



United Energy Maximum Demand Forecasting Method



This page intentionally blank

Table of Contents

1.	Amendment Record.....	5
2.	Purpose	7
3.	Scope	7
4.	Objective.....	7
5.	Process Flow.....	8
6.	Maximum Demand Forecasting Process	10
6.1	Data Sources	10
6.1.1	Internal data sources	10
6.1.2	External data sources	10
6.2	Collecting Actual Maximum Demands	11
6.3	Weather Correction	11
6.3.1	Excluded days	11
6.3.2	Reference temperature points	12
6.3.3	POE temperature limits.....	12
6.3.4	Weather correction philosophy (bottom-up).....	13
6.3.5	Excel tool.....	14
6.4	Generic Zone Substation Growth	15
6.5	New Large Loads / Retired Loads.....	15
6.6	Diversity Factors	16
6.7	Adjustment for HV Cross Border Flows and Railway Loads.....	17
6.8	Adjustment for Losses	18
6.9	NIEIR Terminal Station Growth Rates	18
6.10	Preliminary Zone Substation 10% POE Summer MW Forecast	18
6.11	Final Zone Substation 10% POE Summer MW Forecast.....	19
6.12	Terminal Station Bus Groups.....	19
6.13	Non-coincident Terminal Station 10% POE Summer MW Forecast.....	20
6.14	Non-coincident Terminal Station 50% POE Summer MW Forecast.....	20
6.15	Non-coincident Terminal Station Winter MW Forecasts.....	20
6.16	Non-coincident Terminal Station MVAr Forecasts.....	20
6.17	TSDf Template	21
6.18	Review of Zone Substation Forecasts.....	21
6.19	Review of terminal station forecasts	21
7.	Embedded Generation and Network Support.....	21
8.	High Voltage Feeder Demand Forecasts	22
9.	Definitions	23
10.	Appendix A – NIEIR’s Peaksim Model.....	26
10.1	Background	26
10.2	Functionality of PeakSim.....	26

10.3	Caveats	26
10.4	Conceptual Model	27
10.5	Demand-weather Relationship	27
10.6	Time of day and day of week effects	28
10.7	Stock of electrical equipment	29
10.8	Variability in demand	30
10.9	Empirical model	31
10.10	Regression analysis.....	32
10.11	Simulation models	33
10.12	Derivation of synthetic demands	34
10.13	PeakSim Accuracy	34
10.13.1	Implied historical PoE distribution.....	34
10.13.2	Model Accuracy	35
10.13.3	Results	36
11.	Appendix B – UE’s EViews Model	39
11.1	Model Approach	39
11.1.1	Framework	39
11.1.2	Modelling stages	40
11.1.3	Model specification.....	40
11.1.4	Model specification.....	41
11.1.5	Model variables	41
11.1.6	Model estimates	43
11.1.7	Key Variables Elasticities and Model Interpretation.....	45
11.2	Running EViews Model.....	45

1. Amendment Record

VERSION	DATE	AMENDMENT OVERVIEW
1	N/A	First Published
2	N/A	2013 Update – Treatment of new large loads and embedded generation
3	N/A	2014 Update – Inclusion of PeakSim model and eViews model. Updated MVAr forecast.
4	12/2014	2014 Update – Inclusion of feeder demand forecasting and eViews model updates.
5	06/2017	2017 Update – Revised PoE temperatures and EViews model updates.
6	10/2019	2019 Update – converted to new template and minor updates

DOCUMENT REVIEW	Date
This Document shall be reviewed every five (5) years or earlier if required. The next review is due on or before	01/10/2024

This page intentionally blank

2. Purpose

The purpose of this document is to detail United Energy's Maximum Demand forecasting method.

This document shall be reviewed every five years and amended as required in order to reflect changes and improvements in the process.

All enquiries relating to this document shall be directed to the email address shown below.

Email: planning@ue.com.au

3. Scope

This document discusses the following key points involved in preparation of the UE maximum demand forecast in detail.

- Data sources
- Collecting actual MDs
- Weather correction
- Adjustment for abnormalities (e.g. load shedding)
- Determining generic (underlying) zone substation growth
- Adjustment for new or retired large loads
- Diversity factors
- Adjustment for cross border flows and railway loads
- Adjustment for losses
- Macro-economic growth rates (e.g. NIEIR) with disruptor post-model adjustments
- Preliminary zone substation 10% POE summer MW forecast
- Final zone substation 10% POE summer MW forecast
- Terminal station bus groups
- Non-coincident terminal station 10% POE summer MW forecast
- Non-coincident terminal station 50% POE summer MW forecast
- Non-coincident terminal station winter MW forecasts
- Non-coincident terminal station MVar forecasts
- TSDF (Terminal Station Demand Forecast) template
- Review of zone substation forecasts
- Review of terminal station forecasts
- Review of distribution feeder forecasts

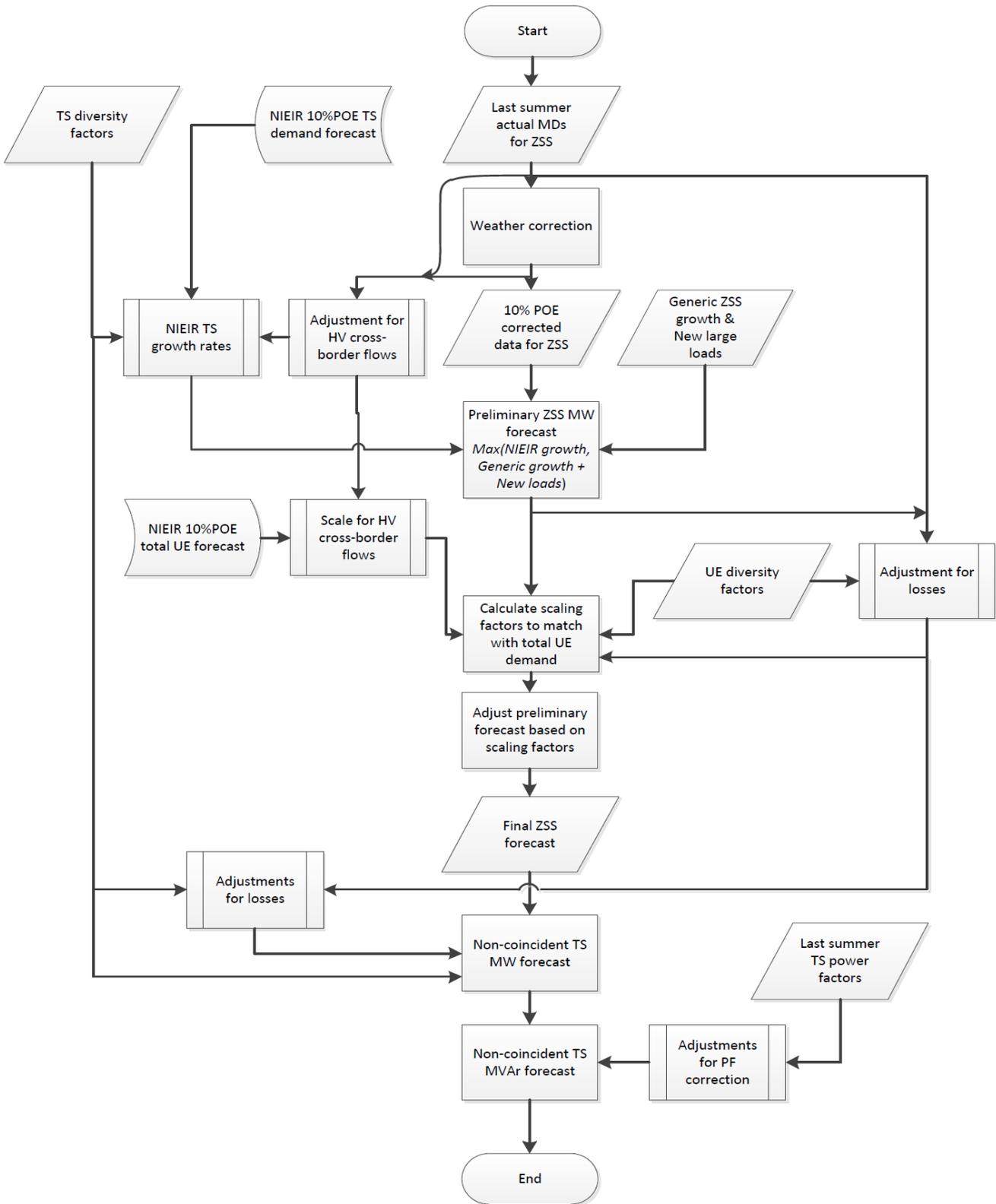
4. Objective

The objective of this document is to ensure:

- a transparent, robust and documented forecasting process;
- a consistent approach to forecasting over time;
- efficient base for future process improvements;
- smooth transition and succession of roles; and
- availability of a suitable training material.

5. Process Flow

A high level flow chart representing the UE Maximum Demand forecasting process is shown below.



6. Maximum Demand Forecasting Process

The UE maximum demand forecasting method is a combination of Bottom-Up forecasting reconciled with Top-Down macro-economic forecasting approaches.

Based on the zone substation weather-corrected actual demands and anticipated localised growth, demand forecasts at individual zone substations are prepared. These zone substation forecasts are aggregated to the corresponding terminal stations based on the relevant diversity factors while adjusting for sub-transmission losses. This will provide the Bottom-Up non-coincident terminal station demand forecasts.

As a first step in the reconciliation, each aggregated Bottom-Up forecast is compared against the non-coincident terminal station Top-Down demand forecasts prepared by NIEIR.

As a second step in the reconciliation, when diversified and aggregated, the Bottom-Up forecast is compared against the total UE Top-Down demand forecast also prepared by NIEIR.

If any difference exists in the Top-Down and Bottom-Up total UE forecasts, the Bottom-Up forecast is scaled to match with the Top-Down total UE forecast, along with all underlying forecasts. This will provide the reconciled demand forecast at terminal stations and zone substation levels. Where the difference is greater than 5%, UE will discuss the variation with NIEIR in order to identify the reason for the discrepancy, then adjust the appropriate forecast accordingly. UE also uses another top-down macro-economic maximum demand forecasting tool developed in eViews¹ by AECOM to provide a basis for comparing the forecasts produced by NIEIR's PeakSim² model. This can also facilitate locating the source of any discrepancy in the forecasts. Further details on these models are provided in the Appendices.

6.1 Data Sources

Both internal and external data are used in the process.

6.1.1 Internal data sources

- **PI historian:** Most of the spreadsheets used in the forecasting process use PI data. All such tools have already been set up and minimal modifications are required. As most of the tools use macros, location of some information and format of the spreadsheets are critical. Due attention should be paid before editing the format (entering new rows or columns, deleting existing rows or columns and moving the existing data into new location) of the tools.
- **IMS:** Interval metering data from the wholesale market is used as inputs in certain places. They are discussed in detail later in this document. Predominantly, this is the same data from the spreadsheets used for the TUOS 10 MD Days calculation. All such data are either highlighted or attached with comments for easy use. Active and reactive power values are generally stored at 30 minute average value intervals in IMS.

6.1.2 External data sources

The NIEIR forecast is the only externally produced document used in the demand forecasting process. The following two forecasts are mainly used in the calculations because these are the forecasts used by UE as part of its probabilistic planning framework across the entire UE network.

- Summer 10% POE total UE demand forecast.
- Summer 10% POE non-coincident TS demand forecast.

However, winter and 50% POE forecasts are used when calculating separate summer/winter 10%/50% POE forecasts for the Terminal Station Demand Forecast (TSDF).

¹ Refer Appendix B

² Refer Appendix A

6.2 Collecting Actual Maximum Demands

As the starting point of the forecasting process, the actual maximum demand, and the date and time of the maximum demand for the last summer need to be collected. Separate spreadsheets have been set up to facilitate extraction of this data as given below. Please follow the hyperlinks for the relevant template.

- [Zone substation](#)
- [Feeders](#)
- [Sub-transmission lines](#)

Data cleansing is not automated in these spreadsheets and due attention should be paid to adjust the demand for abnormalities (load shedding, demand management, load transfers, tripping of sub-transmission lines, transformers and feeders etc. based on records from PI)

These actual maximum demands are calculated assuming the embedded generation at DN (Dandenong Hospital and CoGent) and SS (Springvale and Clayton Landfill) are out of service. Given UE does not have any need for network support agreements with these generators, this approach is considered conservative and appropriate. Depending on the quality of PI data, interval metering data (IMS) may be required to assess the embedded generation contributions. Separate adjustments are made in the zone substation forecast spreadsheet to accommodate the impact of these embedded generators.

