Victorian Electricity Forecast Report 2009

VENCorp

Victorian Energy Networks Corporation

CONTENTS

1 Introduction

This report is a complementary report to the Victorian Annual Planning Report (VAPR) and presents background information to the forecasts including forecast assumptions, approach and methodology. Furthermore, this report provides analysis on the historical relationship between electricity consumption and weather.

In this report:

- Section 2 presents the energy and peak demand forecasts basis;
- Section 3 presents the forecast methodology;
- Section 4 presents the relationship between maximum demand (MD) and temperature;
- Section 5 presents the relationship between Energy and Average Temperature; and
- Section 6 provides definitions of terms used in this report.

2 Forecast Basis

Victorian regional energy and demand projections are prepared in accordance with the definitions, assumptions and procedures agreed by the Load Forecasting Reference Group (LFRG), working group of the Inter-Regional Planning Committee (IRPC), convened by NEMMCO. The LFRG ensures that the projections through the NEM are developed on a consistent basis

NEMMCO engage a consultant to supply medium, high and low economic, demographic scenarios and projections of non-scheduled, exempt and semi-scheduled generation.

The maximum demand forecast output is in the form of a Probability of Exceedence (POE) which refers to the probability that a forecast maximum demand figure will be exceeded. For example, a forecast 10% POE maximum demand figure will, on average, be exceeded only 1 year in every 10. The maximum demand forecast gives 9 outputs e.g. for each economic scenario (high, medium and low) there are a corresponding three POE forecasts (10%, 50% and 90%).

All forecasts are modelled using a ‘business as usual‘ approach meaning that all policy impacts are added to the final forecast and not included as part of the modelling.

2.1 Energy Forecasts

VENCorp produce and publish native energy forecasts with a ten year outlook each year. VENCorp‘s regional energy forecasts are developed using a high level top-down econometric approach.

Energy forecasts are produced for three economic scenarios, representing a medium growth scenario (most likely outcome), a high growth scenario (optimistic outlook) and a low growth scenario (pessimistic outlook). The key drivers for energy consumption growth include:

- economic conditions, in particular Victorian Gross State Product (GSP) growth;
- population growth; and
- energy and environmental policy measures.

2.2 Peak Demand Forecasts

VENCorp produce and publish summer and winter peak native demand forecasts with a ten year outlook each year. Peak demand forecasts are prepared on a regional Victorian basis and on an individual connection point basis.

The projections of demand at individual connection points are supplied by Distribution Network Service Providers (DNSPs) and from directly connected customers at each connection supply point in Victoria's shared electricity transmission network. These connection point, or terminal station, forecasts are developed for the medium case economic scenario and for 50% POE and 10% POE conditions.

VENCorp's regional Victorian demand forecasts are developed using a simulation model. Demand forecasts are prepared for the medium, high and low energy forecasts and for the 10% POE, 50% POE and 90% POE conditions under each energy forecast. The peak demand forecasts exclude any short term demand side curtailment activity managed by retailers.

The key drivers of peak demand usage, in addition to economic and policy impacts, include:

- weather conditions at time of peak;
- air conditioning or electric space heating penetration; and
- customer responsiveness to weather conditions.

2.3 Native Demand

The terms *native* energy and *native* maximum demand (MD) are used to denote load which is supplied by generating units that are dispatched by NEMMCO *and* by significant generating units that are not dispatched by NEMMCO.

Generating units dispatched by NEMMCO, that is units that have their output scheduled by NEMMCO through the central dispatch process, can be classified as either scheduled or semi-scheduled. Note that semi-scheduled is a new registration category that became effective on 31 March 2009. Generating units that are not dispatched by NEMMCO are classified as non-scheduled or exempted. Significant non-scheduled and exempted refers to generating units that have a nameplate rating of 1 MW or more for which VENCorp has access to actual generation data.

Generally generating units with an aggregate nameplate rating of:

- 30 MW or greater are classified as scheduled or semi-scheduled (unless NEMMCO approves otherwise);
- less than 30 MW are classified as non-scheduled (unless NEMMCO approves otherwise); and
- less than 5 MW are exempt from registration.

Generating units with a nameplate rating of 30MW or greater can be classified as non-scheduled if it is not practical for the unit to participate in NEMMCO's central dispatch process. Prior to 31 March 2009 this included generating units with intermittent output such as wind generators. From 31 March 2009 generating units with intermittent output can be classified as semi-scheduled.

3 Methodology

VENCorp engage the National Institute of Economic and Industry Research (NIEIR) to produce independent long-term electricity demand forecasts based on three economic scenarios. NEMMCO engage a consultant to provide reports containing economic forecasts and forecasts of non-scheduled and exempted generation in the NEM regions. NEMMCO make these reports available to VENCorp, and their consultant NIEIR, as well as publishing the reports on their website in July of each year.

