Attachment 7.3.1

Connections, Energy and Demand Forecast Methodology

Access Arrangement Supplementary

Confidential

2 October 2017

Access Arrangement Supplementary (AAS) for the period
1 July 2017 to 30 June 2022

westernpower

Connections, Energy and Demand Forecast Methodology

Confidential

7 August 2017

westernpower

EDM#34382992

Western Power

363 Wellington Street
Perth WA 6000
GPO Box L921 Perth WA 6842

Document Information

Title	Connections, Energy and Demand Forecast Methodology
Subtitle	N/A

Authorisation

	Title	Name	Date
Author	Forecasting & Modelling Team Leader	Ben Jones	19/07/2017
Reviewer	Insights & Analytics Management	Grant Coble-Neal	27/07/2017
Approver:	Head of Business Intel & Data Analytics	David Hebden	07/08/2017 EDM 43327337

Document History

Rev No	Date	EDM Version	Amended by	Details of amendment
1	27/10/2016	12	Grant Coble-Neal	RCP1 preparation
2	31/07/2017	16	Grant Coble-Neal	Updated alignment for AA4 submission

Review Details

Review Period:	2016/17
NEXT Review Due:	July 2018

Contents

List of tables

List of figures

Glossary

The following table provides a list of abbreviations and acronyms used throughout this document. Defined terms are identified in this document by capitals.

Term	Definition
ABS	Australian Bureau of Statistics
Annual average demand	Average electricity demand over the course of one year, usually expressed in MW. In this discussion, annual average demand refers to the annual average measured at five minute intervals. This is equivalent to the average annual volume of electricity consumed.
Annual peak demand or Annual maximum demand	The highest average electricity consumption in any five minute interval during the course of one year, usually expressed in MW.
ARIMA	Auto-regressive Integrated Moving Average
Augmented Dickey Fuller test	An augmented Dickey Fuller test (ADF) tests the null hypothesis of whether a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is used, but is usually stationarity or trend-stationarity.
BDP	Binningup Desalination Plant
Block load	If a customer's requested demand is above the forecast underlying growth in demand, then this is known as a block load. Once added to underlying demand growth, a block load introduces an often permanent step-change into an otherwise smooth trend.
BOM	Bureau of Meteorology
Box plot	A box plot, sometimes called a box and whisker plot, is a type of graph used to display patterns of quantitative data.
CAGR	Compound annual growth rate
CER	Clean Energy Regulator
CO	Customer-owned
Coefficient of variation	The coefficient of variation (CV), also known as relative standard deviation (RSD), is a standardised measure of dispersion of a probability distribution or frequency distribution.
Coincident and non-coincident demand	See section 7.3.3 of this document for the definitions.

Term	Definition
Cooling degree days	Cooling degree days are a measure of how much (in degrees), and for how long (in days), the outside air temperature was above a certain level. They are commonly used in calculations relating to the energy consumption required to cool buildings.
Cross-price elasticity	The cross-price elasticity of demand measures the responsiveness of the quantity demanded for a good to a change in the price of another good, all other relevant factors remaining the same.
Diversity factor	See section 7.3.4 of this document.
EVs	Electric Vehicles
Heating degree days	Heating degree days are a measure of how much (in degrees), and for how long (in days), the outside air temperature was below a certain level. They are commonly used in calculations relating to the energy consumption required to heat buildings.
HIA	Housing Industry Association
HVAC	HVAC (heating, ventilating/ventilation, and air conditioning). Its goal is to provide thermal comfort and acceptable indoor air quality.
kWh	Kilowatt-hour. Is a basic measuring unit of electric energy equal to one kilowatt of power supplied to or taken from an electric circuit steadily for one hour. One kilowatt-hour equals 1,000 watt-hours. One kilowatt-hour can power ten 100 watt light bulbs for one hour.
Load factor	The ratio of annual average demand to annual peak demand. This is a partial indicator of network utilisation.
MAPE	Mean Absolute Percentage Error: For an actual vs forecast comparison the absolute values of the percentage errors are summed and the average is computed.
MBS data	Metering Business System data that is associated with managing revenue meters connected to the Western Power Network.
Multivariate regression	Multivariate regression is a technique that estimates a single regression model with more than one outcome variable.
MVA	MVA stands for Mega Volt Amp or Volts X Amp /1,000,000. If the total load requirement is 1,000 volts and 5,000 amps (1,000 x 5,000 = 5,000,000 VA) it can be expressed as 5MVA. This is called "apparent power" because it takes into consideration both the resistive load and reactive load.
MW	Megawatt. One megawatt equals one million watts and is a measure of the active component of electrical demand.

Term	Definition
MWh	Megawatt-hour. Is a measure of electrical energy i.e. one megawatt-hour equals one million watt-hours. For example, one MWh of electricity can power ten thousand 100 watt light bulbs for one hour.
NetCIS data	Data retrieved from NetCIS which is Western Power's core customer care and billing system. NetCIS stores most of the company's customer information and interactions and is used on a daily basis throughout the organisation. It is the system used to calculate and invoice network access charges and bill these charges to electricity retailers.
NMI	NMI or the National Metering Identifier is a unique identifier that identifies a supply or connection point and is assigned by the providing distributor.
Outliers	Observations in a data set that are substantially different from the bulk of the data. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter may be excluded from the data set.
PoE	Probability of Exceedance: This is the percentage of time that an actual value is expected to exceed the forecast value e.g. a PoE 10 forecast is expected to be exceeded 10% of the time i.e. one year in ten. And a PoE 20 forecast is expected to be exceeded 20% of the time i.e. one year in five.
Power factor	Power factor is the ratio between the MW and the MVA drawn by an electrical load where the MW is the actual load power and the MVA is the apparent load power.
Predictor variable	Is an independent variable that is manipulated in an experiment in order to observe the effect on a dependent variable.
Regression analysis	Regression analysis is a statistical modelling process for estimating the relationships among variables. It includes many techniques for modelling and analysing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables (or 'predictors').
SC	Seasonal Component
SCADA data	The SCADA (Supervisory Control and Data Acquisition) system is Western Power's critical system for managing the electricity network, both day to day and in emergencies. This network data is monitored and recorded.
Serial correlation	Serial correlation is the relationship between a given variable and itself over various time intervals. Serial correlations are often found in repeating patterns, when the level of a variable effects its future level.
Sigmoid function	A sigmoid function is a bounded differentiable real function that is defined for all real input values and has a positive derivative at each point.
SMEs	Subject Matter Experts

Term	Definition
Standard deviation	A common measure of spread in the distribution of a random variable.
Standard error of mean	The standard error of mean (SEM) estimates the variability between sample means that you would obtain if you took multiple samples from the same population. The standard error of mean estimates the variability between samples whereas the standard deviation measures the variability within a single sample.
Summer	Summer refers to the period 1 December to 31 March (inclusive).
SWIN	South West Interconnected Network. Is all the transmission and distribution components of the electricity system. And comprises the Western Power Network and other transmission and distribution assets owned and operated by others.
SWIS	South West Interconnected System. Is the entire electricity system including all of the generators. And comprises the Western Power Network, other transmission and distribution assets owned and operated by others and all of the generators.
Test of unit root or unit root test	A 'unit root test' tests whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root and the alternative hypothesis is either stationarity, trend stationarity or explosive root depending on the test used.
Time series	A time series is a series of data points listed (or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data.
Topaz	A Western Power database that is used to store and maintain up to date information relating to customers' connection applications.
VAR	Vector Auto-regressive
Weather correction	In the context of demand, weather correction refers to the estimation of maximum demand based on expected weather outcomes to create a weather-normalised maximum demand series.
Western Power Network	Is the transmission and distribution element of the SWIN that is owned and operated by Western Power.
Winter	Winter refers to the period 1 May to 31 August (inclusive).
WPN	Western Power–owned
WUN	Wundowie Substation

Document References

Doc #	Title of document
42747934	2017 Maximum demand forecasts (Summer) by zone substation
42774252	Energy & Customer Numbers Forecast - 2017

1. Introduction

1.1 Purpose

This document describes the methodology used to prepare the following forecasts for the fourth access arrangement period commencing 1 July 2017:

1. number of new connections
2. energy forecasts
3. maximum demand.

The scope of this document includes both transmission and distribution networks.

1.2 Structure

This document is organised as follows:

- Section 2 provides an overview of Western Power's forecasting process.
- Section 3 briefly articulates the principles guiding key decisions made in constructing forecasts
- Section 4 explains the data preparation process.
- Section 5 provides a conceptual overview of the structure and organization of the underlying load growth forecast.
- Section 6 describes the methods used to forecast trend growth in underlying load caused by growth in population, household formation and the economy.
- Section 7 explains how the underlying load growth forecasts are used to create maximum demand forecasts.
- Section 8 summarises the key forecasting assumptions and indicates the sources of those assumptions.
- Section 9 provides an outline of the block load forecast method.
- Section 10 lists the range of forecast reports subsequently produced.

2. Forecasting process overview

Key messages:

- As a Transmission and Distribution Network Service provider, Western Power produces and reconciles new connection, energy and maximum demand forecasts at the whole of network level, by load area, by zone substation area and by HV feeder area.
- These forecasts are part of a wider set of forecasts, which extend to: solar photovoltaic power system connections; electricity volume transported via the Western Power Network; and electricity volume imported from distribution connected generation.
- The forecasts are primarily bottom-up forecasts consisting of hundreds of forecasting models. The primary benefit of forecasting at a detailed level is maximum flexibility and simplicity. That is, relatively simple and largely data-driven models are fitted to specific customer segments (i.e. Commercial, Industrial and Residential). Model coefficients are allowed to adjust across regions; meaning that a given customer segment (e.g. residential customers) may contain coefficient estimates that are statistically different across regions. In addition, responses to systematic seasonal variation (e.g. in temperature, sunlight etc) is allowed to vary across forecast region.
- The forecasts at zone substation level and above are a composite of many trends, the most important being: new connection growth, amount of solar photovoltaic generation, response to variation in electricity prices, and economic activity.