Once all the actual demands are ascertained and corrected for abnormalities, they should be copied into the demand forecasting master spreadsheet. Further, as a separate exercise, weather correction is done to the zone substation actual demands in order to estimate the 10% POE equivalent demand during the last summer.

6.3 Weather Correction

For the bottom-up weather correction process, given 2013/14 is the most recent year representing a less than 10% POE profile, this year is treated as the base year to determine the rate of change of demand with high ambient temperature for weather correction purposes. If any year occurs in future with a less than 10% POE, the spreadsheet needs to be updated with that information.

Based on the historical demand profiles in the UE network, a clear difference can be identified in the demand behaviour in the Mornington Peninsula compared with the rest of the network. Given the Peninsula is a holiday destination, peak demands of zone substations in the Peninsula generally occur during the Christmas holiday period or a hot weekend during the summer school holiday period. Therefore, the Mornington Peninsula and the rest of the network are treated independently in the weather correction process. The following zone substations were considered as residing in the Mornington Peninsula.

- Dromana (DMA)
- Frankston South (FSH)
- Hastings (HGS)
- Langwarrin (LWN)
- Mornington (MTN)
- Rosebud (RBD)
- Sorrento (STO)

6.3.1 Excluded days

Excluded days are critical for the base year only as it affects the temperature sensitivity predictions in the bottom-up model.

Mornington Peninsula and the rest of the network were treated differently when selecting excluded days. The following outlines the approach to excluded days for temperature sensitivity predictions:

- Given the Mornington Peninsula is a holiday destination, all the public holidays and weekends were included into the calculation as these are also likely to be high demand days. Only the days having network abnormalities (load transfers, outages, power cuts etc.) were excluded. By nature, this information is zone substation specific and individual entries should be made after observing the load profile of each zone substation.
- The following days were excluded in the calculations for the rest of the network.

- Christmas period – from 15th Dec to 15th Jan
- Weekends
- Melbourne Cup day
- Australia Day
- Labour Day
- Any other days with significant network abnormality
- In order to accommodate any potential omissions and their consequences, a low demand threshold of 55% of the maximum demand was used. Days having peaks below 55% of the zone substation’s annual maximum demand were automatically excluded in the calculation.
- A high demand threshold of 103% of the maximum demand was used to exclude days having abnormally high demands due to load transfers (in case, not captured in abnormal days). A value marginally higher than 100% of the maximum demand was selected here in order to accommodate the data noise that exists in the instantaneous values of the PI data set.

6.3.2 Reference temperature points

In order to represent the temperature profile in the UE network, temperature readings at two BOM weather stations were used in the bottom-up model.

- Mornington Peninsula : Cerberus weather station
- Rest of the UE network : Scoresby weather station

The top-down macro-economic model by comparison uses the Melbourne Olympic Park weather station.

6.3.3 POE temperature limits

NIEIR has defined the 10%, 50% and 90% POE temperature setting for Melbourne based on 50 years of historical data at the Melbourne Regional Office (prior to decommissioning) and Olympic Park weather stations. In 2019 they are as follows³.

POE	Average Daily Temperature ⁴ (°C)
	Summer
10%	34.2
50%	31.0
90%	28.9

In order to establish the corresponding temperatures at Cerberus and Scoresby, UE examined the historical temperature data at these two weather stations. There is not enough historical data (more than 50 years) available at these locations to warrant a site specific POE temperature calculations. However, based on the available data, it was noted that the average temperature at Cerberus is approximately 92% of the temperature at Melbourne Regional Office/Olympic Park during hot days. Similarly, the average temperature at Scoresby is approximately 98% of the temperature at Melbourne Regional Office/Olympic Park.

Therefore the following 10% POE temperature thresholds during summer were defined at Cerberus and Scoresby. These values are to be used in weather correction of the actual maximum demand.

³ Based on NIEIR’s Maximum demand forecasts for United Energy terminal stations to 2030.

⁴ Average of the peak day temperature and the previous night’s minimum temperature.

Location	10% POE Average Summer Temperature (°C)
Cerberus	31.5
Scoresby	33.5

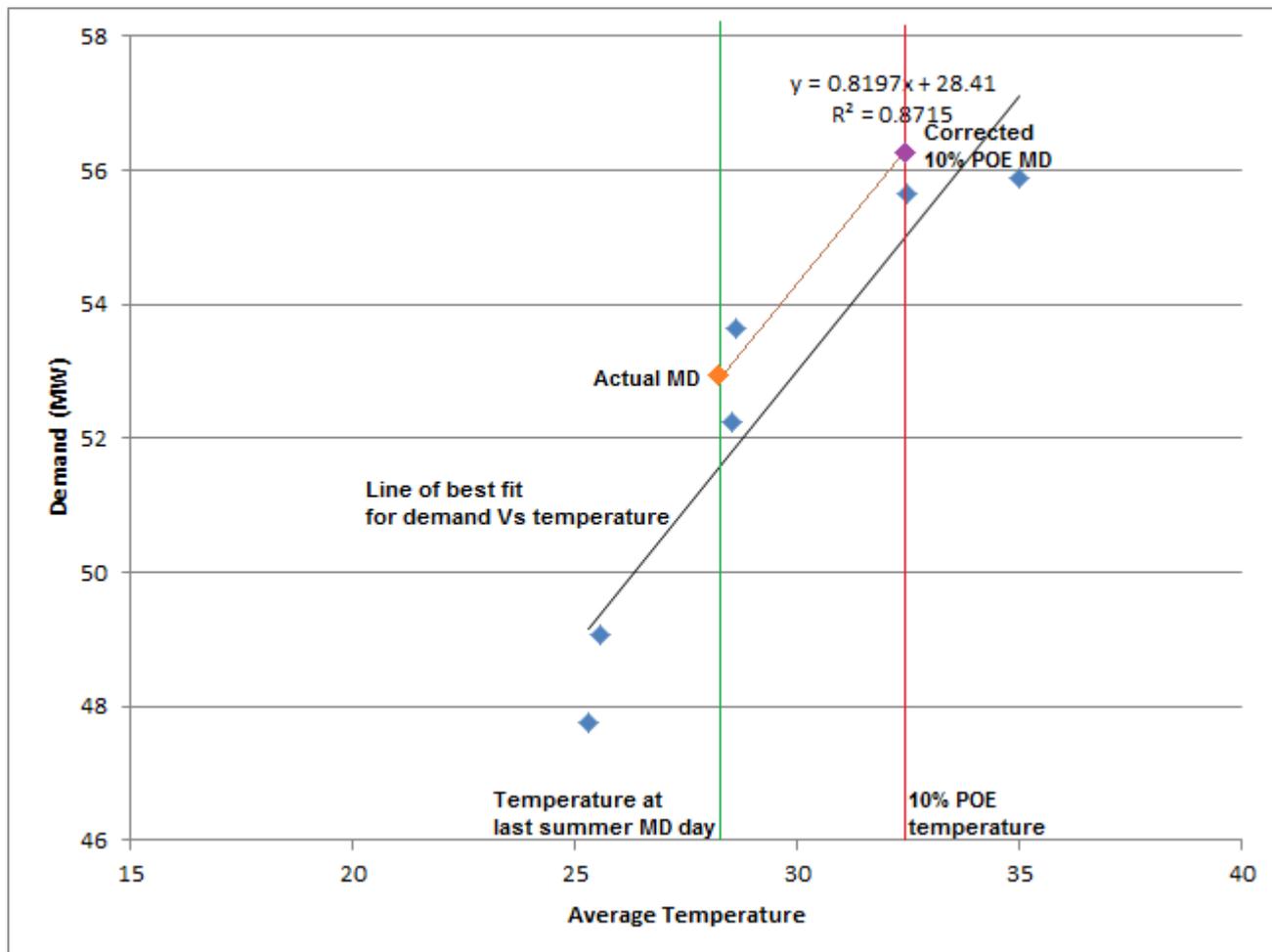
6.3.4 Weather correction philosophy (bottom-up)

The least squares regression analysis was used to estimate the temperature sensitivity of demand at each zone substation based on the demand variations in summer 2013/14 during hot days. Given the demand response is quite different during hot days compared to mild days; the days having average temperature above 25°C were used in the model and this limit is important to capture a reasonable number of data points for the linear regression analysis. For the estimation of the temperature sensitivity of demand in MW/°C, the temperature threshold of a maximum of 3°C less than the average temperature of the MD day or 25°C is selected. This allows the model to capture the saturation effect of the temperature sensitive load as the gradient of the regression line becomes smaller when the average temperature of the MD day increases. Based on this method, the coefficient of temperature sensitivity of demand is estimated at each zone substation.

As the next step, the actual maximum demand at each zone substation together with the average temperature on the peak demand day was recorded. Then the difference between the 10% POE average temperature (31.5°C for Mornington Peninsula and 33.5°C for the rest of the network) and the average temperature on the maximum demand day was multiplied by the estimated temperature sensitivity at relevant zone substation. This will give the demand adjustment in MW for the temperature correction based on the 2013/14 demand characteristic. In order to accommodate growth in temperature sensitive demand, a penetration rate of 1% per annum was assumed and compounded over time. The demand adjustment figure calculated was multiplied by this factor to estimate the total anticipated demand increase due to temperature correction. Given this is an assumption that can have an error accumulating over time, this adjustment should be reviewed annually and if a subsequent summer is less than 10% POE, the demand characteristic should be changed to this subsequent summer. Summation of actual demand and this temperature adjustment will be the estimated 10% POE demand at the corresponding zone substation.

The same approach is used to calculate the 50% POE demand at each zone substation. Instead of 10% POE average temperature, 50% POE average temperature is used in this calculation.

The figure below graphically represents the weather correction philosophy bar the adjustment for growth in temperature sensitive demand.



6.3.5 Excel tool

A separate spreadsheet is prepared to perform the weather correction of actual maximum demands.

The main input data is the last summer actual demand at each terminal station and the date and time that occurred. Further, it may be required to check the relevant PI tag names as they tend to be updated time to time.

Given no aggregated PI tag is presently available to calculate the total demand at RWTS 22kV level, the calculation at RWT is different to the rest of the zone substations. Two separate sheets have been included to perform this calculation. It should be noted that batch processing of weather correction does not include RWT and it should be executed separately as an ad-hoc calculation and updated into the main results sheet.

As a subset of the calculation process, this spreadsheet can produce the UE and TS diversity factors. In order to facilitate this calculation, it requires the times of UE maximum demand and TS maximum demands for the last summer. The “UE 30min boundary load” spreadsheet submitted to NIEIR as input to the Top-Down load forecasting process can be used to extract this information.

Further, this spreadsheet is designed to weather correct the HV metered cross border flows. This is discussed in detail later in the document.

The weather corrected zone substation actual demands should be copied across to the “Zone substations” tab in the master load forecasting spreadsheet.

6.4 Generic Zone Substation Growth

Generic (or underlying) 10% POE growth at a zone substation level is estimated based on the historical forecast at each zone substation. As a start, the least squares regression method was used to estimate the forecast growth based on the last ten years historical 10% POE forecast data. It provides MW/year rate at each zone substation. Where fewer years of historical data was available, the available information or appropriate reference zone substation information was used to calculate the growth.

Given the forecast is going to be based on the 10% POE weather corrected actual demand at each zone substation, this is considered to be an appropriate method. Over time, the growth rate is expected to be self-corrected when forecasts are better refined.

Further, representing the growth as a constant MW/year increase is considered more appropriate compared to a constant percentage increase per year given the nature of the UE network. When a constant percentage growth is considered, the magnitude of growth will increase over time as a result of compounding effect. However, given consideration to the available lands for development and saturation effect, this is considered less appropriate than a constant MW growth per year. Regardless, the reconciliation of the Bottom-Up with the Top-Down forecasts discussed later will adjust this relative growth rate to a rate consistent with the total UE growth rate.

In certain circumstances, the historical forecasts do not provide meaningful trend. Especially when substantial amount of load transfers have been involved, the forecast has been frequently been fluctuated or the change in demand patterns does not reflect in the historical trends. In such cases, it is required to select a suitable data range to obtain an acceptable growth rate or manually enter an appropriate rate.

Estimation of growth rate at individual zone substations requires good understanding about the behaviour of each zone substation and general growth pockets in the UE network.

6.5 New Large Loads / Retired Loads

A separate spreadsheet “Large Loads Register” is used to capture the new load information received from project planners. Network Planning Engineers are required to update this spreadsheet over the year to ensure the forecasting process accurately captures all new large loads.

It is noted that almost of the new loads are now captured in the spreadsheet. However, some of the loads identified may not be materialised as customers have not accepted our offers or only use a part of the initial estimate of their maximum demand. Given this uncertainty, it is considered that only part of the load recorded in the register is to be used in the forecasting process.