VENCorp consults with NEMMCO and the Load Forecasting Reference Group (LFRG) to ensure consistency in forecasts across the NEM states.

This section outlines the methodology used to prepare the forecasts. Forecasts are prepared for the following aspects of demand:

- summer and winter native maximum demand;
- annual native energy;
- annual energy supplied by non-scheduled, exempted and semi-scheduled generating units; and
- contribution at time of peak demand supplied by non-scheduled, exempted and semi-scheduled generating units.

3.1 Load Forecasting Reference Group

The Load Forecasting Reference Group (LFRG) is a working group of the Inter-Regional Planning Committee (IRPC). It advises the IRPC on load forecasting matters and seeks direction and approval from the IRPC. Membership of the working group consists of representatives from each jurisdictional planning body (JPB) and a convenor representing NEMMCO.

The main role of the LFRG is to ensure that the energy and maximum demand projections across the NEM are developed by JPBs on a consistent basis and delivered to NEMMCO in a timely manner for the production of the NEMMCO SOO.

The LFRG meets on an as-required basis to discuss areas of improvement for the load forecasting process.

3.2 Maximum Demand Forecast Methodology

<u>Historical Approach</u>

In VENCorp's Electricity Annual Planning Reviews (EAPRs) up to 2006, the 10%, 50% and 90% POE summer and winter MD projections were based on 10%, 50% and 90% POE of temperatures. For example, the Victorian 10% POE summer MD was based on an average daily temperature of 32.9°C which is the temperature not expected to be exceeded more than 1 in 10 years.

The forecast 10% POE summer MD defined as such:

- also takes into consideration the effect of a sequence of extreme temperatures on demand; and
- is assumed to fall in February when schools and industries return after the extended Christmas – New Year holiday

NEMMCO engaged the consultants KEMA in 2004/05 to review the SOO forecast process including the definition and the forecast method used to generate the POE MD. The KEMA report:

- concluded that the POE of the forecast 10%, 50% and 90% POE MDs based on POE temperatures did not reflect the defined and target POE for the forecast POE MD; and
- recommended that the above definitions and methodologies used by the Jurisdiction Planning Bodies (JPBs) for forecasting summer and winter POE be reviewed

The required changes were implemented for the summer MD forecasts in the 2007 EAPR and NEMMCO's 2007 SOO. In 2008 NIEIR refined the simulation forecast approach and also applied the technique to the winter MD forecasts.

Current Approach

The maximum demand model structure is based on a fairly intuitive conceptual framework. At the core of the conceptual model is the relationship between demand and prevailing weather conditions. Other influences and underlying drivers of demand are then built on and around this relationship. The relationship between weather and demand is driven, in large part, by the use of space conditioning equipment. As weather conditions warm, space conditioning equipment is used in greater numbers and more intensively, driving electricity demand higher. All other things being constant, the extent of additional demand depends on the severity of the weather conditions and the responsiveness of consumers to weather conditions.

The proportion of weather sensitive demand will depend on the weather conditions of day. This is one of the reasons there are large variations in observed demand within days and between days. A certain proportion of electricity demand is, however, insensitive to weather conditions. This part of demand reflects consumer activities that occur, irrespective of the prevailing weather conditions such as activities associated with industrial processes.

Electricity demand has, however, a greater range of influences than prevailing weather conditions. Many business and domestic activities routinely occur at certain points during the day. As a consequence, electricity demand can often exhibit diurnal variations. Some activities such as lighting are also highly influenced by the availability of daylight, which is determined by the time of day. Weather conditions are also reflective of the time of day (the warmest part of the day is typical in the afternoon). Weather sensitive demand will vary with the course of the day in large part, due to available light.

The maximum demand model is designed to measure 'time-of-day' effects on both weather sensitive and insensitive demand. Given the time-of-day influences, the demand-weather relationship itself will vary with the day. For instance, the relationship between demand and weather at say 4:00 p.m., may be quite different to the relationship at, say 12:00 p.m. The above demand-weather relationship, therefore, is modelled individually for (selected) periods during the day. This approach, a common practice in electricity demand modelling, allows a greater focus on the key influence of demand (e.g. weather influences), yet adequately controlling for important time-of-day effects.

Many consumer activities are also influenced by weekly events and public holidays. These activities tend to be associated with business operations. Electricity demand on normal business weekdays is generally higher than on weekend and public holidays. The maximum demand model captures these influences on demand within each half-hourly regression model.