2.1 Purpose of producing forecasts

The Regulation and Investment Management and Finance Treasury and Risk functions require the preparation of forecasting processes to assist with:

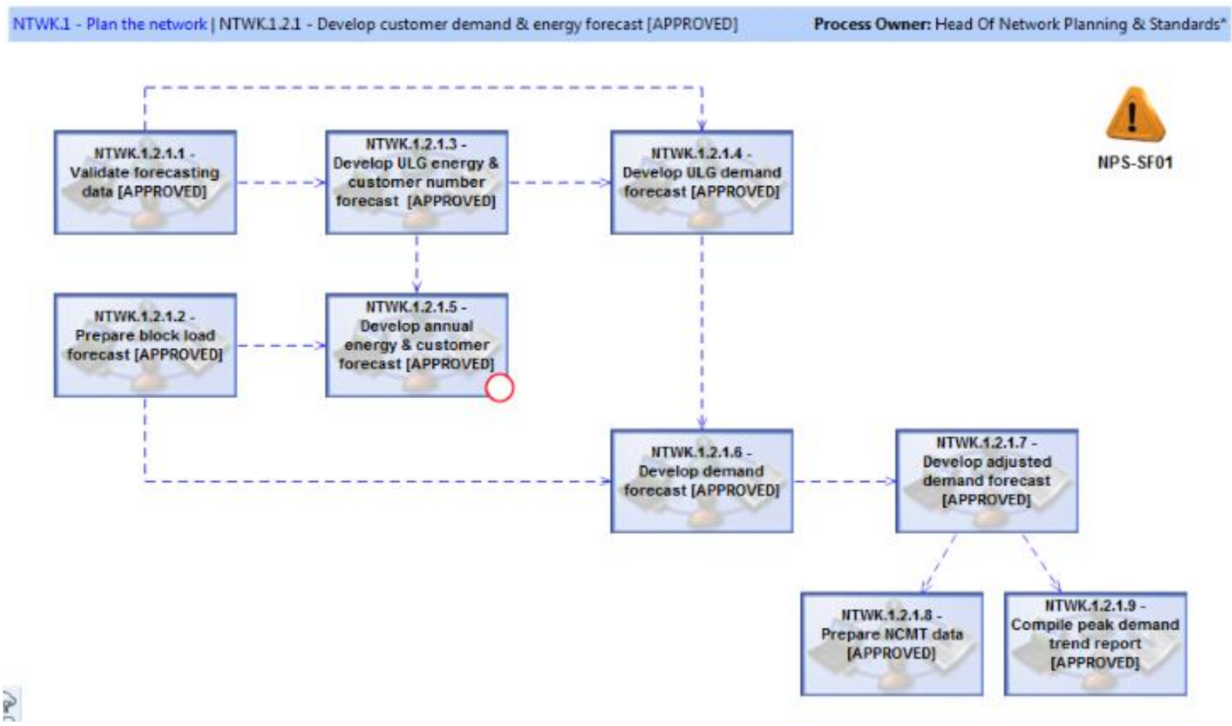
- Review of the annual price list – Allows Western Power to forecast expected revenues, and adjust the price list accordingly.
- Budgeting – Allows Western Power to forecast maintenance requirements.
- Network planning (capacity and reliability performance) – Allows Western Power to forecast growth requirements.

The forecasts produced to assist with these objectives include:

- number of customers/connections
- metered energy sold to customers
- maximum demand
- network reliability performance.

In delivering these outcomes, Western Power follows defined processes described in the Process Library. An overview of the forecasting process is illustrated in Figure 1 (next page).

Figure 1: Process overview



Western Power produces the required forecasts through process NTWK.1.2.1 'Energy and Customer Forecast'. This process defines the validation of forecasting data, development of forecasts, and compiling the reports.

Customer connections and energy forecasts are in accordance with process NTWK.1.2.1.5 'Energy and Customer Forecast'. The process for determining the trends in peak demand and network reliability performance outcomes is process NTWK.1.2.1.9 'Develop customer demand and energy forecast'.

Western Power produces forecasts as defined in Western Power's Process Library. The role of these defined processes is to ensure that the forecasts are produced in a predictable and transparent manner that is fit-for-purpose for use in defined downstream processes, i.e. budgeting, pricing and planning.

2.2 Process description

2.2.1 NTWK 1.2.1 Energy and Customer Demand Forecast

This process delivers the energy (i.e. MWh) and maximum demand (MW) forecasts and consists of nine process steps. The process culminates with the delivery of the:

- Energy and Customer Numbers Forecast required by Strategy, Regulation and Finance for the Annual Price Review and for quarterly budgeting.
- Peak Demand Trend report, which presents peak demand forecasts by zone substation.
- Network Capacity Mapping Tool update, which provides a public view of the available substation capacity net of the forecast demand, excluding the impact of upstream transmission constraints that limit the substation capacity actually available.

2.2.2 Process steps

The process steps are explained in Table 1.

Table 1: Energy and customer demand forecast delivery steps

Process Number	Process Name	Process Description
NTWK.1.2.1.1	Validate forecasting data	Check the data (i.e. monthly kWh and customer numbers, annual maximum demand data and external variables) and ensure that it is suitable for developing forecasts.
NTWK.1.2.1.2	Prepare block load forecasts	Review prospective connection applications and determine which connection applications impose a step change in forecast trends. Apply the Block Load Criteria to determine the magnitude and timing of the connection applications deemed to be block loads.
NTWK.1.2.1.3	Develop underlying load growth energy and customer numbers forecasts	Using the received and validated forecasting data, apply appropriate forecast methods (e.g. times series statistics) to forecast small customer numbers and load. These are typically forecast as energy per active NMI and number of active NMIs.
NTWK.1.2.1.4	Develop underlying load growth forecasts	Calculate monthly GWh forecasts: product of energy per active NMI and the number of active NMIs.
NTWK.1.2.1.5	Develop annual energy and customer forecasts	Add the block load forecast to the underlying load growth forecasts. Convert monthly GWh forecasts to annual.
NTWK.1.2.1.6	Develop demand forecast	Determine load factors by zone substation, transmission load area, scale and convert the annual GWh forecasts to maximum demand (measured in MW).
NTWK.1.2.1.7	Develop adjusted demand forecast	Adjust the maximum demand forecasts to reflect any planned network reconfiguration.
NTWK.1.2.1.8	Prepare the Network Capacity Mapping Tool data	Create a spatial layer using Geographical Information System tools and present on the Network Capacity Mapping Tool layer.
NTWK.1.2.1.9	Compile the peak demand trend report	Create a report, combining both quantitative and qualitative information.

2.2.3 Supply zone classification system

There are many systematic differences in demand characteristics across supply zones, which requires application of different forecast assumptions across supply zones. To facilitate the orderly management of these differences, the supply areas are classified as follows:

- Load area: each zone substation is assigned to one of 15 load areas as defined in the Annual Planning Report, Appendix C.
- Ownership: zone substations are either Customer-Owned (CO) or Western Power–Owned (WPN).

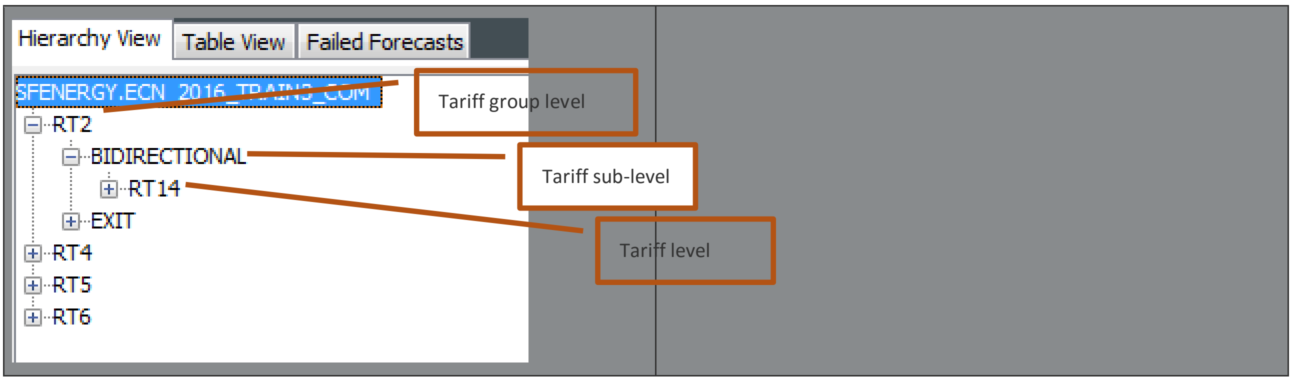
2.2.4 Forecast platforms

Western Power primarily relies on the SAS platforms Enterprise Guide and Forecast Studio for forecasting purposes. The open source software R (by CRAN) is also used for parts of the forecast process. The primary benefit of these platforms is that documentation is created as a by-product of forecasting which is consistent with the principles of transparency and ability to replicate the forecast.

Enterprise Guide is a platform for creating scripted tasks via a ‘point and click’ interface or by direct coding. These are organised into pre-forecast and post-forecast process flows. Use of Order Lists provide a means of specifying the order of task implementation, ensuring that these processes are implemented in the same way each time the process is executed.

Forecast Studio provides state-of-the-art machine generated forecasts, which can then be customised to reflect knowledge about a given forecast that is not already reflected in the data. There are several automatically generated forecasts that can be compared. Forecast Studio also provides a convenient means of reconciling multi-level forecasts.