The following factors were used to scale the identified new large loads so that they can be used as an input to the demand forecast.

- Demand materialisation factor:

Given the total requested load is typically not materialised at once when the service is connected, the following spread is assumed unless more reliable information is available.

- Year 1: 10%
- Year 2: 20%
- Year 3: 40%
- Year 4: 30%

- Utilisation factor:

In most of the cases, the total installed capacity or the requested ultimate demand will not be utilised. Therefore, based on the customer category different utilisation factors are used.

- Commercial: 75%

- Commercial/Residential mixed: 70%
- Data Centre: 60%
- HV Customer 80%
- Industrial: 70%
- Residential: 60%
- Traction 100%

The above mentioned utilisation factors will be used in load allocation, unless there is a high level of confidence that the customer will take a greater proportion of the capacity.

- **Coincident factor:**

The peak demand of the individual new load and the zone substation peak may not perfectly coincide. In order to accommodate this uncertainty, a coincident factor of 80% for ZSS and 85% for feeders are used.

- **Progress factor:**

Not all the applications for new connections proceed to practical completion. In order to accommodate this uncertainty, a progress factor of 80% is used.

Based on these factors, the new large loads captured in the large load register are allocated to individual zone substations and feeders. However, if the demand contribution and timing are certain for a large project (data centres, shopping complexes, multilevel high density residential developments etc.), such information should be used in the forecasting process.

The present spreadsheet is designed to extract the relevant information based on the above mentioned materialisation, utilisation, coincident and progress factors. Any changes required to incorporate an additional impact from a new load should be performed in ad-hoc basis.

Similarly, known large loads disconnecting from the network or reducing their demand on a permanent basis should be included in this register as a negative number.

6.6 Diversity Factors

Two main diversity factors are used in the demand forecasting.

- UE diversity factor

This is calculated by dividing the demand at each zone substation at the time of the total UE maximum demand by the maximum demand of the relevant zone substation. This factor is used to roll up the zone substation demand forecast plus the sub-transmission losses to the total UE maximum demand forecast.

- TS diversity factor

This is calculated by dividing the demand at each zone substation at the time of the relevant terminal station maximum demand by the maximum demand of the relevant zone substation. This factor is used to roll up the zone substation demand forecast to non-coincident terminal station demand forecast.

The weather correction spreadsheet is designed to estimate these diversity factors while doing the weather correction. However, one should be careful when selecting the diversity factors in the process. The last summer diversity factors must be used when reconciling the actual zone substation demands against terminal station or total UE demand in calculating the NIEIR growth rates and making adjustments for sub-transmission losses.

In other cases, if the last summer does not represent 10% POE temperature or close enough, appropriate reference diversity factors are to be used. The most recent time representing high temperature is summer 2013/14. Therefore, the 2013/14 summer diversity factors can be used as representative values for summers having mild temperatures. This is considered appropriate as it can otherwise lead to overestimation of demands at zone substation level once bottom-up forecasts are scaled to match the NIEIR top-down forecast.

6.7 Adjustment for HV Cross Border Flows and Railway Loads

When reporting to AEMO, UE uses the total zone substation demand including the sub-transmission losses irrespective of having HV feeders supplying the customers of other DNSPs. Similarly, where UE obtains HV supply from a zone substation belongs to another DNSP, UE does not report such transfers to AEMO and it is part of the other relevant DNSP's submission. However, it is included into the UE's total demand. This method is accepted and adopted by all the Victorian DNSPs as it simplifies the reporting process and planning responsibility. Therefore, the actual UE demand and demand reported to AEMO at terminal stations can be slightly different. Given NIEIR forecasts the total UE demand, not the terminal station demand reported to AEMO, some adjustment is required to reconcile the difference.

In addition to the HV cross border flows, there are several dedicated sub-transmission feeders to supply Vic Rail. Given their demand is more or less constant, this is excluded from the data set provided to NIEIR.

Therefore before calculating sub-transmission losses, estimating the NIEIR demand growth for the immediate year and scaling the bottom-up forecast to match with the NIEIR top-down total UE forecast, it is required to adjust for the HV cross border flows and Vic Rail's demand.

All the relevant spreadsheets have been set up to accept required inputs and to perform the relevant adjustments.

The terminal stations that require attention due to HV cross border flows and Vic Rail supplies are listed below.

- **MTS 22kV:** five dedicated MTS 22kV feeders supply Vic Rail. They are:
 - MTS 20
 - MTS 22
 - MTS 38
 - MTS 39
 - MTS 126
- **RTS:** two 11kV feeders from CitiPower's BC zone substation supply UE demand and one 11kV feeder from UE's K zone substation supplies CitiPower demand. Therefore, adjustments are needed for these feeders.
 - BC 11
 - BC 23
 - K 11
- **SVTS:** two 22kV feeders from CitiPower's RD zone substation supply UE demand. Therefore, adjustments are needed for these feeders.
 - RD 4
 - RD 10
- **TSTS:** six feeders from UE's WD zone substation supply CitiPower demand. Therefore, adjustments are needed for these feeders.
 - WD 11
 - WD 13
 - WD 21
 - WD 22
 - WD 31
 - WD 32

The weather correction spreadsheet is set up to accept actual demand data of these feeders and correct them for 10% POE temperature. Given the Vic Rail demand is temperature insensitive, no correction is applied to them. Further, EL is used as the reference zone substation for CitiPower's BC zone substation when weather correcting the adjustments at RTS as it resides in the same geographic area with similar customer demographics and growth characteristics.

These weather corrected and actual adjustments are then copied into NIEIR terminal station growth rate calculation spreadsheet.

Further, the difference in demand reporting values at RTS, SVTS and TSTS for AEMO and NIEIR were captured in the master demand forecasting spreadsheet and it is used in the scaling of Bottom-Up forecasts. The relevant information for this calculation can be sourced from the relevant spreadsheets used in the Top 10 MDs evaluation for TUOS calculation.

6.8 Adjustment for Losses

When reconciling zone substation demands and terminal stations demands, it is necessary to make appropriate provision for sub-transmission losses. As the starting point, the difference between the diversified actual zone substation demands and actual terminal station demand after applying any adjustments required to accommodate HV cross border flows and Vic Rail demand is treated as the actual sub-transmission loss at that particular terminal station.

The losses at 10% POE temperature is estimated by adjusting the calculated actual losses by the ratio of squares of the relevant demands. This is considered appropriate as line losses are proportional to the square of the current flow.

6.9 NIEIR Terminal Station Growth Rates

TS Growth Forecast spreadsheet is designed to accept:

- Actual and weather corrected zone substation demands
- UE and TS diversity factors
- Actual and weather corrected adjustments for HV cross border transfers and Vic Rail demand
- NIEIR non-coincident 10% POE terminal station demand forecast

The growth rate after the first year is simply the percentage difference between forecast demands at two consecutive years. However, the expected growth at the first year is calculated based on the actual demand, loss adjustment, other adjustments and the NIEIR forecast for the first year.

Sometimes this calculation results in unacceptably high or low growth for the first year. In such case, it requires to manually adjust the first year growth rate to an acceptable value. The output of the spreadsheet is formatted in such a way that it can directly be copy into the master demand forecasting spreadsheet.

In addition to the growth rates, this spreadsheet reconcile the actual terminal stations demands and corresponding losses. This information is required in the master demand forecasting spreadsheet for loss adjustment calculations. Therefore, that information should be copied across too.

6.10 Preliminary Zone Substation 10% POE Summer MW Forecast

Before starting the forecasting process, it is necessary to insert relevant input data into the master demand forecasting spreadsheet. The input data required for the preliminary zone substation forecast is listed below.

- Update the “Year” tab to set the year of last summer
- Copy actual zone substation maximum demands (MW and MVA_r values) in to the “Zone Substations” tab
- Copy weather corrected maximum demand in to the “Zone Substations” tab
- Update the “ZSS Ratings” tab if required
- Update the “Cap Banks” tab if required
- Update the “Generation” tab with embedded generation and demand management (including storage) data
- Copy terminal station growth rates in to the “NIEIR MG10%” tab
- Update generic zone substation growth rates in the “NIEIR MG10%” tab
- Copy UE and TS diversity factors in to the “NIEIR MG10%” tab
- Copy the new large load information in to the “NIEIR MG10%” tab
- Update load transfer information on the “NIEIR MG10%” tab

The preliminary forecast starts with the 10% POE weather corrected last summer actual zone substation peak demands. Then, the following relationship was used to establish the relevant growth in each year.

Demand growth = maximum (NIEIR TS growth rate, generic growth + net new large loads)

The selected growth rate at each year is used to forecast the demand at each zone substation and the forecast is adjusted to accommodate any planned load transfers. This will produce unadjusted preliminary demand forecast at each zone substation.

6.11 Final Zone Substation 10% POE Summer MW Forecast

Once the preliminary zone substation forecast is completed, it should be rolled up to the total UE demand using UE diversity factors (plus the sub-transmission losses) and compared against the NIEIR Top-Down total UE forecast. Then the Bottom-Up forecast should be scaled to match with the NIEIR Top-Down total UE forecast. In order to do this calculation, the following input data are required.

- Copy UE diversity factors in to the “NIEIR MG10%” tab
- Insert MTS 22kV to MTS 66kV diversity factors in to the ” Terminal Station Forecast” tab
- Insert last summer actual total UE demand to the ” Terminal Station Forecast” tab
- Copy NIEIR 10% POE total UE demand forecast to the ” Terminal Station Forecast” tab
- Copy weather corrected actual TS demands and losses to the ” Terminal Station Forecast” tab
- Insert values reported at RTS, SVTS and TSTS in AEMO and NIEIR submissions in to the ” Terminal Station Forecast” tab

The spreadsheet will automatically calculate the relevant scaling factors to match the Bottom-Up forecast with Top-Down forecast and update the final zone substation 10% POE summer MW forecast based on the provided input data.

This MW forecast is treated as the basis for all the other variations.

UE Zone Substation maximum demand forecasts for a 10-year planning horizon are documented in the Load Forecast Manual ([UE MA 2203](#)).

6.12 Terminal Station Bus Groups

Where terminal stations having four or more 220/66kV transformers, the 66kV bus is split in to two bus groups in order to manage the high fault level concerns. Supplying the UE network, there are four such locations at present. They are listed below.

Terminal Station	Bus Group	Connected Zone Substations
ERTS	12	LD, MGE
ERTS	34	DN, DSH, DVY
RWTS	13	BH, NW
SVTS	12	CDA, OE, NP, SS, SV, SVW
SVTS	34	GW, NO, EB, (RD)

In order to make sure that demand at individual bus groups does not exceed the corresponding ratings, it is required to prepare bus group level forecasts at these terminal stations in addition to the total terminal station forecast.

6.13 Non-coincident Terminal Station 10% POE Summer MW Forecast

Once the final zone substation 10% POE summer MW forecast is locked in, non-coincident terminal station forecasts can be prepared by rolling up the zone substation demand using TS diversity factors and adjusting for losses. In order to do this calculation, the following data are required.

- Copy TS diversity factors in to the "NIEIR MG10%" tab
- Insert the Vic Rail demand information in to the "Terminal Station Forecast" tab

The spreadsheet will automatically update the terminal station 10% POE summer MW forecast.

6.14 Non-coincident Terminal Station 50% POE Summer MW Forecast

50% POE summer MW forecast is prepared by scaling the 10% POE forecast based on the ratio between NIEIR 10% POE summer forecast and NIEIR 50% POE summer forecast at each terminal station. Provided that NIEIR forecast captures the relationship between 10% POE and 50% POE demands, this approach is considered acceptable and appropriate.

In order to perform this calculation, the following input data is required.

- Copy NIEIR's non-coincident TS 10% POE summer MW forecast in to the "Terminal Station Forecast" tab
- Copy NIEIR's non-coincident TS 50% POE summer MW forecast to the "Terminal Station Forecast" tab

The spreadsheet will automatically update the terminal station 50% POE summer MW forecast.

6.15 Non-coincident Terminal Station Winter MW Forecasts

10% POE winter MW forecast is prepared by scaling the 10% POE summer forecast based on the ratio between NIEIR 10% POE summer forecast and 10% POE winter forecast at each terminal station. Similarly, 50% POE winter MW forecast is prepared by scaling the 50% POE summer forecast based on the ratio between NIEIR 50% POE summer forecast and 50% POE winter forecast at each terminal station. Given there is no direct relationship between summer and winter demand characteristics; the best available information for winter demand is the forecast prepared by NIEIR. However, the NIEIR forecast does not include the impact of new large loads and planned load transfers. Therefore, in order to capture the network changes that are not included in the NIEIR winter forecast, scaling of the consolidated summer forecasts based on the ratios derived from NIEIR forecast is considered acceptable and appropriate.