Electricity demand has, also, additional influences than those associated with current events and conditions (i.e. weather, daylight, day-to-day business operations and day of week activities). Demand is also a function of the stock of electrical equipment in residential, commercial and industrial sectors. However, changes in the stock of equipment have a more subtle impact on electricity demand. For instance, an increase in the stock of electrical equipment does not necessary imply an increase in demand. The conditions, such as warmer weather conditions or higher production orders, need to be present for the stock change to have any effect on observed electricity demand.

Another premise underlying the maximum demand model is that electricity demand consists of two parts: a systematic part and a random or stochastic part. Observed electricity demand is an outcome of an enormous number of (largely) independent decisions by households and businesses to use electrical equipment. These decisions are reflective of current events and circumstances faced by a wide range of residential, commercial and industrial consumers. However, like any human behaviour, there is an element of randomness or irregularity in the decision to use an electrical appliance. Individual consumers may respond differently to precisely the same circumstances for no obvious or measurable reason.

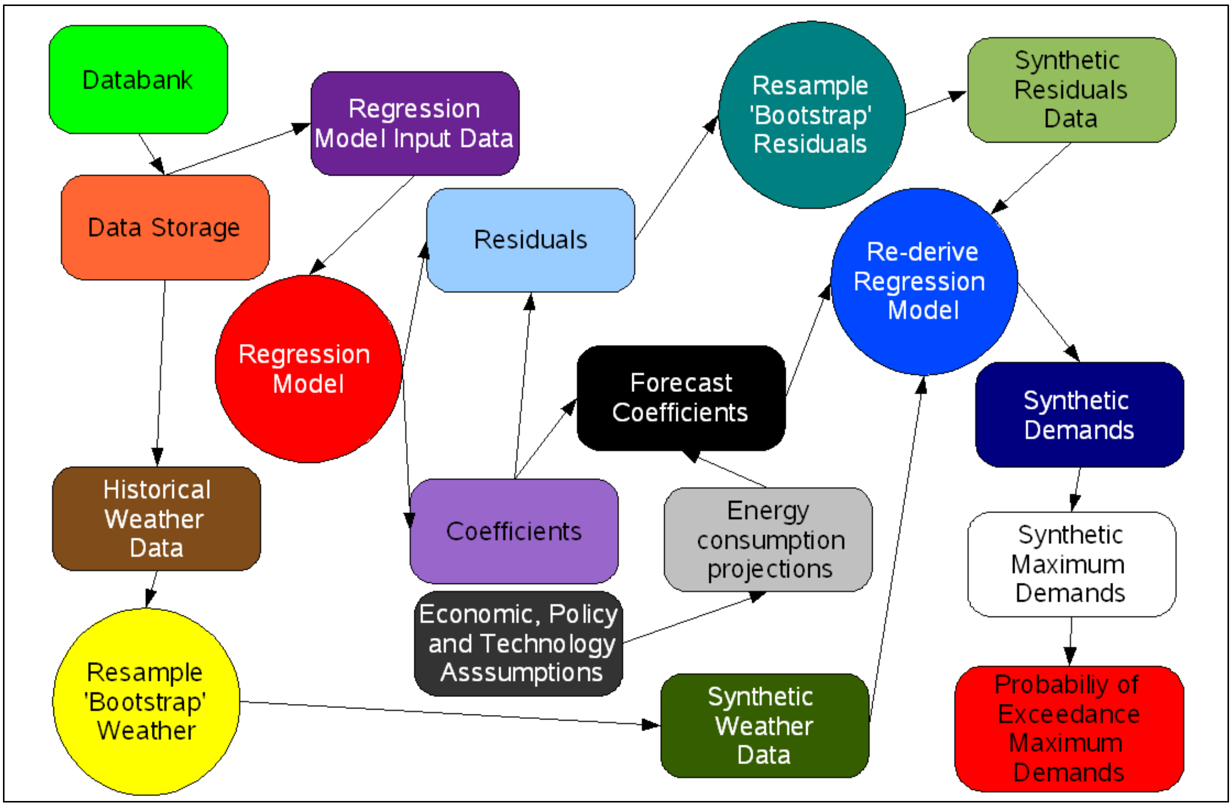
The randomness of consumer behaviour, however, only accounts for a part of the instantaneous unpredictability of electricity demand. The conditions that consumers face are also random; namely, weather conditions. While weather conditions follow some systematic patterns such as yearly seasonality, there is an element of randomness to the conditions observed on any particular day. As a consequence of this randomness, alternative realisations of electricity demand could have been observed had a different set of (random) weather conditions occurred. Thus, the historically observed levels of electricity demand are just one set of many possible alternative realisations of electricity demand.

The maximum demand model utilises the variability of both consumer behaviour and historical weather conditions to generate alternative realisations of electricity demand. A statistical sampling technique called ‘bootstrapping’ is used to generate synthetic or artificial sequences of residuals and weather conditions. These sequences are re-combined with the estimated regression parameters to create a synthetic sequence of demand.