Figure 2: Illustration of forecast hierarchy for commercial customer numbers forecasts for commercial customers



The primary benefit in multi-level forecasting is the ability to reconcile small area dynamics with tariff level and network level demand profiles. This reduces forecast bias and consequently enhances accuracy while maintaining insights with respect to the individual contribution of distinct trends such as population and technology trends, which are typically identified in network and tariff level models.

R is an industry standard tool that provides specialist algorithms which are simple to implement and may in some cases produce an easier to customise process. There are also packages in R, such as GGPLOT2, which provides enhanced visualisation of data.

3. Forecasting principles

Key messages:

- Before engaging in the complexities of forecasting, it is important to establish principles to guide the multitude of decisions that need to be made
- Principles guide choices about how the forecasts are done, particularly where there are trade-offs in outcome. For example, simplicity versus comprehensiveness, speed versus insight
- The three primary principles applied by Western Power are accuracy, transparency and evidence-based decisions

Western Power strives to deliver forecasts that are:

- accurate and unbiased
- transparent and repeatable
- evidence-based and data-driven.

In doing so:

- identify and incorporate key trend drivers
- design, validate and test forecast models
- ensure consistency of forecasts at different levels of aggregation
- use the most recent input information available.

3.1 Application of principles in practice

3.1.1 Accurate and unbiased

Western Power monitors the accuracy of past forecasts, with a primary focus on the most recent forecasts, by comparing actual data against the forecasted data. By continually adding actual data into the forecasting processes the analysis becomes more accurate. Periodic forecast accuracy assessments are conducted with a focus on:

- monitoring the typical level of accuracy
- understanding the causes of inaccuracy

Evidence of this practice is available in the Annual Planning Report.

Any evidence of bias is incorporated in adjustments made in the design of new forecast models, which extends consideration to the type and quality of the data relied on to calibrate forecast models.

3.1.2 Transparent and repeatable

Western Power employs good practices, such as:

- development of clear work (i.e. task) instructions that adequately describe each task performed in producing the forecasts

- clearly identifying the source of information and maintaining adequate records of where and when the data was sourced
- use of good practice model development techniques (e.g. separation of source data, intermediate calculations and final output)
- scripts (e.g. R or SAS code) are presented in a readable style that avoids use of hard coded values in the body of scripts, and minimises duplicate code
- producing reports that adequately document the forecasting process and outcomes.

3.1.3 Evidence-based and data-driven

Western Power ensures that data (both quantitative and qualitative) can be relied on for forecasting purposes by:

- identifying the source of information (e.g. data) and determining its likely credibility
- evaluating the received information in terms of its usefulness for forecasting purposes
- demonstrating the relevance of the source information
- demonstrating how the source information is used to develop the forecasts
- use of sound logical reasoning that is recorded in forecasting documents.

4. Data preparation

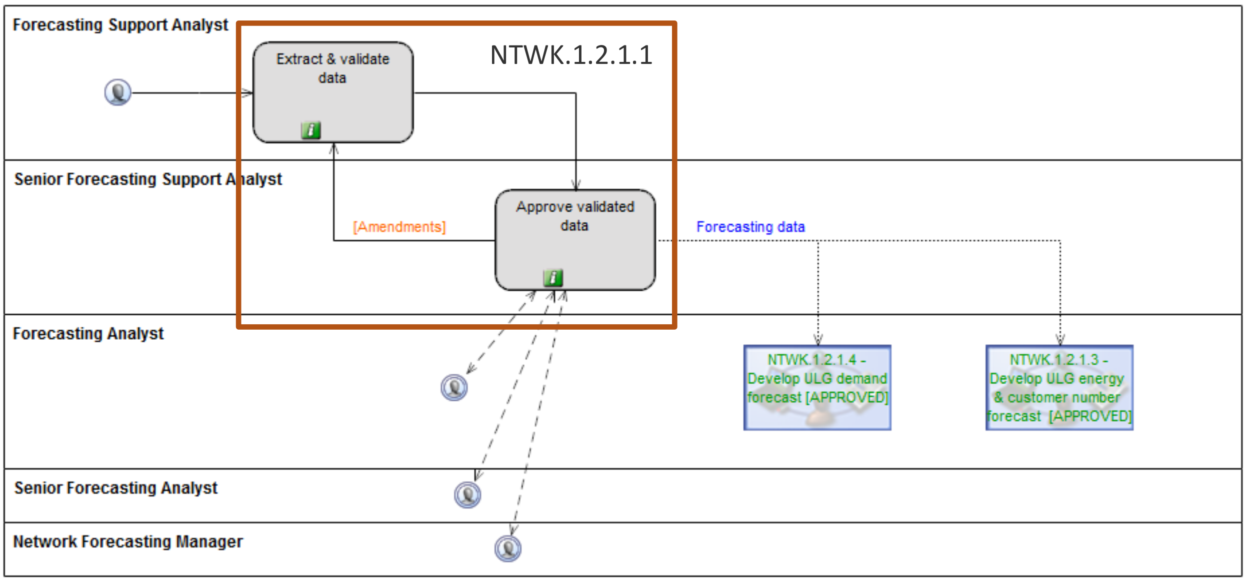
Key messages:

- Western Power undertakes thorough data preparation through data cleansing and formatting
- Data preparation enables the selection of appropriate forecasting methods

4.1 Extract and validate data

This process is covered by NTWK.1.2.1.1 'Validate forecasting data' and describes the data validation process in the Process Library. The process produces data which feeds into NTWK.1.2.1.3 'Develop underlying load growth energy and customer numbers forecasts' and NTWK.1.2.1.4 'Develop underlying load growth forecasts'.

Figure 2: Responsibilities for extracting and validating data



The key steps are:

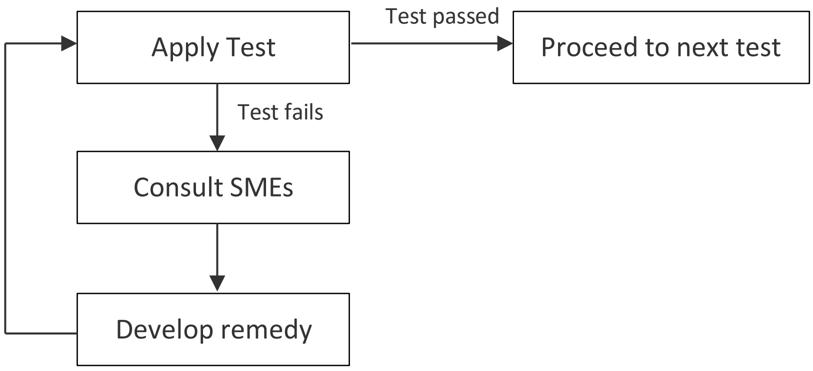
- extract and validate data
- approve the validated data.

Data validation is a test-driven process. The first test is to establish expectations about the data and then examine the data to determine if the extract matches those expectations. The process bifurcates based on the following criteria:

- If the data extract satisfies a specific test, accept the data without further investigation; otherwise
- Investigate why the data fails to satisfy the test.

On failure of a test, Western Power contacts relevant Subject Matter Experts (**SMEs**) within the business for advice and assistance in investigations and developing remedies.

Figure 3: Iterative loop process flow



Tests against established benchmarks

The first round of tests is based on benchmark comparisons between:

- The last validated data set for any overlapping history
- Where there is no overlapping history:
    a. Comparison based on an alternative credible data source
    b. More detailed benchmarks based on past data properties (i.e. does the latest data exhibit the same data properties as the earlier validated data)
    c. Any established rules based on logical reasoning.
- The second round of tests is based on determining the signal strength in the underlying data. This involves statistical profiling such as:
    a. Calculating summary statistics including the standard deviation of the raw data, standard errors of means, and coefficient of variation for each time series
    b. Identifying the time series properties of the data including serial correlation patterns, test of a unit root, and presence of trend.

The second round of tests provides information about how best to forecast the data. For example, strong time series properties suggest that time series methods would perform well. The key test in this round is one of signal strength. If this test fails, then alternative forecasting methods would be considered, such as simulation methods.

4.2 Tolerance for imperfection

As with any data set containing measurements (as opposed to simulated data), the data that Western Power relies on for establishing forecasts contains imperfections, such as measurement error. Thus, previous data extracts are validated in the sense that they are considered clean enough to produce a forecast that is likely to remain within acceptable accuracy parameters.

As a broad guideline, an imperfect data set can be deemed valid for forecasting purposes if:

- It can be demonstrated that the forecasting methods are unlikely to be biased as a result of the inherent data imperfections.

- The imperfections are known and can be effectively mitigated before the data is relied on for forecasting purposes.

In practice, the established heuristic is acceptance of the data where there is less than a 2% variance with established benchmarks. This is known as the materiality test. Where this test is not satisfied, a root cause analysis is conducted.

4.3 Root cause analysis

As the term suggests, root cause analysis identifies the root causes of faults. There is a distinction between a causal factor and a root cause. The defining attribute is that once a root cause has been removed, the fault ceases to exist. In the context of energy volume and connection numbers data, a double count in a query script is a good example of a root cause. Effective root cause analysis:

- is performed systematically
- is backed up by evidence, typically specimens illustrating a source of the fault
- has an adequate description of each problem
- ensures recommended corrective actions are undertaken.

Problems are identified when a formal comparative benchmark test fails. Comparative tests are established in a top-down order. An example of a comparative test relating to reconciliation of Balcatta zone substation data is presented below.