In order to perform this calculation, the following input data are required.

- Copy NIEIR's non-coincident TS 10% POE winter MW forecast in to the "Terminal Station Forecast" tab
- Copy NIEIR's non-coincident TS 50% POE winter MW forecast to the "Terminal Station Forecast" tab

The spreadsheet will automatically update the terminal station 10% and 50% POE winter MW forecasts.

However, these winter forecasts then need to be reviewed against the historical observed winter maximum demands at each terminal station. Sometimes, adjustments are required to the launch point to align the forecast with the historical actuals. The spreadsheet has a provision for this adjustment.

6.16 Non-coincident Terminal Station MVAr Forecasts

Terminal station summer and winter MVAr forecasts will be prepared by using the consolidated MW forecasts, and the actual power factor at each terminal station during last summer and winter. In order to perform this calculation, the following input data is required.

- Insert the actual power factor at each terminal station during last summer and winter peak demand days into the "Terminal Station Forecast" tab

The impact of hot weather on the station power factor was assessed by comparing the actual operating power factor at terminal stations during 2011/12 summer (which was a very mild) and 2008/09 summer (which was very hot). It was observed that there are no significant differences between operating power factors in these two summers. Therefore, it is considered that using the last year's power factors for MVAr calculation is appropriate.

This approach is essentially presumed that the operating power factor at the terminal stations remains constant over time. Given the present UE power factors at terminal stations (without considering the terminal station 66kV capacitor banks) are acceptable; UE's strategy going forward is to use the zone substation capacitor banks and line capacitors to maintain the present level of power factor. Therefore, the assumption of constant power factor at terminal stations over time is considered acceptable.

However, given the long sub-transmission lines in the Mornington Peninsula, line losses are expected to increase substantially with demand growth compared to rest of the network. Therefore, it is expected that extra reactive power compensation may be required to maintain the power factor at TBTS 66kV bus.

It should be noted that the reactive power loss through the 66/22kV transformers at MTS is not captured in the metering data. Therefore, some adjustment will be required to accommodate the extra losses in these two transformers. The incremental loss is a function of demand connected at MTS 22kV level and estimated to be around 2MVAR at peak demand.

6.17 TSDF Template

UE needs to annually prepare the terminal station demand forecast to facilitate the Transmission Connection Planning Report (TCPR) published together with the Distribution Annual Planning Report (DAPR). The general time line for this submission is end December each year.

The "TSDF Template" tab in the master demand forecasting spreadsheet automatically captures the forecasting information and updates itself for use in Transmission Connection Planning Report (TCPR) process.

6.18 Review of Zone Substation Forecasts

A separate tab, "ZSS Comp", is set up in the master demand forecasting spreadsheet to graphically review the new demand forecast in comparison to the historical data. Before using this tab, it requires to open the "DSPR" tab and run the **Load Data** macro. It takes some time to load all the historical and current data into this tab. Once that is completed, "ZSS Comp" tab can be used to review the zone substation forecasts.

If any change needs to be made, that can be done in the relevant tab and it will automatically update the forecast. However, in order to reflect the change on the "ZSS Comp" tab, the **Load Data** macro in the "DSPR" tab needs to be re-run.

Further, some of the changes made in the background tabs will not automatically reflect on the main output tab "summer". It is required to run the **Load** macro in that tab to ensure all the latest information is correctly loaded onto the tab.

6.19 Review of terminal station forecasts

A separate tab, "TS Comp", is set up in the master demand forecasting spreadsheet to graphically review the new terminal station demand forecast in comparison to the historical data. Historical actuals sitting at the bottom of this sheet need to be updated annually. Further, if AEMO connection point forecast are available, they can be copied to the "AEMO" tab for comparison. Before using the "TS Comp" tab, it requires to refresh the two pivot tables in the "TS Summary Pivot Tables" tab. The first table summarises the current forecast and the second table summarises the historical forecast.

If any changes are made to the current forecast, it is required to refresh the first pivot table again to reflect that change on "TS Summary Pivot Tables" tab.

Given ratios calculated based on the NIEIR forecast are used to develop 10% and 50% POE winter forecasts, there is a potential of results being deviated from the expected trend. In such discrepancies are noted in results during the review, those ratios will need to be updated.

7. Embedded Generation and Network Support

Historically, UE has four large embedded generation sites:

1. Dandenong Hospital generator (NMI 6407642354) – Connected to ERTS34 via DN
2. Clayton Land Fill generator (NMI 6407649172) – Connected to SVTS12 via SS

3. Springvale Land Fill generator (NMI 6407649171) – Connected to SVTS12 via SS
4. CoGent generator (NMI 6407815891) – Connected to ERTS34 via DN

When calculating the total actual UE demand at terminal stations or for the overall service area, the impact of these embedded generators is netted out, that is, they are assumed to be switched off. The netting out of the actual output of the embedded generators is done by separately presenting the embedded generation output in the data sheet provided to NIEIR, aggregated by terminal station.

Similarly, the impact of Demand Management initiatives that provide network support through generators are to be considered when calculating the total actual UE demand at terminal stations or for the overall service area. For example, the effect of GreenSync generators that provide network support in the Mornington Peninsula on the maximum demand of Tyabb Terminal Station, its zone substations, and the overall UE network is to be included into the assessment.

The impact of voluntary demand reduction (e.g. Summer Saver Program) and RERT support through DVMS are not corrected during data extraction as no exact metered data is available for quantification. Such assessments are separately conducted and reported as part of the Network Loading Report.

8. High Voltage Feeder Demand Forecasts

Similar to zone substation forecasts, actual feeder maximum demands during the previous summer are the starting point for feeder demand forecast. Collection of actual maximum demands is discussed in Section 6.2. However, unlike zone substation actual maximum demands, feeder actuals are not weather corrected in the forecasting process. Instead, the 10% POE feeder forecasts are derived based on the weather corrected zone substation growth rates. This means, it is presumed that the temperature sensitivity of all the feeders are similar to the temperature sensitivity of the zone substation to which those feeders are connected.

For the first year of the forecasting period, zone substation growth is calculated based on the raw actual zone substation maximum demand and the 10% POE forecast for the first year. Therefore, this value is typically higher than the average growth of the zone substation. This method is used to intrinsically accommodate the weather correction into the feeder forecast.

Within the UE Load Forecasting Spread-sheet, there is a flexibility to overwrite the average zone substation growth rates that are applied across all the feeders. This feature is specifically used to update the growth rates of the dedicated feeders of which demand is more or less constant unless the customer asked for a capacity increase.

In addition to the average growth rate of the zone substation, the identified new load connections and retirements are taken into account when preparing the feeder forecasts. Treatment of new large loads and retirements are discussed in Section 6.5. When new loads are included into the forecast, the average growth rate for the first year of that feeder may need to be reviewed and updated to prevent double counting.

Further, the impacts of known projects are to be included into the feeder forecast. This includes proposed load transfers, capacity augmentations (affect the rating only) and new pole top capacitors.

Finally, the reserve capacity arrangements and available demand management solutions including storage are to be updated in “Feeders” tab. These are treated as adjustments to the base feeder forecast and the net values are presented in the load forecast spreadsheet.

UE High Voltage Feeder maximum demand forecasts for a 5-year planning horizon are documented in the Load Forecast Manual ([UE MA 2203](#)).

9. Definitions

Abbreviation	Description / Definition
AEMO	Australian Energy Market Operator
BC	Balaclava zone substation
BH	Box Hill zone substation
BOM	Bureau of Meteorology
CDA	Clarinda zone substation
DAPR	Distribution annual planning report
DMA	Dromana zone substation
DN	Dandenong zone substation
DNSP	Distribution Network Service Provider
DSH	Dandenong South zone substation
DVMS	Dynamic voltage management system
DVY	Dandenong Valley zone substation
EB	East Burwood zone substation
EL	Elsternwick zone substation
EW	Elwood zone substation
FSH	Frankston South zone substation
GW	Glen Waverley zone substation
HGS	Hastings zone substation
HV	High Voltage (typically referred to 22kV in this document)
IMS	Interval Meter Store
K	Gardiner zone substation
KBH	Keysborough zone substation
LD	Lyndale zone substation

LWN	Langwarrin zone substation
MD	Maximum demand
MGE	Mulgrave zone substation
MTN	Mornington zone substation
MTS	Malvern terminals station
NIEIR	National Institute of Economic and Industry Research
NO	Notting Hill zone substation
NP	Noble Park zone substation
NW	Nunawading zone substation
OE	Oakleigh East
POE	Probability of exceedance
RBD	Rosebud zone substation
RD	Riversdale zone substation
RERT	Reliability and emergency reserve trader
RTS	Richmond terminal station
RWTS	Ringwood terminal station
SS	Springvale South zone substation
STO	Sorrento zone substation
SV	Springvale zone substation
SVTS	Springvale terminal station
SVW	Springvale West zone substation
TCPR	Transmission connection planning report
TS	Terminal station
TSDF	Terminal station demand forecast
TSTS	Templestowe terminal station

TUOS	Transmission use of system
UE	United Energy
WD	West Doncaster zone substation

10. Appendix A – NIEIR’s Peaksim Model

This section provides a high level description of the NIEIR PeakSim model used to develop UE’s top-down maximum demand forecasts.

10.1 Background

The PeakSim model has evolved out a number of lines of research at the National Institute. The key initial research began several years ago with a request to provide greater information about the probabilistic nature of seasonal maximum demands. This research pulled together earlier work undertaken by the National Institute in the 1990s and work done by various planning bodies in Australia and around the world.

While the research is on-going, the model has reached a significant milestone in its development. In past few years, the model has been incorporated into on-going demand modelling and forecasting work. PeakSim is now important tool in our capacity to assist electricity supply industry in long-term planning.

10.2 Functionality of PeakSim

The primary function of PeakSim is to generate probability of exceedance (PoE) projections of seasonal maximum demand that encompasses:

- variations in economic, financial and industrial conditions;
- current and forecast energy market conditions;
- existing and proposed energy and environmental policy measures;
- existing and likely technological developments;
- developments in stock and usage of electrical appliances (in particular space conditioning equipment and lighting);
- variations in temperature patterns (after controlling for climate variations due to urban and global warming); and
- random or stochastic variations in residential, commercial and industrial consumption.

In addition to generating PoE projections of seasonal maximum demands, the PeakSim has the capacity to perform:

- retrospective (ex-post) analysis of historical seasonal maximum demands; and
- projections of seasonal maximum demands.

The model can also generate probability distributions over monthly, weekly and even daily timeframe for historical and future time periods.

10.3 Caveats

Electricity demand is an outcome of a large and diverse number of residential, commercial and industrial activities. As such, electricity demand modelling is a challenging exercise. Modelling such heterogeneous activities in a single framework is never easy.

Maximum demand modelling is an even more challenging exercise. A maximum demand, by its definition, is a rare event; only one maximum demand occurs per period. A maximum demand is also an extreme event; by definition, it is the highest reading in a period (i.e., season/year). Maximum demand modelling is unlike most economic modelling exercises, where the primary metric of interest is the ‘most likely’ outcome (the centre of the probability distribution). The focus of maximum demand modelling is the upper end of the distribution of possible demand levels.

Maximum demand events at the very top end of the demand distribution very rarely occur; these events are ‘rare instances of a rare event’. For example, a 10% probability event is only expected to occur once in a ten-year period. The conditions that generate such an event are very difficult to measure, largely because they rarely occur themselves.

As with any modelling and forecasting, extreme caution should always be exercised when interpreting model outputs. The limitations highlighted above re-enforce the need to use a range of information when making important decisions. Decision makers should always use a combination of:

- statistical information;
- model-generate outputs (preferably from more than one model);
- insight and intuition;
- experience; and
- anecdotal evidence.

Modelling is an important tool in developing our understanding of a process or event, it cannot (should not) make decisions for us.

10.4 Conceptual Model

PeakSim's 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 contemporaneous influences and underlying drivers of demand are then built on and around this relationship.