By generating a large number of alternative demand sequences, a picture of the range and frequency of electricity demand can be generated from synthetic demand sequences. Pooling the synthetic demand sequences together, a (relative) frequency distribution of possible demand readings can be created. This frequency distribution can be used to estimate the likelihood of a particular value occurring. Importantly, it can say something about the likelihood of values that may not have been observed in the original historical demand readings.

Figure 3-1 presents a diagrammatical representation of the dataflow of the maximum demand empirical model.

Figure 3-1: Dataflow of the maximum demand model



The starting point of the dataflow model is the 'Databank' (denoted by the light green rectangle). The 'Databank' contains historical readings of electricity demand and weather. Data from this file are transferred to a database file, called a 'recordset'. This is denoted by the orange rectangle labelled 'data storage'. The dataflow model branches off into two directions: regression analysis and weather bootstrapping.

Regression analysis

Data from the recordset file is filtered by season and important weather indicators are derived (denoted by 'regression model input data'). This data is used in the regression analysis (denoted by the red circle). The maximum demand regression model encompasses the following linear structure.

$$
\begin{aligned}
D_{d,,h,\,y} = {} & a0_{h,\,y} + a1_{h,\,y} * CDHH_{d,h,\,y} \\
& + a2_{\,h,\,y} * Sat_{d,y} \\
& + a3_{\,h,\,y} * Sun_{d,y} \\
& + a4_{\,h,\,y} * Aus_{d,y} \\
& + a5_{\,h,\,y} * Outlier_{d,y} \\
& + ed_{\,h,\,y}
\end{aligned}
$$

Where:

- $D_{d,h,y}$ is the demand readings for day d, half hourly interval h in year, y;
- $CDHH_{d,h,y}$ is the cooling degree half hour reading for day d, half hourly interval h in year, y;
- $Sat_{d,y}$ is a dummy flag for Saturdays, $Sun_{d,y}$ is a dummy flag for Sundays, $Aus_{d,y}$ is a dummy flag for Australia Day public holiday on a weekday, $Outlier_{d,y}$ is a dummy flag for Outliers; and
- $e_{d,\,y}$ is the estimated model residuals for day d in a year,y.

CDHH is calculated using the following formula:

$$CDHH_{d,h,y} = \max(0, \text{Composite Weather Indicatordh,y} - 22) * (T_{d,h,y} / M_{d,y})$$

Composite Weather Indicator is calculated using the following formula:

$$\text{Composite Weather Indicator}_{d,h,y} = x*T_{d,h,y} + y*O_{d,y} + z*M_{d,y}$$

Where:

- $T_{d,h,y}$ is the contemporaneous temperature reading on day d, half hourly interval h in year, y;
- $O_{d,y}$ is minimum or overnight temperature on day d in year, y;
- $M_{d,y}$ is maximum temperature on day d in year, y; and
- x, y, and z are selected constants.

Using least squares methods, the above equation is estimated separately for each half hourly interval, h, in each year, y. In total, there are (y times h) equations estimated. The estimation period for each equation encompasses weeks 3 to 10 (that is, most of January, all of February and the first week of March). The other days of summer are excluded to keep the model's functional structure simple.

The regression model has two key outputs (denoted by the rectangles labelled 'residuals' and 'coefficients' in the dataflow diagram). As demand grows, the residuals' dispersion is likely to grow too. To ensure the residuals are interchangeable between years, the residuals edh,y are normalised relative to the coefficient estimate, a1h,y. The normalised residuals form the sample for the bootstrapping (i.e. the creation of synthetic residual sequences).

<u>Simulation models</u>

One thousand synthetic residual sequences for each half-hour interval, h, in each year (historical and forecast) are simulated using a block bootstrap method (denoted by the green circle labelled 'Resample 'Bootstrap' Residuals' in the dataflow model). To preserve the error structure of the equation, the residuals are sampled by daily blocks, ensuring residual edh,y is sampled into its respective half hour interval, h. In total, there are (1000 times h time d) synthetic residual observations generated for each year.

Separately, one thousand synthetic weather series for each half-hour interval, h, in each year (forecast and historical) is simulated using a similar sampling technique (This is denoted by the yellow circle in the dataflow diagram). The synthetic weather series are sampled from daily and half-hourly readings over the period 1995-96 to 2008-09. These synthetic series were simulated using a 're-weighted' fixed block bootstrap method. To preserve the dynamic structure of the short-term and seasonal weather cycles, the weather data are sampled by weekly blocks that are matched with corresponding weeks in the synthetic sequence. Also, to ensure that warming in climatic conditions due to urban and global warming is adequately reflected in the derived weather distribution, a 're-weighted' bootstrap technique is used . The 're-weighted' approach assigns a greater likelihood to recent year's weather data relative to older historical data in the sampling process.