Box 1: Comparative benchmark test example

Measurement error is a primary risk when forecasting demand. Examples of measurement error include: occasional SCADA sensors fail; incorrect calibration and reassignment of PI tag with a lag in updates of database records.
For these reasons, Western Power regularly and systematically validates and corrects data before use in forecasting processes. Determining whether measurements can be considered to be correct involves a series of cross-checks across SCADA measurements of electricity flows entering, transitioning and exiting zone substations. In addition, Western Power cross-checks SCADA and metering data by zone substation.
This process identified that approximately 2,000 Balcatta zone customers were incorrectly configured in the metering data. Correcting this led to a material re-evaluation of trend across Balcatta zone substations with respect to the neighbouring zone substations.

Comparative benchmark testing involves comparing latest data extracts to previous extracts and cross-matched against similar extracts from other sources (e.g. MBS, NetCIS extracts can be cross-matched against SCADA data for at the Load Area level). The test fails if the average difference is outside a prescribed tolerance (e.g. more than 2%). On failure, the following activities are undertaken:

1. Determine if a data correction has been implemented since the last extract. If so, document the previously unidentified problem with the previous extract.
2. If there is no correction implemented:
    - Examine the time series of energy values to determine if there has been a step-change in energy numbers at a point in time. If this is identified, check that this is genuine, e.g. confirm that there was a new customer that used that energy.

- Compare connection numbers. If this test passes, then there must be erroneous meter readings.
- If this test fails, then there is likely to be a problem with meter counts. Follow up with a test of the Data Generating Process. This assumes that the latest data extract will exhibit the same data properties as previous extracts based on any one of the following:

Box plot overlay of the latest data points. Latest monthly observations should fall within the “box”.

Similar seasonal pattern as defined by the SAS DECOMP procedure. Compare the seasonal patterns available in SC (SAS “**Seasonal Component**”).

Similar correlations and Augmented Dickey Fuller test results to those as previously established.

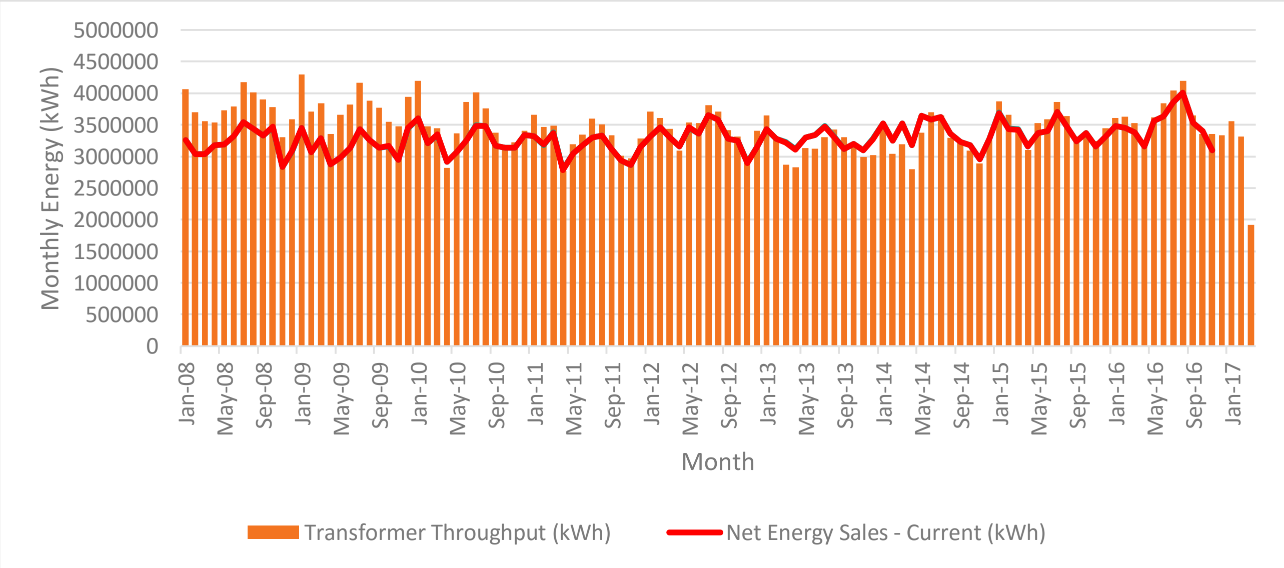
4.4 Data validation quality checking process

Western Power follows good industry practise and has implemented a robust data validation and quality checking process. The Senior Forecasting Analyst checks to ensure that:

- data validation process has been followed by the analysts preparing the data
- data either conforms to established benchmarks within prescribed tolerances or there is an evidence-based reason for identified anomalies.

Below is an example of the data validation process used in 2017, using the Wundowie (WUN) substation as an example.

Figure 4: Wundowie (WUN) substation data from the validation process



In this example, the net energy sales roughly align with the substation transformer throughput, given expectations of distribution losses and metering inaccuracies (with declining accuracy in the past). The alignment demonstrated in WUN provides a high degree of confidence in the metering and SCADA data for all forecasting including customer, technology, energy and demand.

5. Overview of underlying load growth forecast methods

Key messages:

- Western Power separates the trend in underlying load growth into three separate trends to reliably track and forecast the complex mixture of socio-economic forces in play that result in highly dynamic and evolving electricity demand patterns.
- The three separate trends are solar photovoltaic power system adoption; customer connections; and energy per customer
- Western Power further segmented these forecasts into area and customer type to enable sophisticated statistical methods and rules-based methods to produce the composite connection numbers, energy and maximum demand forecasts

5.1 Introduction

The underlying load growth forecasts are defined in processes NTWK.1.2.1.3 'Develop underlying load growth energy and customer numbers forecasts', and NTWK.1.2.1.4 'Develop underlying load growth forecasts'. The forecasts typically consist of a trend (often a composite of several trends), one or more cyclical components (e.g. seasonal effects) and an irregular/volatile component (e.g. consisting of rare extremes in temperature that deviate materially from the typical seasonal component).

Given the complexity, significant time and effort is devoted to forecasting underlying load growth. Underlying load growth typically applies to supply areas that connect tens of thousands of commercial and residential customers. These supply areas exhibit highly dynamic and evolving demand patterns caused by a range of distinct causal forces.

In order to forecast these forces accurately, the forecasts have been structured along causal lines. That is, customers first determine their energy demand and decide how to acquire that energy. Consequently, solar photovoltaic system forecasts are produced first, followed by network connection counts. Next, energy per connection (reflecting intensity of use of the electricity network to satisfy energy demand) models groups of customers likely to have similar demand profiles. These stratified forecasts are then combined and aggregated to produce the desired connection numbers, energy and maximum demand forecasts.

Organising the forecasting process this way also serves to simplify the process and maximise model flexibility.

5.2 New connection forecasts

The customer numbers data is monthly counts of each National Metering Identifier (NMI) or connection counts (e.g. streetlights and unmetered supplies).

New connection forecasts are produced primarily using the following time series statistics methods:

- Auto-Regressive Integrated Moving Average (ARIMA) method with external regressors as well as Vector Auto-Regressive (VAR) methods
- Unobserved Components Models
- Exponential Smoothing Models.

These forecasts are organized by customer type (i.e. Transmission, Business and Residential), by supply area (i.e. zone substation) and hierarchy (i.e. network level, zone substation, tariff group, and tariff).

5.3 Energy per connection trend forecasts

Energy per connection trend forecasts are produced using the ARIMA method with external regressors. These are largely generated automatically with the occasional model manually created. Diagnostic tests for seasonality, stationarity, and auto-correlation are employed to guide construction as well as forecast error statistics, typically out-of-sample Mean Absolute Percentage Error (MAPE).

These forecasts are organized by customer type (i.e. Transmission, Business and Residential), by supply area (i.e. zone substation) and hierarchy (i.e. network level, zone substation, tariff group, and tariff).

5.4 Composite trend forecasting

The underlying load growth forecast is a composite of distinct forecast layers:

- trend in solar photovoltaic counts
- trend in connection counts
- trend and cycle in energy (e.g. kWh) exports per NMI.

The source monthly observational data is compiled by zone substation and by customer group (i.e. residential, commercial, industrial). These groups are further organised into an internally consistent hierarchy of aggregate groups such as Tariff, Load Area and Network.

The solar photovoltaic trend is added to the explanatory data for energy per NMI. In areas of high solar photovoltaic penetration, solar photovoltaic counts will be included as an explanatory variable/predictive modelling in forecast models.

The forecast models are largely machine generated time series models, which incorporate chosen explanatory data. For example, there are population and household count forecasts in the explanatory data set used to forecast network connection growth. Note that insufficient variation in a variable that is known to be a fundamental cause of growth may not be explicitly included in the preferred forecast model. For example growth in household counts causes growth in connection counts, but may not be explicitly included in the forecast model. This does not mean that there is necessarily anything wrong with the connection counts forecast. Instead, it is likely that the household forecast data lacks sufficient variation to lead to a statistically precise estimate of the relationship. In such cases, time series statistics methods will likely utilise past observations of connection counts to forecast the trend. The rationale is time series forecasts are more accurate when there are persistent time series patterns are directly used in the forecasting algorithm.

The forecast trend in energy is the product of energy per connection and the number of connections by zone substation. The energy forecasts are then converted to average demand (i.e. power) by summing the monthly data to an annual kWh and dividing by time in hours per year.

6. Underlying load growth forecast model description

Key messages:

- Western Power applies time series statistical models to most of the commercial and residential customer forecasts
- Western Power manually constructs some residential and commercial forecasts where required, typically as a correction to an automatically generated forecast
- Western Power manually adjusts industrial forecasts when advised of changes in demand. These forecasts are typically flat (i.e. no growth)
- Western Power's forecasts do not include all possible anticipated technological innovations (e.g. electric vehicles); however, they are being monitored and may be included in future forecasts if received evidence suggests that inclusion would be prudent.