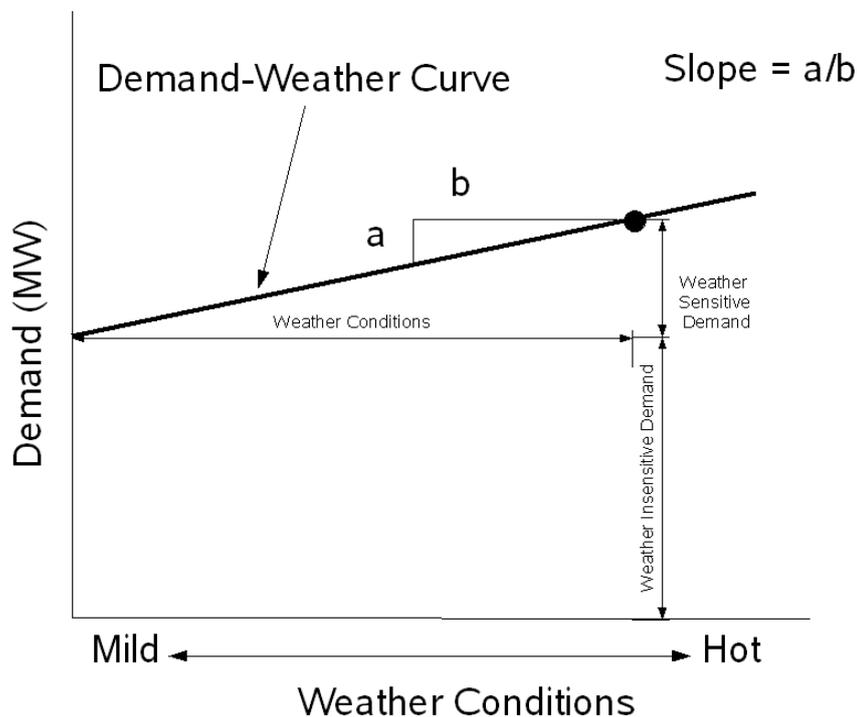
10.5 Demand-weather Relationship

Figure 10.5 presents a hypothetical representation of the relationship of electricity demand and weather during summer (illustrated by the upward sloping line). A similar relationship is observed during winter except that the 'weather conditions' profile moves mild to cold. This relationship 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 constants, 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. 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.

The diagram below shows weather insensitive demand as a greater proportion of total demand. This is a hypothetical illustration only. In some instances, the weather sensitive demand can account for a greater proportion of total demand than weather insensitive demand. The relative proportion of weather-sensitive and insensitive demand will depend on the characteristics of the customer base (i.e. composition of residential, commercial and industrial customers).

Figure 10.5: The relationship between electricity demand and weather during a typical summer



In regression analysis, the slope of this relationship can be estimated by the coefficient on a weather variable. The weather insensitive component of demand can be measured by the intercept (or constant) terms. These two estimated parameters are important metrics in PeakSim. They tell us much about the underlying consumer demand and help us project forward future demand (more about this later).

10.6 Time of day and day of week effects

Electricity demand has, however, a greater range of influences than prevailing weather conditions. Many domestic and business 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 late afternoon). Weather sensitive demand will vary with the course of the day in large part, due to available of sunshine light. These time-of-day influences overlap with weather effects, making the relationship between demand and weather substantially more complex than the above diagram implies.

PeakSim 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) intervals 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. PeakSim captures these influences on demand within each half-hourly regression model.

10.7 Stock of electrical equipment

Contemporaneous events and conditions (i.e. weather, daylight, day-to-day business operations and day of week activities) are not the only influences on electricity demand. Electricity 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 necessarily 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.

As an example, consider electricity demand for space-conditioning equipment. Demand in this case reflects two decisions:

- a decision to use space conditioning equipment; and
- an earlier decision to purchase equipment.

Figure 10.7 provides an illustration of the connection between these two decisions for a hypothetical household. The decision to use space conditioning equipment largely reflects contemporaneous conditions such as indoor climatic conditions which are, in turn:

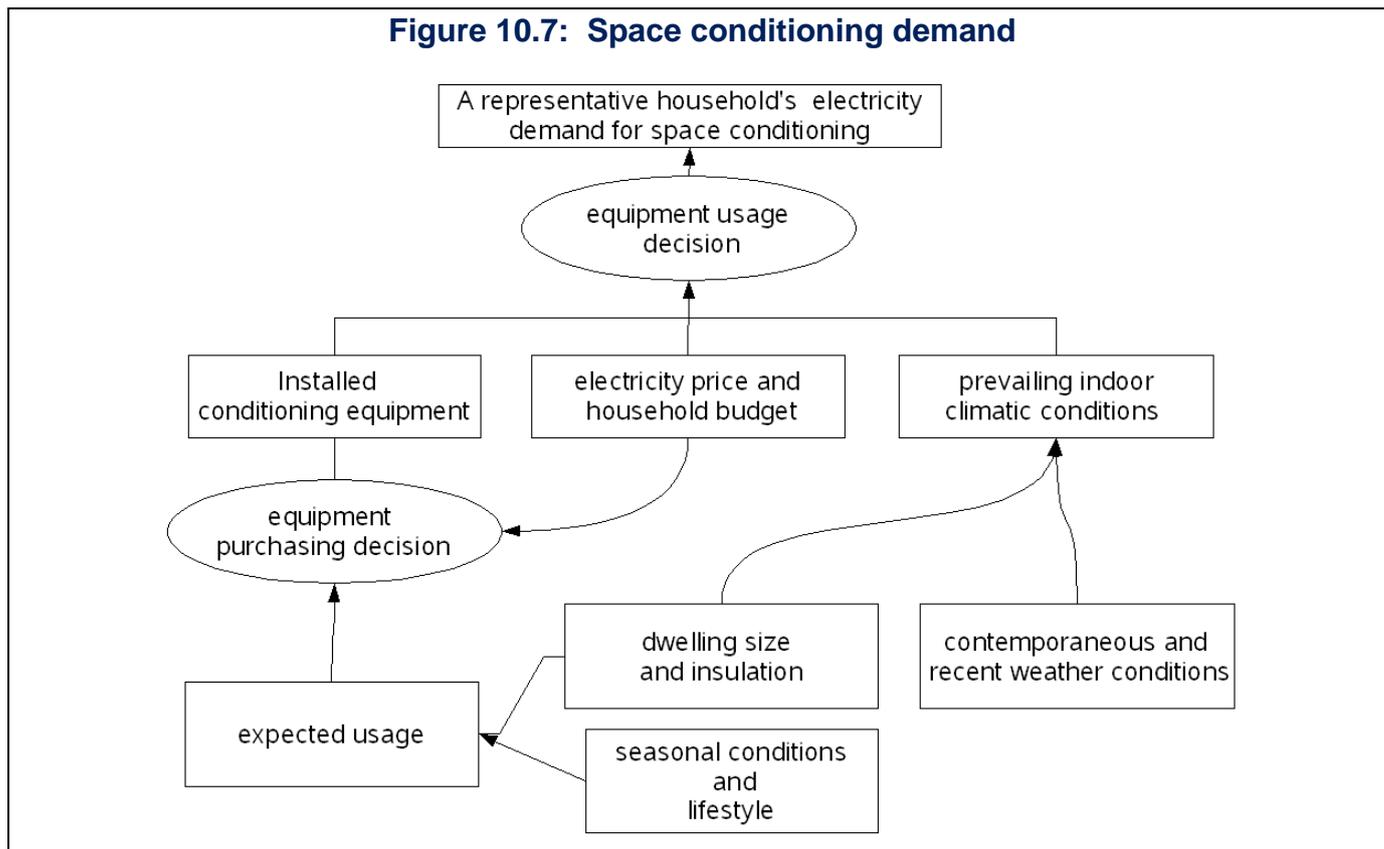
- strongly influenced by the prevailing outdoor weather conditions and
- quality of dwelling or building insulation (which reflects another earlier decision).

It also reflects the household's contemporaneous (and perceived) financial position. In this aspect of the household's decision, the cost of operating the equipment (such as the price of electricity) is important.

The decision to use space conditioning equipment is also dependent on the availability of working equipment. The electricity demand is, therefore, an outcome of an earlier decision to purchase space conditioning equipment. This purchasing decision is most likely to reflect household's (current perceived) financial circumstances at the time of the purchase as well as household characteristics (such as floor space) and financial/economic expectations.

Similar purchasing decisions are replicated in other activities in residential, commercial and industrial sectors. Unlike weather and other contemporaneous factors, which have a more noticeable impact on day-to-day variations in electricity demand, equipment purchasing decisions will have a gradual impact on demand. These decisions can sometimes only be inferred from demand data over long timeframe such as a year.

Figure 10.7: Space conditioning demand



The PeakSim model has been designed to gauge the impact of electrical equipment purchasing decisions on electricity demand. The half-hour models described above are estimated individually for each year (season). The year-to-year variations observed in the key estimated parameters (intercept and weather coefficients) provide some insights into the purchasing decisions of consumers. An increase in the intercept from one year to the next is indicative of an increased stock of electrical equipment associated with weather insensitive demand activities. Similarly, an increase in the weather coefficient is indicative of an increased stock of electrical equipment associated with weather sensitive demand activities (such as air conditioning equipment).

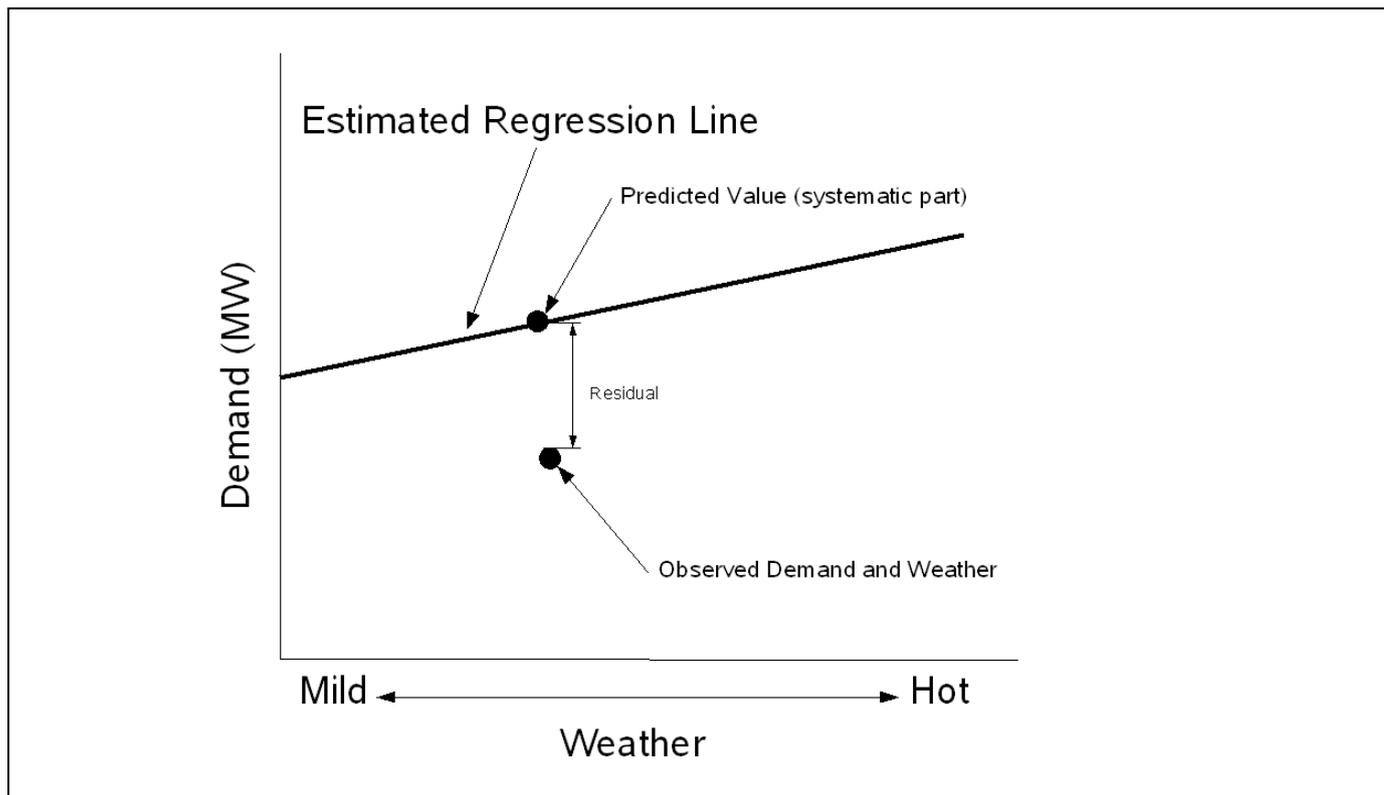
10.8 Variability in demand

Another premise underlying PeakSim is that electricity demand consists of two parts: a systematic part and a random or stochastic part. As described above, 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 contemporaneous 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.

In regression analysis, the random part of consumer behaviour is, in theory, approximated by the residuals while the systematic part is approximated by the sum product of the coefficients and regressors (i.e. explanatory variables such as the weather variable and the dummy variables).⁵ The residuals measure the difference between the level of demand that occurred and the level of demand that the systematic part of the regression predicts (see Figure 10.8).