<u>Derivation of synthetic demands</u>

A key input into the derivation of synthetic demand sequences is the estimated regression coefficients. For forecast years, these estimated coefficients are projected for using energy consumption projections. These projections are developed outside the maximum demand model framework.

The estimated constant, a0h,y, is projected forward using growth in weather insensitive energy consumption projections. The estimated dummy coefficients, a2h to a4h, are also projected forward using growth in weather insensitive energy consumption projections. The forward projections of the weather coefficient, a1h,y, are derived from growth projections of weather sensitive energy consumption.

One thousand synthetic demand series for each half hour interval, h, are derived for each year (historical and forecast) using the synthetic temperature and residual information, and the respective historical and forward coefficient estimates. This is denoted by the blue circle labelled "re-derive regression model" in the dataflow diagram.

The highest summer reading from each of the 1,000 synthetic summer demand series is then identified for each (historical and forecast) year. The 90th, 50th and 10th percentile values of these one thousand maximum demand readings are calculated. The 90th, 50th and 10th percentile values provide the 10%, 50% and 90% probability of exceedence projections, respectively.

3.3 Annual Energy Forecast Methodology

The energy projections take into account:

- economic, financial and industrial conditions;
- stock and technological changes in the electrical equipment and appliances; and
- energy and environment policy measures and price assumptions.

Native energy forecasts

Native energy forecasts are generated using the following approach:

- forecasting end-use energy consumption for the residential, commercial, industrial and public lighting sectors; then
- adding distribution and transmission losses to the above end-use energy forecasts; and
- adding forecast load used by generators.

Forecast end-use energy is derived from an econometric model which includes the following input variables:

- Victorian GSP projections;
- projected energy prices (gas and electricity);
- Alcoa annual energy forecasts provided by VicPower Trading;
- major new private and government projects;
- projected population growth and residential building activities;
- projected household disposable income;
- projected penetration of appliances including air-conditioner units and unit capacity;
- impact of energy conservation measures including the use of innovative technologies to drive energy efficiency; and
- impact of the Victorian and Commonwealth government energy policies or proposals.

3.4 Non-Scheduled generation forecasts

NEMMCO engaged KPMG to prepare the non-Scheduled generation forecasts for the NEM, which involves the following process:

- NEMMCO, in conjunction with the Load Forecasting Reference Group (LFRG), surveyed the operations of existing non-scheduled generating units connected to their networks.

The survey also covered registered wind farm operators in each region. NEMMCO provided the survey results to KPMG and VENCorp.

- VENCorp provided KPMG with details of new wind farm projects which are likely to connect to the Victorian transmission system over the next 10 years. KPMG also determined the expected contribution factors and annual capacity factors of these wind farms.
- KPMG prepared the projections using NEMMCO's survey results, VENCorp's information and KPMG's own database of non-scheduled generation projects. The projections also take into consideration the impact of the Commonwealth and State governments' energy policies and initiatives.

4 Relationship between Maximum Demand and Average Temperature

Summer native maximum demand

This section discusses:

- the relationship between Victorian summer native MD and temperatures; and
- the increasing trend in the temperature sensitive component of summer native MD.

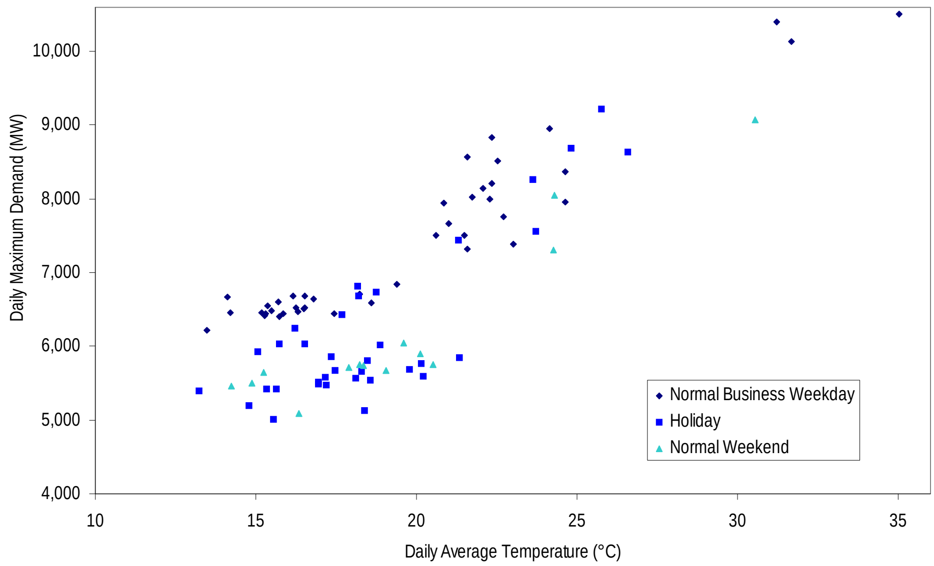
Victorian summer native MD is highly dependent on weather and normally peaks around 4:00pm (AEST) on most summer weekdays. However, an early cool change in weather before 4:00pm on a hot summer day will see the demand falling sharply within a short space of time.