6.1 Time series statistics methods

All models are created using Forecast Studio by SAS as discussed in process NTWK.1.2.1.6 Develop demand forecast , which employs three broad styles of time series forecast models:

- ARIMA
- unobserved components models
- multivariate regression.

Forecast Studio uses best practice forecast diagnostic and model building processes. Forecast studio has a number of automatic functions including diagnosing data (i.e. testing for trends, seasonality, autocorrelation, functional form etc.), constructing trial forecast models according to diagnostic test results, and selecting the best fitting models from the competing alternatives using holdout forecast error statistic (e.g. MAPE) scores.

Forecasters can also add customised models and call standard models from a model repository.

The forecasts are produced in a hierarchy, which permits the use of both space and time dimensions to maximize model flexibility, resulting in improved precision in model coefficients. In addition, the forecasts are reconciled so that the forecast sub-groups add up to the total.

In 2016, several bidirectional tariffs were introduced with customers reallocated from unidirectional tariffs. For example, customers who own solar photovoltaic power systems were allocated to RT1 in 2015. In 2016, these customers were reallocated to RT13. The reallocation of energy volume and customer numbers to the new tariffs impedes comparison of tariff based customer numbers and energy volumes between forecast reports. To overcome this issue an approximate reconstruction of the previous tariff structures can be produced for the purposes of comparison.

Note that while most of the forecasts are produced automatically, forecast models can (and have been) manually constructed and selected. Forecast Studio provides a wide array of diagnostic test results that are relatively easy to interpret, but do require a high degree of expertise to use effectively.

Another important benefit of Forecast Studio is its visual interface, which facilitates easier review by auditors, managers and stakeholders.

6.2 Econometric forecasts

Given that a large number and wide variety of statistical models are used to produce the forecasts, it is not practical to describe each forecast model applicable to each tariff.[1] Instead, this report describes the models employed within broader stylistic structures and themes.

6.2.1 Benefits of employing reduced form models

In previous rounds of energy and customer numbers forecasting, long-run structural models provided direct estimates of economic effects such as responses to variation in electricity tariffs and income or economic activity.

While such models are highly desirable for long-term business planning, directly estimated structural models often perform poorly as forecast models due to an array of statistical issues such as incorrectly specified dynamics and insufficient variation in explanatory variables, such as tariffs. Forecast Studio overcomes such problems by employing data-driven time series methods.

In describing these models, it is important to note that most of the models represent reduced-form models as opposed to structural models.[2] That means, for example, that the estimated coefficients are not economic parameters such as long-run price and income elasticities.

The benefit of employing reduced form models is that data-driven diagnostic and model building methods capture the short-run dynamics contained in the data. For example, most of the monthly energy volume series exhibit a high degree of serial correlation. This means that ARIMA models, which exploit serial correlation, produce accurate short-term forecasts. Methods described in econometric textbooks provide a way to obtain meaningful structural parameters from these models.[3]

6.2.2 Underlying drivers of electricity demand

This section provides a description of the external (i.e. independent) variables included in the forecast training data set[4]. Selection of these variables is justified by economic or demonstrated statistical relevance. Note that other variables could also have been included but are either not available or are difficult to obtain reliable forecasts.

The following categories apply to the selected external variables:

- economic activity: variables that measure the level of activity in the economy
- price: volumetric component of the electricity price
- seasonal: temperature and other weather variables
- substitution: capture any influence of alternatives to network delivery electricity.

---

[1] Note that any forecast model can be easily inspected in Forecast Studio

[2] See James D. Hamilton (1994), Time Series Analysis, Princeton University Press, pp. 244-246

[3] Bo Sjö, Lectures in Modern Economic Time Series Analysis, (30 October 2011) Linköping University <https://www.iei.liu.se/nek/730A16/filarkiv/1.299872/tsbook24.pdf>Chp 19

[4] The training data set, also known as the estimating data set, is the data used to calculate forecast model parameters

Table 2: External variable description

Category	Variable	Description
Economic	CPI	Consumer Price Index (Annual, Monthly, Change)
Economic	WPN Popn A	WA Tomorrow Popn Forecasts (A band; WPN area)
Economic	WPN Popn B	WA Tomorrow Popn Forecasts (B band; WPN area)
Economic	WPN Popn C	WA Tomorrow Popn Forecasts (C band; WPN area)
Economic	WPN Popn D	WA Tomorrow Popn Forecasts (D band; WPN area)
Economic	WPN Popn E	WA Tomorrow Popn Forecasts (E band; WPN area)
Economic	Regional Final Demand	WPN Regional Demand Forecasts (Annl, Mthly, Change)
Economic	Gross Regional Product	WPN GRP Forecasts (Annl, Mthly, Change)
Price	Tariff A1	Synergy Retail Variable Residential Tariff
Price	Tariff L1	Synergy Retail Variable Business Tariff
Seasonal	Public Holiday	Count of Public Holidays per Month
Seasonal	School Holidays	Count of School Holiday days per month
Seasonal	Days in Month	Count of Days per month
Seasonal	Average Temp	Avg Temperature observed at nearest reputable BOM station
Seasonal	CDD	Cooling Degree Days calculated
Seasonal	HDD	Heating Degree Days calculated
Seasonal	Max Temp	Max temperature observed at nearest reputable BOM station
Seasonal	Min Temp	Min temperature observed at nearest reputable BOM station
Substitution	PV Count	Count of Bidirectional customers
Substitution	PV Capacity	Sum of PV Inverter capacity

As indicated above there are many variables included in the estimating data set. Many of these variables are highly correlated, so most of Western Power's forecast models only include a small subset of these variables based on a balance of goodness of fit and forecasting accuracy criteria.

The variables and associated data are from published documents by Western Australian Government agencies, Bureau of Meteorology (BOM), Australian Bureau of Statistics (ABS), Clean Energy Regulator (CER), Housing Industry Association (HIA), and BIS Shrapnel.

Gross Regional Product is a broad measure of economic activity that typically accounts for a small component of monthly variation in electricity demand. Nevertheless, it will have an influence on the long-run trend in electricity demand since electricity is one of the inputs for productive activity.

Note that other economic measures of overseas demand for Western Australia's exports (such as exchange rates, the terms of trade, commodity prices etc.) are also likely to be influential on electricity demand. However, the relatively short time series of electricity demand impedes precise estimation of the impact on electricity demand. Moreover, the high volatility of these series and the absence of credible long-term forecasts for these additional economic variables limit the suitability of their use.[5]

Electricity prices have an inverse relationship with electricity demand, or at least network delivered electricity demand. Assuming fixed customers' budgets in the short-term, a higher price (i.e. higher electricity tariffs) should have a persistent dampening effect on electricity demand. This is an important factor for long-term forecasting.

An issue limiting the usefulness of the tariff is limited variation in prices. Typically, consumer electricity prices update just once a year. With just nine years of time series data, it is difficult to estimate a statistically precise relationship between electricity prices and the demand for network delivered electricity.

The number of solar PV electricity generation systems is a marginal substitute for network delivered electricity. A price series for solar PV use would be better than the quantity for measuring cross-price elasticity, but is not available. In the absence of the price series, we use the quantity series as a control for the substitution effect.

In considering alternatives to network delivered electricity, a notably absent variable is the price of natural gas. Given the extensive reach of the gas distribution network, it is likely that electricity and gas services compete, particularly in heating and cooking services. However, gas prices have typically increased at a faster rate than retail electricity prices, suggesting a long-term consumer preference for electricity. In turn, this suggests a high market share for electricity in supplying energy services.

Nevertheless, the prospect of gas prices to consumers beginning a long-term relative trend decline suggests that the prospect of competition from gas is more likely in the future.

Finally, cooling and heating degree-days per day control for the annual seasonal cycle. Temperature extremes tend to increase electricity demand, primarily to satisfy refrigeration and space heating demand.

Forecasting solar PV installations

The absence of reliable long-term forecasts for the number of solar PV installations is a serious impediment to developing accurate forecasts for electricity demand. Although the mass introduction of solar PV installations is a relatively recent phenomenon, the rate of adoption has had a material demand-reducing impact.

Given its importance, Western Power has conducted several investigations into forecast methods. The primary focus has been the investigation of sigmoid functions (otherwise known as diffusion curves) to forecast the expected duration of the exponential growth phase as well as the longer-term market saturation level.

[5] Note that these variables could be forecast using the International Monetary Fund's global VAR models.

The investigation has revealed that aside from large changes to government subsidy for solar PV systems, the rate of adoption has been approximately constant. This suggests an approximately linear relationship with the growth in the housing and commercial building stock. In addition, the rate of growth in solar PV installations is not sufficient to demonstrate the short-term superiority of a non-linear forecast.

At this point, the key assumptions are:

- there is a higher proportion of new solar PV systems on new buildings
- installations on commercial buildings are likely to be larger than on residential buildings. Hence, faster demand reduction will occur across commercial tariffs.

The difference in growth rates across the bidirectional tariffs is a matter of judgement with relatively little support from observable trends. Western Power will continue to closely monitor these growth rates and warn that there may be material inaccuracy in forecasting the bidirectional tariffs.

For example, a likely error would be the misallocation of the growth proportions over time. However, given that there are far fewer commercial premises, the rate of change in the proportion of solar PV systems should decelerate quickly.

Forecasting cooling and heating degree days

Long term temperature forecasts have been developed by sampling the historic temperature per weather station. Where medium term forecasts exist for weather, the relevant percentile was forecast; else, forecast weather is expected to take the median. In addition, there may be a changing relationship between temperature variation and associated electricity demand, such as:

- Continuing increases in penetration of temperature-dependent loads like air-conditioners (larger systems, or more split systems per household), will continue to increase the electricity demand impacts of extreme temperatures.
- Changes in demographics and technology adoption; for example, with a higher proportion of retirees with air-conditioners and solar PV systems, own-use of solar PV generated electricity may be increasing. This would appear as a daytime reduction in temperature related network demand.
- Changes in appliance and building efficiency; this is likely to be a subtle but persistent effect over time. Various estimates produced for the Australian Electricity Market Operator suggest this influence could amount to 0.5% per year. This efficiency effect remains unidentified in Western Power’s demand models due to the difficulty in statistically separating the efficiency effect from other trends evident in the data.

