waste creation?

AVOID
REDUCE
REUSE
RECYCLE
RECOVER
TREAT
COLLECT
DISCARD
POLLUTE

REUSE x1000 better than
RECYCLE
in terms of waste reduction

~70%

Diversion from landfill
(SA, 2012)

Is this accurate?
What does it mean?

IS THERE A DEMAND FOR WASTE?

“Waste is…

…a misallocated resource”

Prof. Steffen Lehmann

Waste can be a combination of many resources…
…a compromise that reveals priorities…

~~WASTE DEMAND~~

RESOURCE DEMAND

So… is

ETW…M

more appropriate?

RESOURCE DEMAND

IS DEPENDENT ON

DESIGN AND BEHAVIOUR

What are the barriers to long-term forecasting?

MOBILITY
BORDERS
OFFSHORING
TIME FRAMES
INNOVATION
VALUE

What different ways can we use the tool?

PREDICTIVE
EXPLORATORY
PREVENTATIVE
SPECULATIVE
BACKCASTING

WASTE AVOIDANCE:

BUILT ENVIRONMENT

LIFESTYLE

MINDSET/PURPOSE

SCENARIO A vs. SCENARIO B

SCENARIO A	SCENARIO B
LOCAL	GLOBAL
SELF BUILT	DEVELOPED
ZERO WASTE	FOR PROFIT
SELF-SUFFICIENT	RESOURCE DEPENDENT
DECENTRALISED	CENTRALISED
ADAPTABLE	FIXED
NATURAL	ARTIFICIAL
AFFORDABLE	MORTGAGED
HOME	INVESTMENT

Which scenario seems more “low carbon” or “zero waste”?

Avoidable waste is caused by
a mismatch of intent
between consumer and producer

>

Who should be using our tool?

ZERO WASTE
IS A MOVING TARGET*

Real-time data
Feedback
Short-term forecasting
Participatory design
Investment strategies
Governance
Adaptation
Innovation