Daily average temperature can be used to demonstrate the temperature sensitivity of summer native MD. See Section 6 for the definition of daily average temperature.

Figure 4-1 depicts the dependence of the 2008/09 summer native MD on temperatures for three different day types:

- normal business weekdays: these are Mondays – Fridays outside the extended Christmas – New Year period;
- normal weekends: these are Saturdays and Sundays outside the extended Christmas – New Year period; and
- holiday: 20 December 2008 to 23 January 2009. In general, the demand between Christmas and New Year holidays is the lowest (about 5,000 MW) but gradually ramps up after New Year to reach typical levels of demand by the end of the third week in January.

Figure 4-1 Daily 2008/09 summer native maximum demands and daily average temperatures



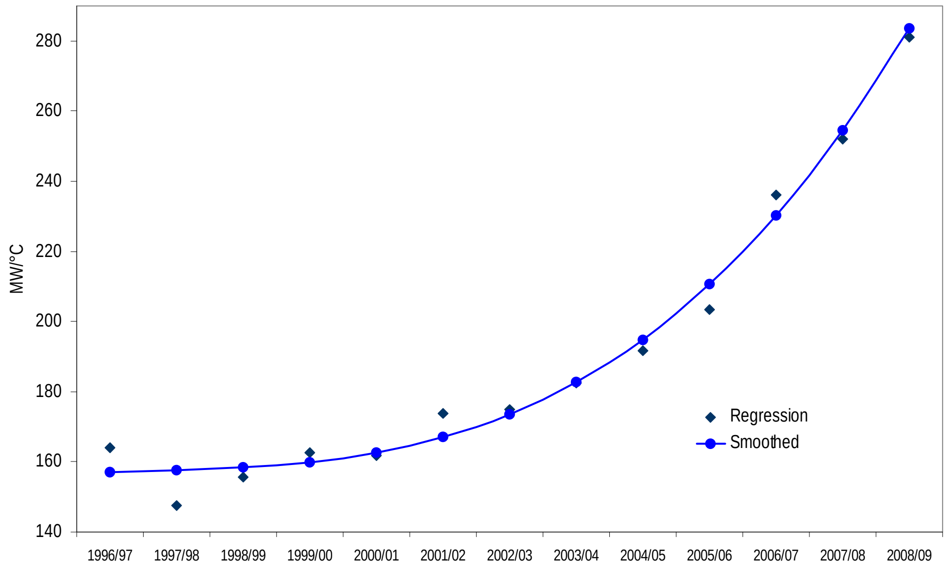
The temperature sensitive component of summer native MD depends on the average temperature of the current day and:

- temperatures of previous days;
- the maximum temperature of the current day, when it occurs and how long it lasts. A cool change in temperature in the early afternoon will result in a lower MD than what would have normally been expected;
- the overall summer weather conditions;
- day type (weekdays, weekends and holidays); and

- time of the season. For example, temperature sensitive demand in January is normally lower due to school closures.

Figure 4-2 shows that the temperature sensitivity for summer weekday native MD has grown rapidly over the last 10 years from about 160 MW/°C in 1996/97 to about 281 MW/°C in 2008/09. In relation to native MD, temperature sensitivities measure the increase in native demand for each degree change in daily average temperature. The increase is due largely to increased air-conditioning penetration and population growth.