Prospect of further substitution via new technology

Since the 2015 forecasting round, speculation about mass adoption of other network competing technologies has intensified. Widespread adoption of battery storage systems could have a negative impact on network delivered electricity demand.

Western Power is monitoring developments in battery related marketing such as the Tesla PowerWall® system. 2017 is the first time that battery systems are being included in the forecast.

Factors affecting mass adoption of battery systems are:

- The present value cost of a battery system against the present value of the cost of purchasing network delivered electricity. If the present value of battery systems offers a lower cost (i.e. a net saving), wider adoption will occur.
- Consumer preference bias; if consumers perceive a positive utility in owning a battery storage system, then there need not be a net saving before mass adoption occurs. Measuring the desirability of battery systems is within the domain of marketing experts. Consequently, Western Power has been exploring the possibility of using marketing based models, such as EYC3's Simulait model.

Western Power has completed customer incentive modelling to compare the net present costs of:

- Grid Supply (drawing all load requirements from the grid)
- Partial Load Defection (installing batteries and PV's to self-supply 60-70% of required load)
- Full Load Defection (installing batteries and PV's to self-supply >95% of required load)
- Grid Defection (installing sufficient technology to allow full disconnection).

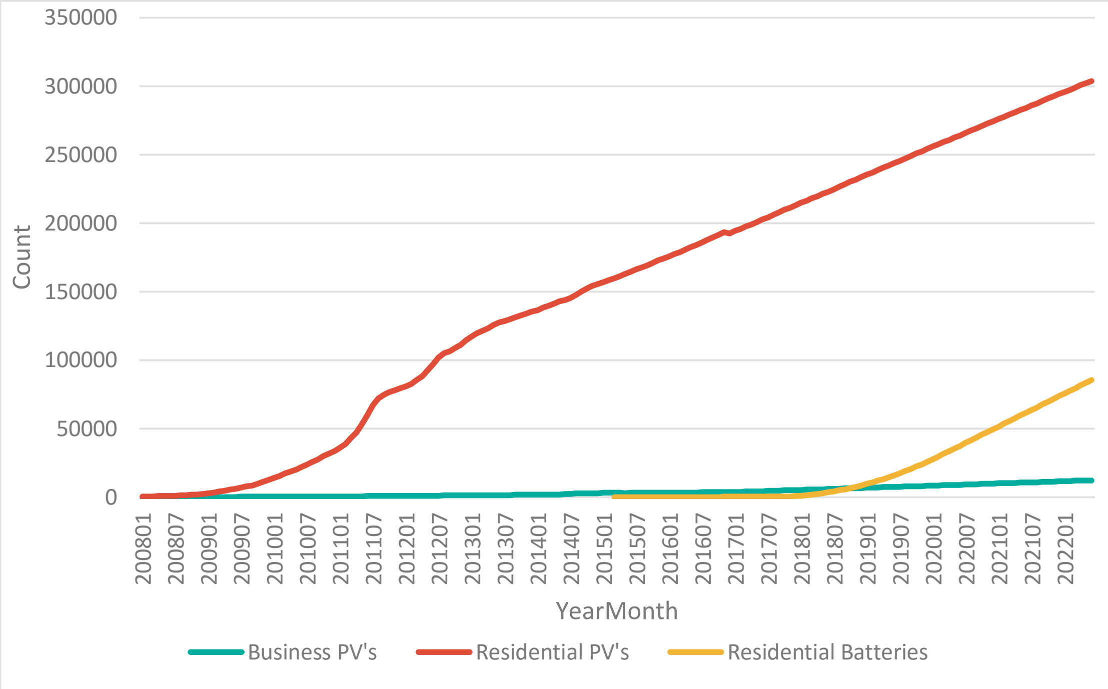
With the following results:

Table 3: customer incentive modelling of customer supply scenarios

Scenario *	2017 Net Present Cost	2027 Net Present Cost	2037 Net Present Cost
Grid Supply (A1)	$8,256.05	$10,805.24	$14,231.14
Partial Load defect	$15,359.90	$10,837.77	$10,003.55
Full Load defect	$36,047.24	$22,757.15	$21,039.51
Grid defect	$51,294.80	$33,624.31	$31,156.38

The table indicates that the average customer does not currently have the incentive to install batteries, but that most customers will have the incentive to partially load defect in the next 5-10 years. As such, substantial battery uptake has been assumed as shown in the technology forecasts shown below.

Figure 5: Technology Forecasts



7. Maximum demand forecasts

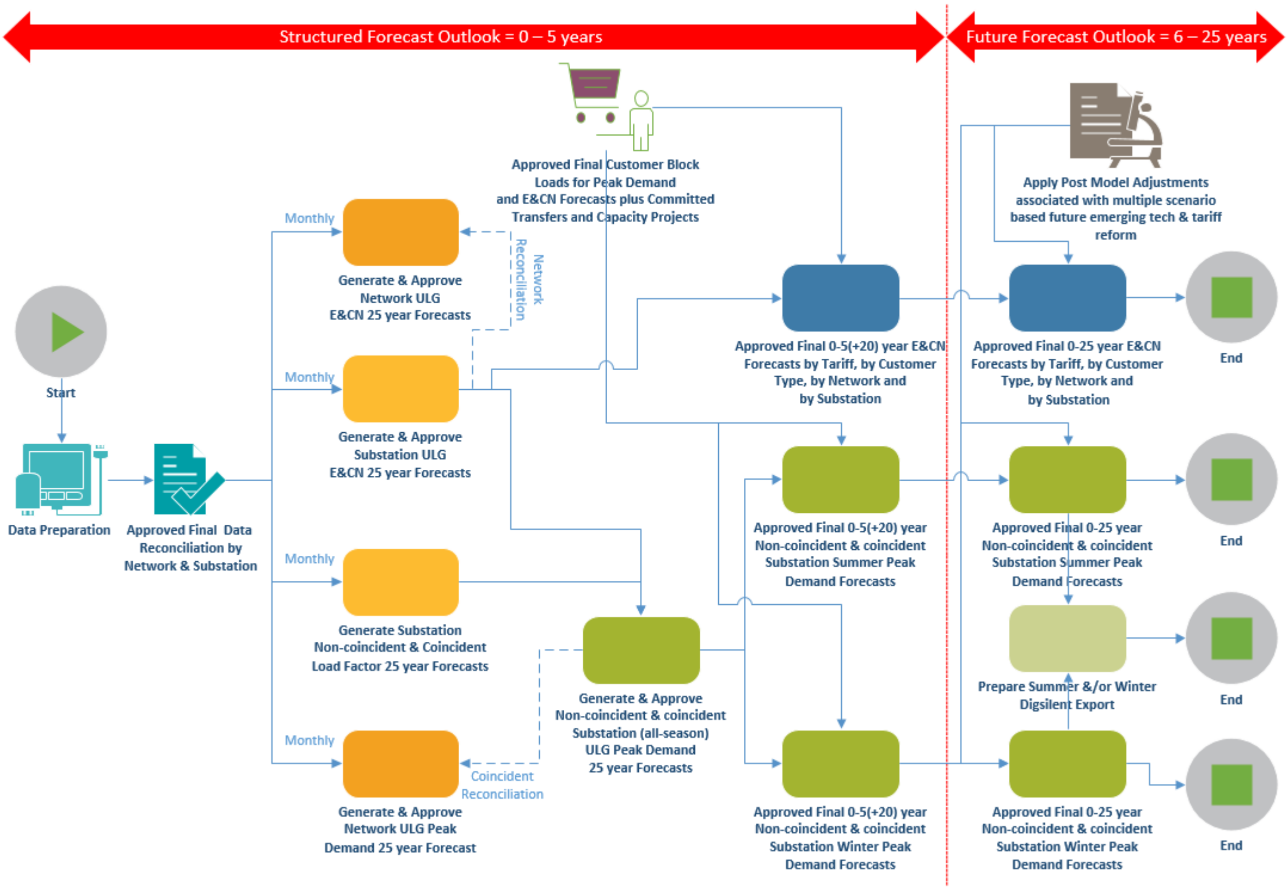
Key messages:

- Western Power applies a series of easy to follow rules to simplify the complexity of forecasting maximum demand
- Western Power converts the 5 year forward view of monthly electricity forecasts into monthly average demand, then applies several scaling factors (referred to as load factors, diversity factors and uncertainty bands) to create the monthly maximum demand forecasts. These are subsequently converted to annual maximum demand forecasts and extrapolated to present a 25 year forecast view.

7.1 Introduction

This section is linked to process NTWK.1.2.1.4 ‘Develop underlying load growth forecasts’ which provides a step-by-step conceptual overview of the maximum demand forecast. The key steps are described below with subsequent elaboration on key concepts that explain load factors, uncertainty bands and coincident and non-coincident maximum demand. Additionally, Figure 6 presents a simplified sequenced overview of the ‘end to end’ process that combines all the processes involved in developing the final Connections, Energy and Demand Forecasts.

Figure 6: Simplified overview of the ‘end to end’ process used to develop the final forecasts



7.2 Overview of the key steps

Maximum demand forecasts are produced at several distinct hierarchical layers: HV Feeder; zone substation; load area; and Western Power Network. The zone substation forecasts are the most important forecasts for network planning and are updated annually. In previous years the other maximum demand forecasts (HV feeder, load area and Western Power Network) were produced on request only. However, the 2017 forecast provided for annual updates of all maximum demand forecasts except for HV feeders. This section focuses primarily on the production of the annual zone substation maximum demand forecasts but it should be understood that the load area and Western Power Network annual demand forecasts that were generated this year were co-products of this year's annual forecast update.