Figure 10.8: Hypothetical estimated regression line

⁵ The residuals may also capture errors arising from the modeling process, namely model specification, measurement and sampling errors. As long as these errors are not abnormal, the residuals can be representative of the random elements of consumer behaviour.



The randomness of consumer behaviour implies that a different level of electricity demand could have been observed (for a variety of reasons); that is, it is by chance that the observed level of demand occurred. Hence, the historically observed levels of electricity demand are just one set of many possible alternative realisations of electricity demand.

The randomness of consumer behaviour, however, only accounts for a part of the contemporaneous 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. Once again, the historically observed levels of electricity demand are just one set of many possible alternative realisations of electricity demand.

The PeakSim 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.

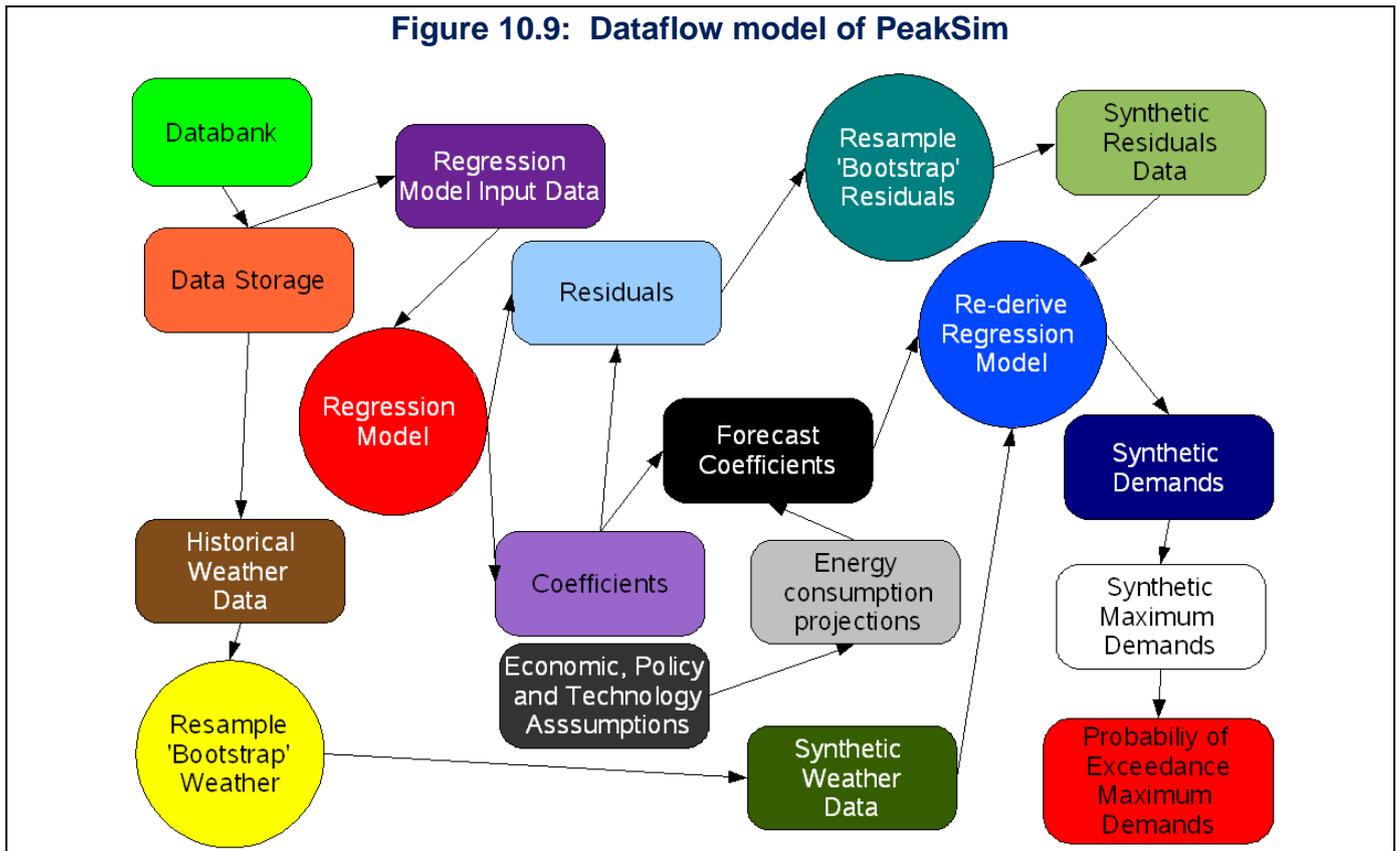
By generating a large number of alternative demand sequences, a picture of the range and frequency of electricity demand can be generated from synthetic demand sequences. Pooling the synthetic demand sequences together, a (relative) frequency distribution of possible demand readings can be created. This 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.

10.9 Empirical model

Figure 10.9 presents a diagrammatical representation of the dataflow of the PeakSim empirical model.

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

Figure 10.9: Dataflow model of PeakSim



10.10 Regression analysis

Data from the record set file is filtered by season and important weather indicators are derived (denoted by 'regression model input data'). These data used in the regression analysis (denoted by the red circle). PeakSim's regression model encompasses the following linear structure.

$$\begin{aligned}
 D_d^{h,y} = & a_0^{h,y} + a_1^{h,y} * CDHH_d^{h,y} + \\
 & + a_2^{h,y} * Sat_d^y \\
 & + a_3^{h,y} * Sun_d^y \\
 & + a_4^{h,y} * Aus_d^y \\
 & + a_5^{h,y} * Outlier_d^y \\
 & + e_d^{h,y}
 \end{aligned}$$

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.

e_d^y is the estimated model residuals for day d.

CDHH is calculated using the following formula:

$$CDHH_d^{h,y} = \max(0, \text{Composite Weather Indicator}_d^{h,y} - 22) * (T_d^{h,y} / M_d^y)$$

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 is the contemporaneous temperature reading on day d , half hourly interval h in year, y .

O_d is minimum or overnight temperature on day d in year, y .

M_d is maximum temperature on day d in year, y .

x , y , and z are arbitrarily 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 $e_d^{h,y}$ are normalised relative to the coefficient estimate, $a_1^{h,y}$. The normalised residuals form the sample for the bootstrapping (i.e. the creation of synthetic residual sequences).

10.11 Simulation models

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 $e_d^{h,y}$ is sampled into its respective half hour interval, h . In total, there are (1000 multiplied by h multiplied by d) synthetic residual observations generated for each year.

Figure 10.11 presents an example of a simple bootstrapping exercise for illustration purposes. In this example each value in the original series has an equally likely chance of being drawn. The value drawn is determined by a random number generator.

Figure 10.11: Simple bootstrap example

Original series

Reference	A	B	C	D	E	F
Value	2	3	2	7	1	10

Synthetic series 1

Reference	A	B	C	D	E	F
Original series reference	C	E	B	A	A	F
Value	2	1	3	2	2	10

Synthetic series 2

Reference	A	B	C	D	E	F
Original series reference	F	B	D	A	E	C
Value	10	3	7	2	1	2

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 recorded at Melbourne Airport over the period 1973-74 to 2013-14. 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.

10.12 Derivation of synthetic demands

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 PeakSim framework. 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.

The estimated constant, $a_0^{h,y}$, is projected forward using growth in weather insensitive energy consumption projections. The estimated dummy coefficients, $a_2^h - a_4^h$, are also projected forward using growth in weather insensitive energy consumption projections. The forward projections of the weather coefficient, $a_1^{h,y}$, 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 exceedance projections, respectively.

10.13 PeakSim Accuracy

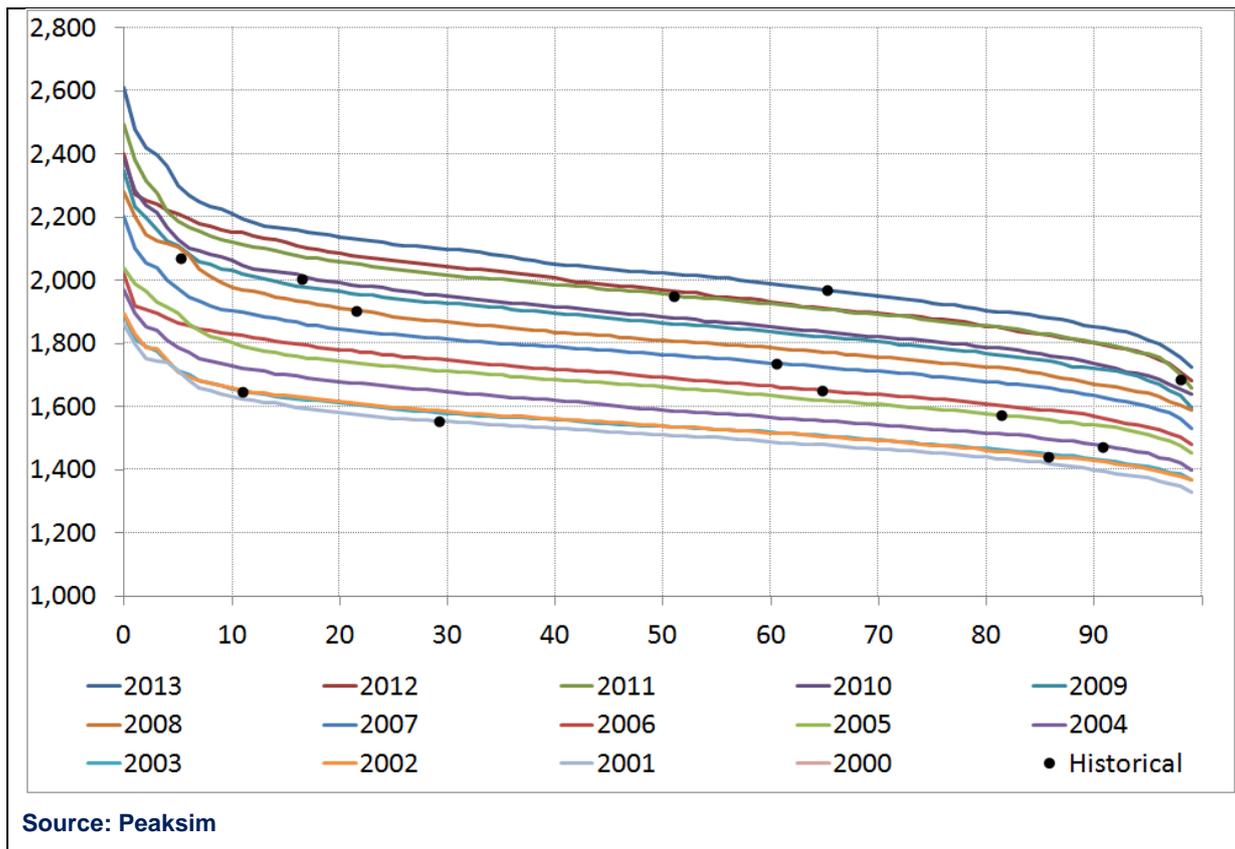
This section examines some of the other metrics and useful diagnostic computed by the model.

10.13.1 Implied historical PoE distribution

The discussion so far focuses on projected maximum demand for three key probability levels: 10%, 50% and 90%. The model underlying these three projections generates projections for the full spectrum of probability levels.

Figure 10.13.1 shows probability of exceedance curves of maximum demand (as implied by the model) for each summer over a 15 year period. The chart illustrates the likelihood of maximum demand level for a given year. The y-axis (i.e. the vertical axis) measures the maximum demand level in megawatts (MW) while the x-axis (the horizontal axis) measures probability of exceedance levels (expressed as a percentage). The time dimension is represented by the different coloured lines.

Figure 10.13.1: Implied summer maximum demand (MW) for each % probability of exceedance



Each line on this chart represents a different summer; for instance, the dark blue line at the top shows the 2012-13 summer. It shows the full range of possible maximum demand levels⁶ that could have occurred in summer 2012-13. Please note this curve is quite different from a duration curve. It shows the potential levels of maximum demand for the specific season given the prevailing economic environment, seasonal conditions and stock of technology in use.⁷ It shows the levels of maximum demand if extreme weather conditions and consumer responses to other prevailing conditions had been different.

These curves shows that the shape of the probability distribution has remained relatively constant over the past 15 years although the level of the curve have moved up (and down) with changes in the economic environment, seasonal conditions and stock of technology in use.

The black dot on the each curve shows the level of maximum demand observed during the respective summer. From position of the dot, one can infer the implied probability of exceedance percentage (as shown on x-axis). For instance, the summer maximum demand in 2012-13 was 1966 MW; this equates approximately to a 66% probability of exceedance.