Figure 4-2 Temperature sensitivities for summer weekday Scheduled maximum demand



Winter native maximum demand

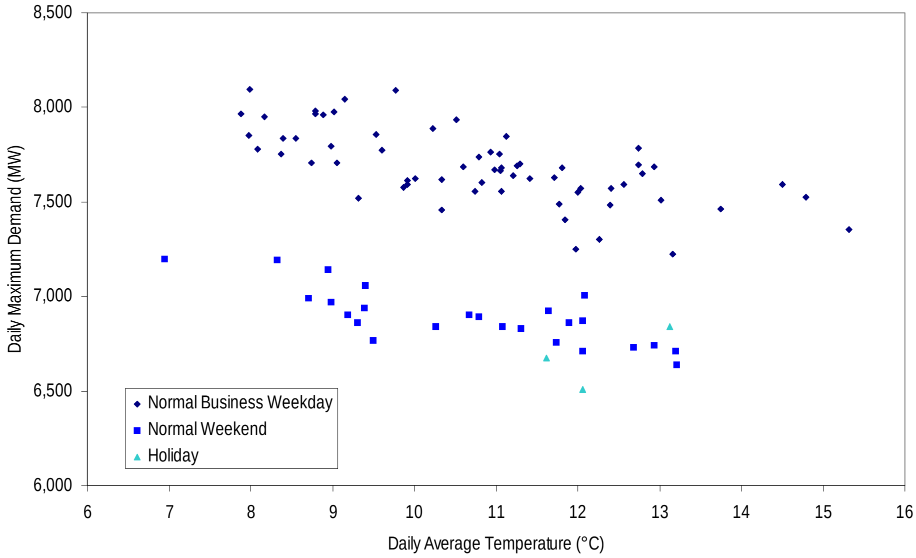
This section discusses the dependence of Victorian winter native MD on temperatures.

Victorian winter native MD normally peaks around 6:00pm or 6:30pm on most winter weekdays. Winter native MD is less dependent on weather because gas is used for space heating in about 80% of Victorian homes. The volatility in winter native MD is related to other household activities such as cooking, lighting and entertainment which occur at times of winter peak demand.

Figure 4-3 depicts the dependence of the 2008 winter native MD on temperature for three day types:

- normal business weekdays: these are Mondays – Fridays except Queen's birthday Monday;
- normal weekends: these are Saturdays and Sundays except the weekend before Queen's birthday; and
- holiday: Queen's birthday weekend and Monday.

Figure 4-3 Daily 2008 winter native maximum demands and daily average temperatures



Temperature sensitivity for winter native MD is about 75 MW to 110 MW/°C.

5 Relationship between Energy and Average Temperature

This section discusses the relationship between of native energy and temperatures.

Victorian daily electricity consumption peaks in summer and winter because of increased electricity used for space cooling and heating. Figure 5-1 and Figure 5-2 plot daily Victorian native energy between March 2008 and March 2009 and show that:

- there is a strong correlation between daily native energy and daily average temperatures;
- Saturday and Sunday native energy is lower than weekday native energy by about 10% and 15%, respectively;
- the highest daily native energy occurred in summer; and
- the lowest daily native energy occurred on Christmas day and Public Holidays (PH).

Figure 5-1 Daily native energy and daily average temperatures (March 2008 – March 2009)

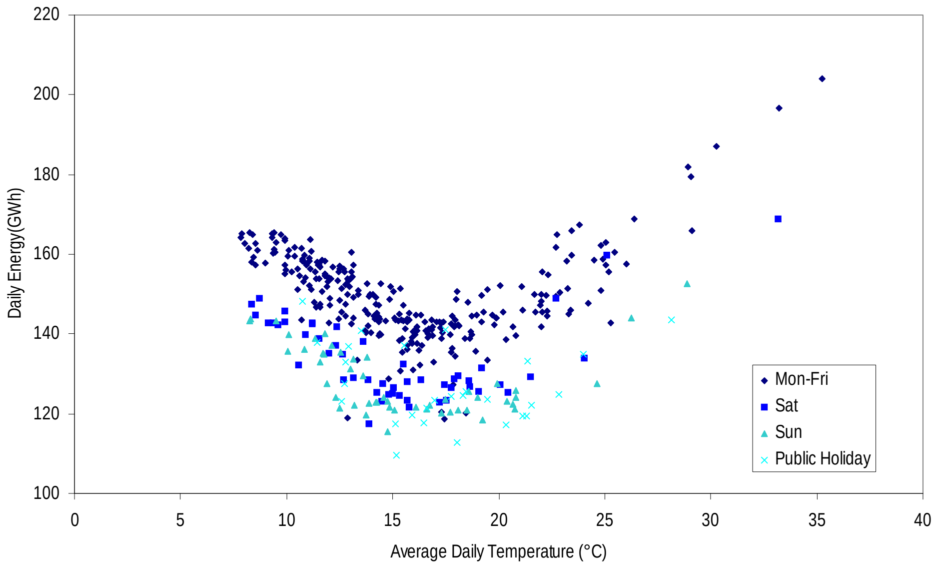
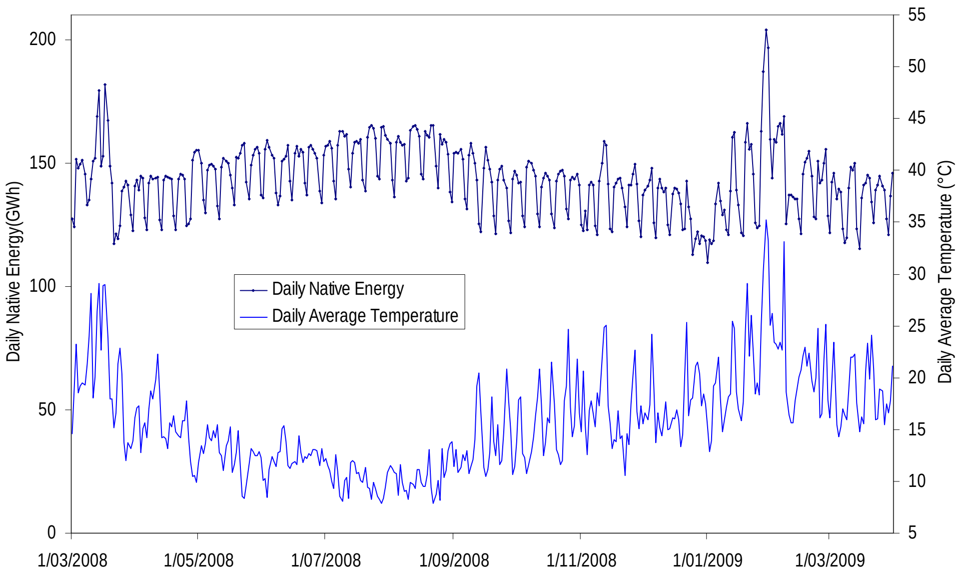