The zone substation forecasts are produced on both a coincident and non-coincident maximum demand basis. Coincident means the zone substation demand at the time of the overall network maximum demand and non-coincident means the highest zone substation demand at any time (not necessarily coincident with the overall network maximum demand). See section 7.3.3 for more detailed explanation.

These forecasts are created using a largely rules-based approach. These rules are as follows:

- Conversion of monthly expected energy sales into monthly average demand over five years.
- Monthly average demand is scaled up to monthly Probability of Exceedance (PoE) 50 non-coincident maximum demand using load factor forecasts that were developed consistent with each zone substations highest monthly demand.
- The monthly non-coincident PoE 50 maximum demand forecast is annualised and extended from five to 25 years by applying a net growth factor to zone substations deemed to exhibit permanent underlying load growth. All other zone substations are assumed to exhibit no underlying load growth. These are typically privately owned zone substations, such as the Binningup Desalination Plant (BDP) zone substation, which are normally directly transmission connected to the Western Power network. There are, however, several distribution connected zone substations that display no underlying load growth – these are treated similarly.
- The corresponding 25 year coincident PoE 50 maximum demand forecasts are generated using the same method used to generate the 25 year non-coincident PoE 50 maximum demand forecast but differ as they utilise the load factor forecasts that were developed consistent with each zone substation demand that occurred at the time of the overall network maximum demand. The PoE 10 forecast is created by scaling the PoE 50 forecast by the standard deviation of the corresponding monthly load factor forecast, corrected for any level shifts induced by load transfers, block loads, changes in wheeling agreements etc.

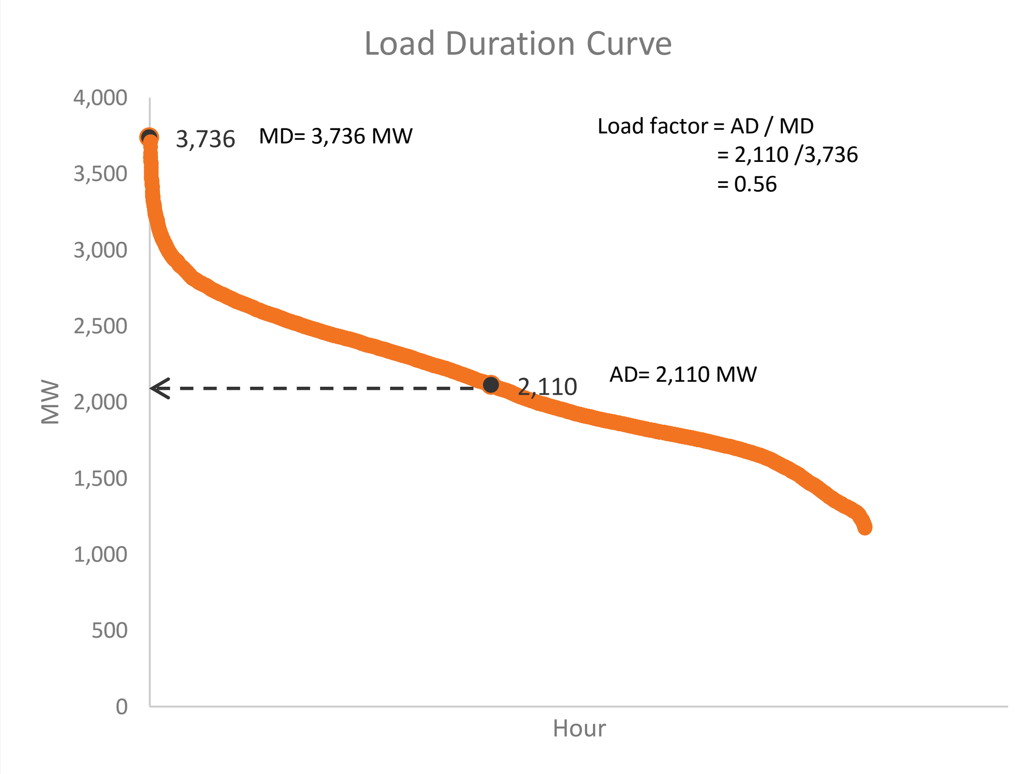
7.3 Scaling average demand to calculate maximum demand forecasts

The monthly average demand forecast is scaled by dividing the forecast average demand by the appropriate monthly load factor forecast to derive a PoE 50 maximum demand forecast for each zone substation.

7.3.1 Scaling by load factor

The load factor is defined as the ratio of average demand to maximum demand. Figure 7 shows the average and maximum demand on a load duration curve. Load duration curves provide an indication of network utilisation over a year.

Figure 7: Load factor calculation example



A low load factor indicates a relatively low level of network utilisation. Figure 7 indicates that demand exceeds 3,000 MW for a short duration over a few hours of the year, typically a few days each summer. An ideal load factor would be a horizontal line, indicating a consistent level of demand over a given year.

Comparing load duration curves over the years indicates a declining network utilisation trend, i.e. there is a trend in the load factor. As more customers connect to the network, maximum demand has been increasing at a faster rate than average demand. In recent years, the main causes have been the use of HVAC (Heating, Ventilation & Air Conditioning) and solar photovoltaic power systems. HVAC use typically coincides with extremes in temperature, causing higher than normal demand for network delivered electricity in summer and winter. Solar photovoltaic power systems have contributed to the trend in declining load factor by reducing customer demand during the day faster than maximum demand is reducing. Note that the solar photovoltaic power systems impact on load factor is expected to dissipate over time[6] since there is an upper limit to electricity self-supply and maximum electricity demand is capped to total appliance capacity.

This suggests that the trend in load factor is bounded and cannot continue to trend linearly indefinitely. This means that forecast load factors are bounded between an upper and lower limit.

7.3.2 Uncertainty bands

Both the 50th and 90th percentile forecasts are developed and relabelled as PoE 50 and PoE 10, respectively. The numbers 50 and 10 relate to the probability of maximum demand observations exceeding

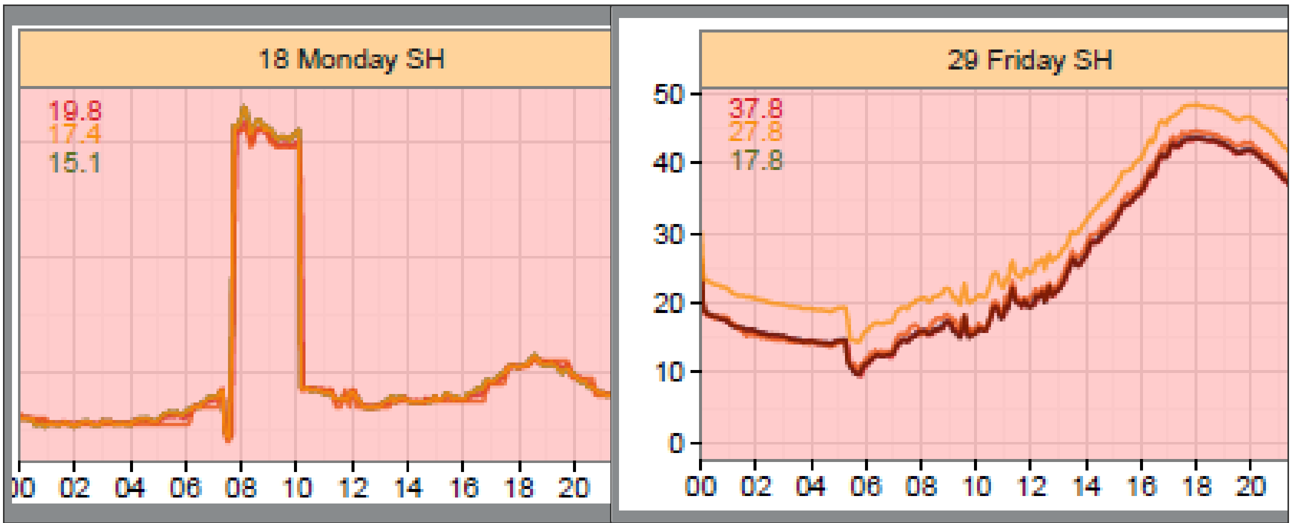
[6] The impending emergence of batteries storage systems and smart controls will increase customer self-consumption from PV over time, but could also help to manage customer peak demand.

the forecast. Observed maximum demand is expected to exceed the PoE 50 forecast 50% of the time whereas maximum demand is expected to exceed the PoE 10 forecast 10% of the time. Given the skewness of the load profile shown in Figure 7, most network-wide maximum demand observations would not exceed 3,000 MW most of the time. On the occasions when maximum demand does exceed 3,000 MW, it can do so by an unexpectedly large amount. Such large demand spikes were observed in 2016 and prompted reconsideration of how the PoE 10 band is calculated. At present, the difference between the PoE 50 and PoE 10 forecasts is relatively narrow compared to those observed spikes.

The difference between PoE 50 and PoE 10 is due to volatile factors such as demand responses to extremes in temperature. Occasionally, manual adjustments are made where there is strong evidence of the need to do so. For example, zone substation maximum demand forecasts are adjusted when changes in block loads impose a step-change on the underlying load growth forecast.