10.13.2 Model Accuracy

To measure the “accuracy” of the modelling, the National Institute has applied two different approaches. One approach is simply based on the common point-estimate accuracy measures such as a root mean squared error (RMSE) statistic. The logic of this measure is well established. In this context, we would expect, on average, most of the observed maximum demand events to congregate around the historical implied 50% Probability of Exceedance value as this is the centre of the distribution. A RMSE type measures attempt to detect any bias in the implied outcomes relative to the 50% Probability of Exceedance value.

The second approach attempts to gauge the accuracy of the whole probability distribution; not just relative to the centre of the distribution. This approach compares the relative dispersion of observed maximum demand events with the probability distribution implied from the model.

⁶ As implied by model given the economic and seasonal conditions.

⁷ Seasonal factors can also impact the level of the curves.

The logic of this second approach is quite simply. For illustration, consider the following example. Over a ten year period one would expect (on average) a 10% Probability of Exceedance maximum demand level to be exceeded just once. Extending this logic further, one would expect a 20% Probability of Exceedance maximum demand level to be exceeded just twice over a ten year period. Furthermore, we would expect a 30% Probability of Exceedance maximum demand level to be exceeded just thrice over a ten year period.....And so on, and so on. This logic can be extended across the whole probability distribution.

For a set historical period, the expected number of maximum demand events for each probability of exceedance level can be compared with the observed number of maximum demand events above that probability of exceedance level. The absolute difference between the expected number of events and the observed number of events provides a gauge of the relative accuracy at various points in the distribution. The absolute difference is often expressed as a percentage of total number of periods and is called the 'excess percentage'. Kolmogorov-Smirnov Statistics for the absolute excess percentage is another way of expressing the excess percentage.⁸

There are several limitations to first and second approaches. An important limitation of both approaches is that they may lead to erroneous conclusions about the relative accuracy of the modelling if the sample size is small (i.e., where the sample size is less than 25 observations). A key difficulty in measuring the accuracy of a probabilistic model is that parts of probability distribution, namely the extreme tails, are rarely observed; for instance, 10% probability of exceedance level is expected, on average, to be exceeded once in a ten-year period. By definition, a historical sample of nine observations may not even contain a 10% probability of exceedance event.

10.13.3 Results

Tables 10.13.3 present a study of the accuracy statistics for implied historical 50% of probability of exceedance level for past summers.

Table 10.13.3: Accuracy measures of implied 50% probability of exceedance summer maximum demand level	
Sample	2001-2013
Number of observations:	13
Root Mean Squared Error	123.9
Root Mean Square Percentage Error	7.1%
Mean Absolute Error	100.6
Mean Absolute Percentage Error	5.8%
Theil Inequality coefficient	3.5%
Bias Proportion	1.2%
Variance Proportion	6.9%
Covariance proportion	91.9%
Bias Proportion	1.2%
Regression Proportion	0.5%
Disturbance proportion	98.4%
Kolmogorov-Smirnov Statistics	1.93

Note: * Insufficient data points to draw valid inference from these statistics

Source: PeakSim

The root measure square error is a commonly-used measure of the difference between predicted and observed values. This statistic suggests that, on average, the difference between observed maximum demand and implied 50 per cent probability of exceedance level is approximately 124 MW. Root mean square percentage error is a variant of the root measure square error.

⁸ See Hyndman (2008) 'Evaluating peak demand forecasts' ESIPC website (www.esipc.sa.gov.au), for discussion of this measure.

The mean absolute error is a similar measure of difference. The mean absolute percentage error measures the difference in expected and observed values as proportion of the observed value. This measure provides a scale to the difference between expected and observed values.

The Theil inequity coefficient is another popular measure of difference. (For reference, this measure is based on the U1 formulation). The coefficient can be decomposing into two separate ways:

1. Bias, variance, and covariance proportions
2. Bias, regression and disturbance proportions

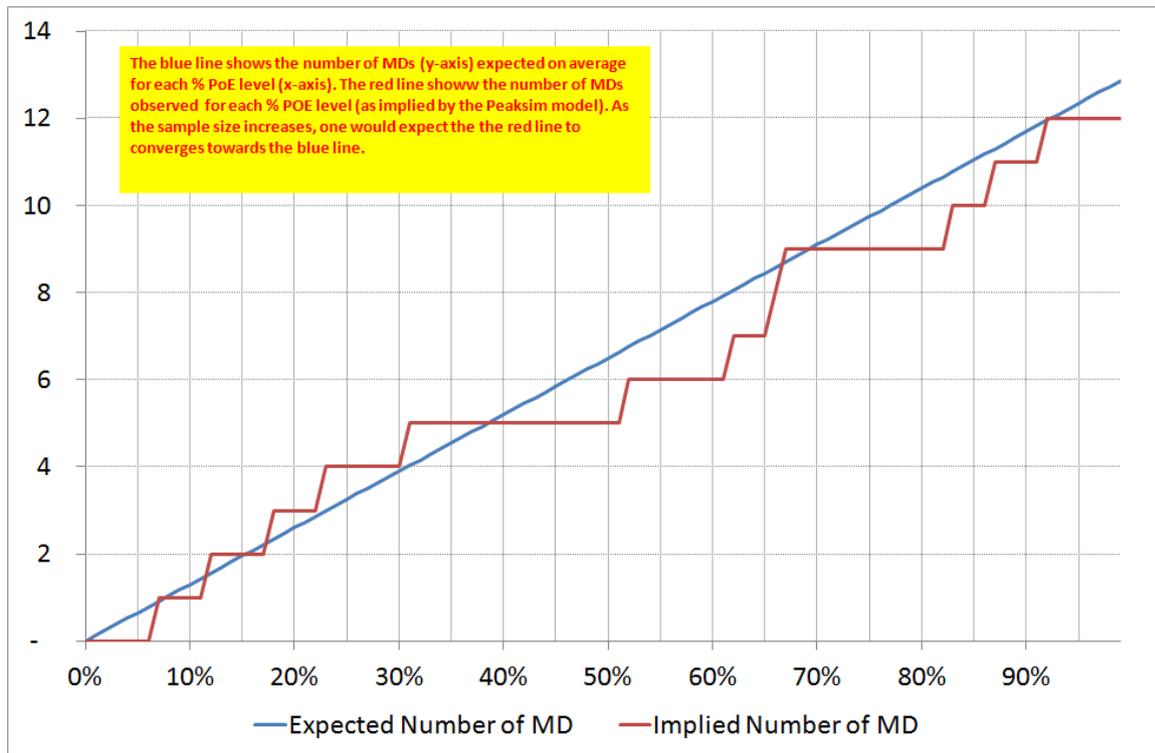
The bias proportion measures how far the mean of the expected values is from the mean of the observed values. The variance proportion measures how far the variance of the expected values is from the variance of the observed values. The covariance proportion measures the remaining unsystematic difference.

The regression proportion measures of how far the systematic component of expected values is from the systematic component of the observed values. The disturbance proportion measures the remaining unsystematic difference.

The bias, variance and covariance proportions sum to 1. Similarly, the bias, regression and disturbance proportions sum to 1. Expected values are considered good predictors, if the bias and variance proportion are small or bias and regression proportions are small.

The Figure 10.13.3 shows the number of maximum demand events expected over a 15-year period for each probability of exceedance levels (blue line) and the number of maximum demand events over the past 15 summers for each probability of exceedance levels (red line) as implied by the model. This figure indicates that the observed maximum demand events deviate only slightly from the expected number of maximum demand in many parts of the probability spectrum.

Figure 10.13.3: Observed and implied number of maximum demand events for past summers



Source: Peaksim

The Kolmogorov-Smirnov Statistics for the absolute excess percentage for both summer and winter is 1.9 observations. This suggests that the projections (at most) under- or over-predicts the number of maximum demand events by 1.9 at any point on the distribution.

11. Appendix B – UE’s EViews Model

In 2012-2014, UE engaged AECOM to develop a top-down macro-economic method and model to forecast maximum demand in UE’s distribution network. UE uses this model as an internal annual demand forecasting tool for the purposes of validating and reconciling the NIEIR forecasts.

11.1 Model Approach

11.1.1 Framework

Essentially, the AECOM modelling method followed the approach suggested in ‘Density forecasting for long-term peak electricity demand’ by Hyndman and Fan (August 2008) which expresses demand for each half-hour period as:

$$\log(y_{t,p} - o_{t,p}) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^J c_j z_{j,t} + n_t$$

Where:

- $y_{t,p}$: is the demand at time t (measured in half-hourly intervals) during period p.
- $o_{t,p}$: is the major industrial demand for time t during period p.
- h_p : models all calendar effects
- f_p : models all temperature effects
- $c_j z_j$: is a demographic or economic variable at time t (such as GDP, electrical prices, air conditioners and PV); its impact on demand is measured via the coefficient c
- n_p : is the model error at time t

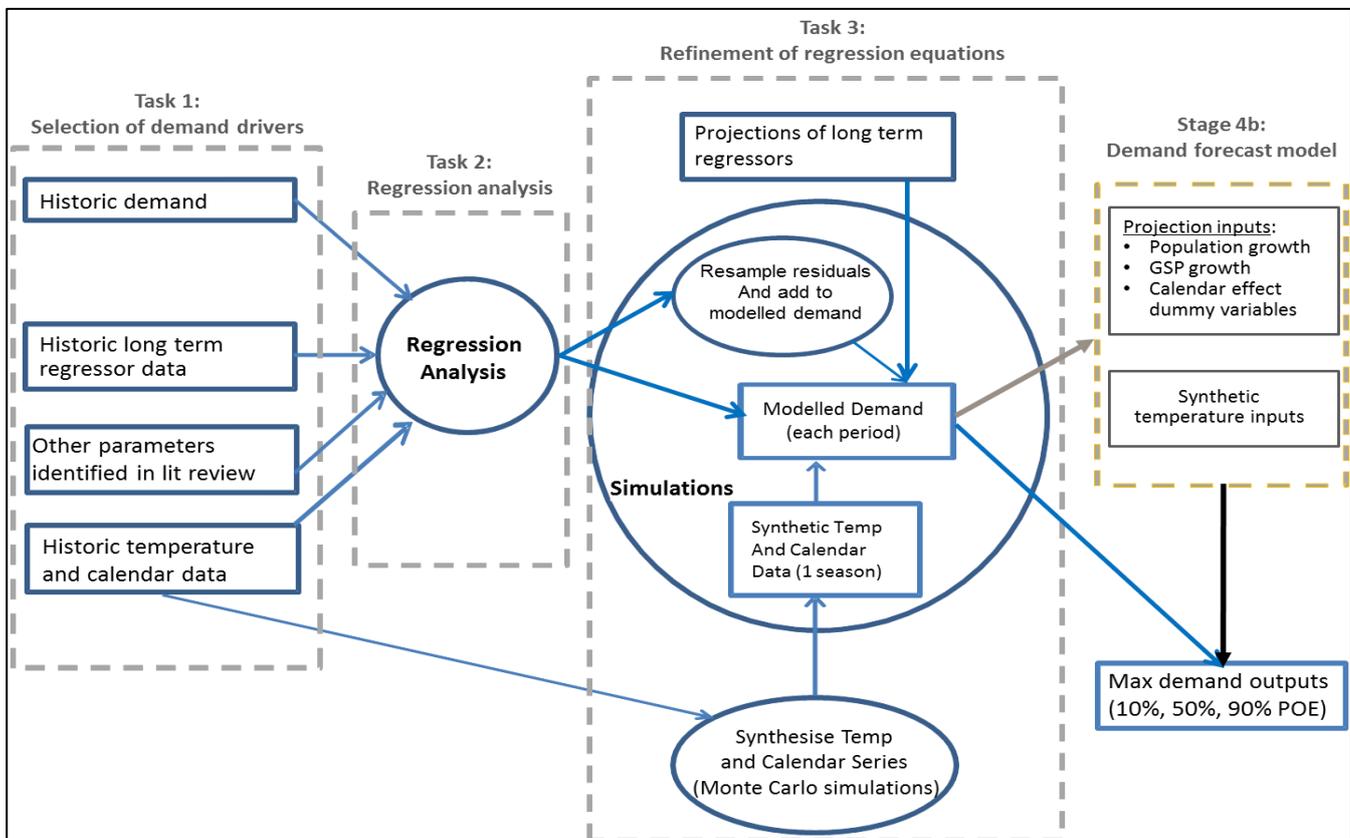
The above model is combined with the simulation of synthetic temperature variables and random regression errors to produce peak demand forecasts for temperature conditions at 10%, 50% and 90% PoE (probability of exceedance).