Figure 5-2 Daily native energy and daily average temperatures (March 2008 – March 2009)



Electricity energy used for space cooling and heating was a small component of daily native energy in the past. However, the increased penetration of air-conditioners in homes, and warmer and longer summers in recent years, have seen a rapid increase in the temperature sensitive component of daily electricity consumption.

6 Definitions

Term	Defnition
Central Dispatch	The process managed by NEMMCO for the dispatch of Scheduled generating units and other services in accordance with Clause 3.8 of the Rules.
Demand-Side Response Aggregator	An organisation or agency for the provision and administration of demand-side responses/participation.
Demand-Side Participation	The act of voluntarily shedding load by prior arrangement.
Daily average temperature	The average of the daily maximum temperature (from 9:00am) and the overnight minimum daily temperature (to 9:00am) of a given day measured at the Melbourne weather station.
Generating Auxiliary Load	Load used to run a power station, including supplies to operate a coal mine (otherwise known as “used in station load”).
Generating-Terminal Basis	Refers to the demand for electricity as measured at the generating terminals. This measure includes generating auxiliary loads.
Market non-Scheduled generating	A class of generating (being a generating or a group of generating units) that derives spot market income and whose output is not scheduled as part of central dispatch, either because: • the combined capacity is less than 30 MW; or • they are classified as such (pursuant to he Rules). For example, some producers of intermittent generation, such as wind generation, are classified in this way.
Native Demand	The electricity demand supplied by scheduled and semi-scheduled generating units and significant non-scheduled generating units. Native demand is measured on a generating-terminal basis. For a region, the measure includes the output of scheduled, semi-scheduled and significant non-scheduled generating units within the region plus net imports (imports into the region minus exports from the region).
Non-market non-Scheduled generating	A generating whose entire electricity output is: • sold directly to a local retailer or customers at the same connection point under a power purchase agreement (not through the spot market); and • not scheduled by NEMMCO as part of central dispatch.
Probability of Exceedence (POE)	Refers to the probability that a forecast maximum demand figure will be exceeded. For example, a forecast 10% POE maximum demand figure will, on average, be exceeded only 1 year in every 10.
Region	As recommended by NEMMCO and approved by the AEMC in accordance with Clause 3.5 of the Rules, this is an area served by a particular part of the transmission network and containing one or more major load centres, or generation centres, or both.
Scheduled Demand	That part of the electricity demand supplied by scheduled generating units and net imports. It excludes that part of the demand supplied by non-scheduled generating units. Scheduled demand is measured on a generating-terminal basis. For a region, the measure includes the output of scheduled generating units within the region plus imports into the region minus exports from the region.

Sent-out basis	A measure of demand and energy at the connection point between the generatings and the network. The measure includes consumer load, and transmission and distribution losses.
Significant Non-Scheduled Generation	Refers to all: • market non-scheduled generating units; and • non-market non-scheduled generating units and generating units exempted from registration (with an aggregate capacity greater than 1 MW) for which NEMMCO and the jurisdictional planning bodies have sufficient data to enable the development of energy and maximum demand projections. In Victoria significant non-scheduled generation (i.e. where data is available) is dominated by wind generation projects.
Summer	December to February of a given fiscal year.
Winter	June to August of a given calendar year.