The approach to development of the maximum demand forecast model is through regression demand analysis and simulation modelling.

11.1.2 Modelling stages

The staged approach to maximum demand forecasts is illustrated in Figure 11.2.2

Figure 11.1.2: Maximum demand forecasting – key tasks



Source: AECOM

11.1.3 Model specification

The dependent variable is total UE’s demand load (TNILOAD) for the half hours from mid-day to mid-night.

The selected sample for the summer model covers only the Summer season because this is where maximum demand most likely occurs, inclusion of other months would compromise the relationship. A separate model was prepared for Winter using data for the winter season and producing different coefficient estimates i.e. a different explanation for energy use behaviour.

The Log form of the dependent variable means the change on the RHS would cause an equivalent percentage increase in the demand load TNILOAD. If the RHS variable is also in log form, then the coefficient is the estimated elasticity e.g. electricity price.

A single model was estimated that captures all considered half hours, by inclusion of respective dummy variables (HH_26 to HH_48). Further, interaction terms (HHT_26 to HHT_48) for the half hours and temperature are included to measure the differential sensitivity of demand load to temperature at different time of the day.

The above model specification provides the following advantages:

- Ensure that the relationships are based on available data as far as possible
- Produce consistent coefficient for macro-economic variables for all the half hours considered. The model, in deed, incorporates relationships for each of the specified half hour.
- Use the variations in behaviour across the half hours to measure certain impacts such as PV effect during time with strong sunlight (12.00-5.00 PM);

Note that in 2017 the way the model operates was altered slightly due to issues found with collinearity between key variables (GSP, population and price). To get around the collinearity problems identified, the model was re-specified with electricity consumption per capita, as the dependent variable. This model specification has been commonly used in various Australian studies.

Because electricity consumption per capita is not convenient for directly forecasting and simulating future demand load, an equivalent version of the model was specified for estimation where restrictions are applied to the coefficients of variables as follows:

- Log(Population) :denominator being moved from LHS to RHS with coefficient 1; and
- Log(Price) : being the respective coefficient estimate obtained from the consumption per capita regression equation.

11.1.4 Model specification

The summer model is specified in the respective batch program as follows:

```

Dependent Variable: LOG(TNILOAD)
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 07/24/19 Time: 09:30
Sample: 1/01/2002 00:00 3/31/2019 23:30 IF SUMMER_SEASON=1 AND
(HH>24)
Included observations: 50327
LOG(TNILOAD) = +C(1)+C(2)*TEMP+C(3)*TEMP(-8)+C(4)*TEMP(-9)
+C(5)*TEMP(-48)+C(6)*TEMP_MAX_DAY+C(7)*TEMP_AVG_3DAYLAG
+C(8)*END_OF_YEAR+C(9)*IND_OFF+C(10)*HOLIDAY+C(11)
*WORK+C(12)*WKDAY1_MON+C(13)*WKDAY3_WED+C(14)
*WKDAY4_THUR+C(15)*WKDAY5_FRI+C(16)*WKDAY7_SUN+C(17)
*HHT_26+C(18)*HHT_27+C(19)*HHT_28+C(20)*HHT_29+C(21)
*HHT_30+C(22)*HHT_31+C(23)*HHT_32+C(24)*HHT_33+C(25)
*HHT_34+C(26)*HHT_35+C(27)*HHT_36+C(28)*HHT_37+C(29)
*HHT_38+C(30)*HHT_39+C(31)*HHT_40+C(32)*HHT_41+C(33)
*HHT_42+C(34)*HHT_43+C(35)*HHT_44+C(36)*HHT_45+C(37)
*HHT_46+C(38)*HHT_47+C(39)*HHT_48+C(40)*WORKTEMP
+C(41)*HH_26+C(42)*HH_27+C(43)*HH_28+C(44)*HH_29+C(45)
*HH_30+C(46)*HH_31+C(47)*HH_32+C(48)*HH_33+C(49)*HH_34
+C(50)*HH_35+C(51)*HH_36+C(52)*HH_37+C(53)*HH_38+C(54)
*HH_39+C(55)*HH_40+C(56)*HH_41+C(57)*HH_42+C(58)*HH_43
+C(59)*HH_44+C(60)*HH_45+C(61)*HH_46+C(62)*HH_47+C(63)
*HH_48+C(65)*LOG(RGSP_CAP)+PRICE_ELAS*LOG(PRICEM)+1
*LOG(TNI_POP)+C(67)*PV_OP+C(68)*AC_OP

```

11.1.5 Model variables

The following variables were used in the Summer Maximum Demand Model.

Table 1 :Variable description

Variable	Description
C	Constant term
temp	Temperature at that half hour
temp(-8)	Temperature lagged by 8 half hours
temp(-9)	Similar to above

temp(-48)	Temperature at same time previous day
temp_max_day	Maximum temperature for that day
temp_avg_3daylag	Average temperature for 3 days previously
end_of_year	A day that is at end of year's period
ind_off	Day that industry closes for business
holiday	A holiday – dummy variable
work	A workday
wkday1_mon	Monday
wkday3_wed	Wednesday
wkday4_thur	Thursday
wkday5_fri	Friday
wkday7_sun	Sunday
Worktemp	Interaction term for workday and temperature.
HH_26 to HH_48	26th half hour or 12.30-1.00 PM; to 48th half hour or 11.30-12.00 PM
HHT_26 to HHT_48	Interaction term for HH and temperature
log(rgsp_cap)	Gross State Product per capita (log form) (1)
log(elec_price)	Nominal retail electricity price (ABS quarterly series for Victoria used) (log form) (2)
log(tni_pop)	UE population (log form) (3)
Log(air_con_cap)	Number of air conditioners installed (log form) (4)
Ac_op	Interaction term for air_con with specified half hours (25-38 i.e. afternoon to early evening hours) (log form)
pv_op	Interaction term for capacity of PV installed with specified half hours (25-34 i.e. afternoon hours with significant sunlight) (log form) (5)

External data sources:

- <http://www.abs.gov.au> – for historical GSP, Historical population and electricity prices
- <http://www.dtf.vic.gov.au> - for GSP forecast (or NIEIR)
- <https://www.planning.vic.gov.au> – for population forecast (or NIEIR)

- NIEIR forecast inputs – for forecast GSP, Population, PV forecast, Electric Vehicles.

11.1.6 Model estimates

Table 2: Regression Coefficients for Summer Maximum Demand Model as determined in 2014

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-16.28854	0.817236	-19.93126	0
TEMP	0.011612	0.000468	24.82508	0
TEMP(-8)	0.003359	0.000781	4.303236	0
TEMP(-9)	0.004616	0.000743	6.210569	0
TEMP(-48)	0.001934	0.000141	13.71551	0
TEMP_MAX_DAY	0.000651	0.000126	5.155356	0
TEMP_AVG_3DAYLAG	0.002456	0.000228	10.79249	0
END_OF_YEAR	-0.113402	0.002537	-44.69468	0
IND_OFF	-0.078607	0.001143	-68.74986	0
HOLIDAY	-0.053203	0.002723	-19.53678	0
WORK	0.109582	0.004297	25.50012	0
WKDAY1_MON	-0.003658	0.001694	-2.159091	0.0308
WKDAY3_WED	0.009493	0.001703	5.57569	0
WKDAY4_THUR	0.016053	0.001704	9.42319	0
WKDAY5_FRI	-0.018826	0.001707	-11.02595	0
WKDAY7_SUN	-0.037409	0.001696	-22.05513	0
LOG(RGSP_CAP)	0.607748	0.038658	15.72132	0
LOG(ELEC_PRICE)	-0.108025	0.007129	-15.15241	0
LOG(TNI_POP)	0.944712	0.085223	11.08519	0
PV_OP	-0.003759	0.000363	-10.35549	0
AC_OP	0.216158	0.011992	18.0255	0
R-squared	0.852911	Mean dependent var		6.845145
Adjusted R-squared	0.852624	S.D. dependent var		0.219022

Table 3: Regression Coefficients for Summer Maximum Demand Model as determined in 2016

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-15.2991	0.475684	-32.1624	0
TEMP	0.015705	0.000577	27.23478	0
TEMP(-8)	0.00327	0.000795	4.113178	0
TEMP(-9)	0.003578	0.000765	4.678348	0
TEMP(-48)	0.003045	0.000159	19.14727	0
TEMP_MAX_DAY	0.00082	0.000145	5.644594	0
TEMP_AVG_3DAYLAG	0.001214	0.000258	4.703801	0
END_OF_YEAR	-0.11207	0.002588	-43.3093	0
IND_OFF	-0.0757	0.001172	-64.5714	0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HOLIDAY	-0.05262	0.002789	-18.8688	0
WORK	0.147121	0.004453	33.03785	0
WKDAY1_MON	-0.00383	0.001728	-2.21592	0.0267
WKDAY3_WED	0.005306	0.001737	3.055104	0.0023
WKDAY4_THUR	0.015551	0.001738	8.94901	0
WKDAY5_FRI	-0.01731	0.001742	-9.93285	0
WKDAY7_SUN	-0.03796	0.00173	-21.941	0
LOG(RGSP_CAP)	0.530852	0.045907	11.5637	0
LOG(ELEC_PRICE)	-0.12218	0.006932	-17.6273	0
LOG(TNI_POP)	1.068423	0.066188	16.1423	0
PV_OP	-0.00103	0.000452	-2.2777	0.0228
AC_OP	0.088685	0.010191	8.702456	0
R-squared	0.847612	Mean dependent var		6.843551
Adjusted R-squared	0.847315	S.D. dependent var		0.219558

Table 4: Regression Coefficients for Summer Maximum Demand Model as determined in 2018

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-10.72732	0.096954	-110.6435	0
TEMP	0.009816	0.000434	22.61909	0
TEMP(-8)	0.004943	0.000678	7.295883	0.0000
TEMP(-9)	0.005507	0.000644	8.549149	0.0000
TEMP(-48)	0.003053	0.000134	22.71437	0.0000
TEMP_MAX_DAY	-8.58E-05	0.000126	-0.682808	0.4947
TEMP_AVG_3DAYLAG	0.003038	0.000218	13.95161	0.0000
END_OF_YEAR	-0.114714	0.002424	-47.32885	0.0000
IND_OFF	-0.073140	0.001107	-66.07783	0.0000
HOLIDAY	-0.053830	0.002603	-20.67856	0.0000
WORK	0.106709	0.004007	26.63235	0.0000
WKDAY1_MON	-0.006219	0.001616	-3.847907	0.0001
WKDAY3_WED	0.009151	0.001623	5.636776	0.0000
WKDAY4_THUR	0.015353	0.001624	9.454214	0.0000
WKDAY5_FRI	-0.016491	0.001626	-10.14304	0.0000
WKDAY7_SUN	-0.036429	0.001617	-22.52505	0.0000
LOG(RGSP_CAP)	0.733579	0.023263	31.53398	0
LOG(PRCEM)	-0.174625	0.002275	-76.76204	0
PV_OP	-0.006465	0.000397	-16.29740	0
AC_OP	0.125382	0.008760	14.31276	0
R-squared	0.824030	Mean dependent var		-7.226822

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Adjusted R-squared	0.823785	S.D. dependent var		0.224105

11.1.7 Key Variables Elasticities and Model Interpretation

Table 5 demonstrates the changes in key variable elasticities from the EViews model runs in 2014, 2016 and 2018.

It should be noted that in 2017 there was a minor structural change to the model due to collinearity issues identified between the gross state product per capita (RGSP_CAP), UE population (TNI_POP), and the retail electricity price (ELEC_PRICE). There have also been other minor changes between years as a result of changes in the input data and methodology due to using different sources of data (due to availability) and forecasts. This will mean that the elasticities between the 2014, 2016 and 2018 models may not be directly comparable.

Despite this, the elasticities seem have remained relatively stable and with the correct sign and order of magnitude over the modelled years.

Overall, the model provides a good identification of the factors that contribute to demand load and the extent to which they influence its variation over time.

The adjusted R² at approximately 0.85 and less also indicates the model has a high goodness of fit.

Table 5: EViews Elasticity Changes

Description	EViews Variable	2014	2016	2018	Average
Economic Output	LOG(RGSP_CAP)	0.608	0.531	0.734	0.625
Retail Electricity Price	LOG(ELEC_PRICE)	-0.108	-0.122	-0.175	-0.135
Solar PV	PV_OP	-0.004	-0.001	-0.006	0.004
Air Conditioning	AC_OP	0.216	0.0887	0.125	0.143

11.2 Running EViews Model

Refer to UE PR 2202 - Network Modelling Procedure for detail instruction on how to run the EViews forecast model.