Given the PoE 50 forecast for maximum demand, it is necessary to acknowledge the inherent volatility in maximum demand. The volatility is primarily caused by the use of HVAC systems and other temperature-dependent loads like refrigeration and water pumping (e.g. operation of swimming pool pumps) during periods of extreme temperature. However, other factors such as operation of distribution connected generators can add or subtract from the temperature induced volatility. To illustrate the distinction, maximum demand induced by different causes is shown in the left-hand chart in Figure 8. This left-hand chart shows that the temperature reached a maximum of 19.8 C. This spike in demand was likely caused by a temporary load transfer. The right-hand chart indicates the temperature was 37.8 C and increased at a steady rate during the day. This surge in demand was likely caused by high temperature on top of the normal customer daily demand profile which peaks in the evening.

Figure 8: Example of a maximum demand spike caused by a factor other than weather



Load transfer induced maximum demand	Temperature induced maximum demand

A distribution (or uncertainty band) is overlayed to indicate the degree of volatile variation, which is often due to weather variation (e.g. temperature spikes and heat waves). Note that other causes of spikes in maximum demand are also considered for some areas, such as the Eastern Goldfields. In that case, wheeling arrangements[7] in place between private power suppliers and large customers can lead to sudden reversals in electricity flows at Western Power's entry and exit points.

7.3.3 Coincident and non-coincident demand

Zone substation coincident maximum demand measures the demand in MW at each zone substation at the time of the network or system maximum demand. Zone substation non-coincident maximum demand measures the demand in MW at the time that each zone substation registers its maximum demand for the year. Typically, coincident and non-coincident maximum demands occur at different times and may occur on different days.

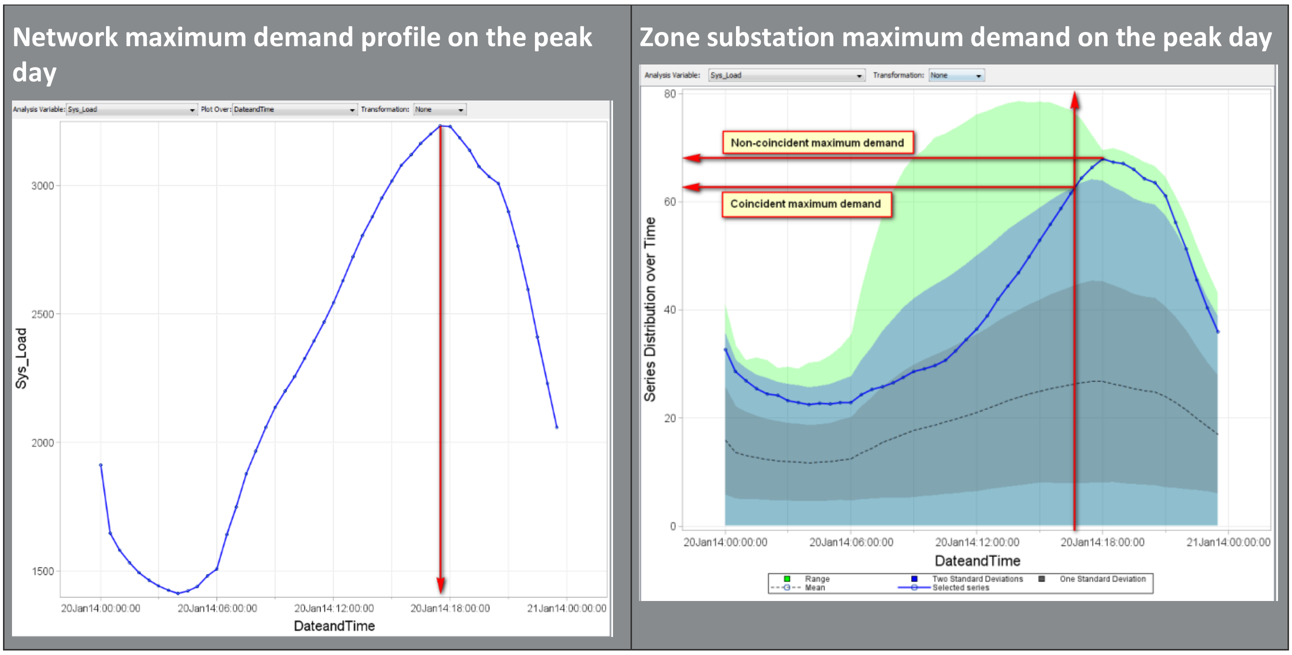
By convention, maximum demand is measured on an annual basis and is implicitly tied to either summer or winter. For example, since the Western Power Network registers maximum demand during the summer, the coincident maximum demand at each zone substation corresponds to summer. By contrast non-coincident maximum demand can occur in a different season. For example, the Albany zone substation typically registers its non-coincident maximum demand during winter.

Note that forecasters classify zone substations as either summer or winter peaking.

A real example is depicted in Figure 9 below. The left hand side chart shows the demand profile for the entire network on the peak demand day. The right hand side chart shows the demand profile for the Mandurah zone substation, which in this case happens to be the same day. The vertical arrow on both charts marks the time of maximum network demand. The coincident maximum demand reading for Mandurah zone substation is measured at the point where the vertical arrow intersects the blue demand curve (right hand side chart). The non-coincident maximum demand reading for Mandurah zone substation is the maximum value on the blue demand curve (right hand side chart).

[7] In electric power transmission, wheeling is the transportation of electricity from one electrical network to another

Figure 9: Coincident versus non-coincident maximum demand



The current specifications for the annual maximum demand forecasts by zone substation are as follows:

- PoE 10 & PoE 50 Non-coincident and PoE 50 coincident maximum demand by zone substation in MW. Note that forecasts are generated in MW.

7.3.4 Alternative maximum demand forecast model selection

In addition to generating maximum demand forecasts using the load factor scaling method described above also generates several alternative maximum demand forecasts for most zone substations in the Western Power network. The inbuilt statistical forecasting capability of SAS Forecast Studio[8], displays load demand trend growth that is typically driven by variables such as (but not limited to); economic, population, climatic and/or other influences. These zone substations are usually associated with the supply of power to residential and/or commercial customers connected to the distribution network.

Privately owned zone substations in the Western Power network are mainly transmission connected and do not usually display load demand trend growth. Increases or decreases in load demand usually occur at these substations due to incremental block loads associated with either operational up/down turns or expansion projects.

Western Power uses the following rules to generate and/or select the preferred maximum demand forecast for each zone substation to include in its final maximum demand forecast output.

- If the zone substation is transmission connected or displays no load demand trend growth and is distribution connected then the rule to generate and select is to extrapolate the latest validated non-coincident and coincident actual peak demand without applying any growth factor.

[8] SAS Forecast Studio is a module that is part of Western Power's SAS suite of forecasting tools.

- If the zone substation is distribution connected and displays a load demand trend growth the forecasting team will critically evaluate the load factor maximum demand forecast. This will be compared against the SAS Forecast Studio generated alternative and the most appropriate maximum demand forecast will be selected for each zone substation. Selection is based on the underlying statistical structure of the history data, the forward views generated and expert local knowledge.

8. Forecasting assumptions

Key messages:

- Western Power utilises specialised independent forecasters for external variable forecasts (e.g. population and economic activity)
- Western Power produces solar photovoltaic power system and weather forecasts as no suitable independent forecasters currently offer forecasts for the Western Power Network area
- The independent forecasters have advised Western Power that the five-year outlook is a deceleration in growth rates for population and economic activity.

8.1 Introduction

There are advantages and disadvantages to using external variables for forecasting. In cases where external variables are easy to forecast and statistically relevant, there can be an improvement in forecast accuracy by using them. In other cases, it can introduce complications and add to the complexity of forecasting.

Forecasts have been included for the following variables:

- WA Tomorrow population projections
- BIS Shrapnel forecasts of Gross Regional Product and/or Regional Final Demand
- cooling and heating degree days per day
- solar photovoltaic power systems and battery storage system forecasts
- business and residential tariff price forecasts.

8.2 Medium term (five year) forecast assumptions

Table 4 presents the key external variable forecast assumptions.

Table 4: External variables forecasts

Variable	Variable description	Jan 2018	Jan 2022	CAGR
HDD	Heating degree days	50^{th} Percentile	50^{th} Percentile	n.a.
CDD	Cooling degree days	10^{th} Percentile	50^{th} Percentile	n.a.
Avg_temp	Average temperate	10^{th} Percentile	50^{th} Percentile	n.a.
Min_temp	Minimum temperate	10^{th} Percentile	50^{th} Percentile	n.a.
Max_temp	Maximum temperate	10^{th} Percentile	50^{th} Percentile	n.a.
IMPORTING	Bidirectional customers	219,803	307,405	8.7%
PV_CAPACITY	Cumulative Inverter capacity	680 MW	1,044 MW	11.3%
BATTERY	Installed Battery Count	993	75,468	195.3%

Variable	Variable description	Jan 2018	Jan 2022	CAGR
Tariff A1	Electricity tariff for residential customers (nominal)	27.4	31.0	3.1%
Tariff L1	Electricity tariff for business customers (nominal)	31.4	35.5	3.1%
WPN Popn C	Western Power Network portion of WA_Pop_C	2,569,990.0	2,747,510.0	1.7%

Notes: CAGR: Compound Annual Growth Rate

The forecast increase in electricity tariff (Bus_Price = Tariff L1 and Res_Price = Tariff A1) is based on information sourced from the Public Utilities Office.[9] The 2016-17 starting base for both tariffs is sourced from the Government of Western Australia: Department of the Premier and Cabinet.[10]

8.3 Long-term (six plus years) forecast assumptions

The current forecasting methodology implemented by Western Power is considered statistically capable of producing reliable maximum demand forecasts for a 5 year forward view. Beyond this time the generated forecasts become statistically unreliable and demonstrate large variations that are unsuitable for use by network planning.

Network Planning requires a 25-year maximum demand forecast for each zone substation. Each zone substation's 5 year maximum demand forecast is extrapolated to produce a 25 year view using a technique based on log linear regression modelling[11]. Extrapolating to the 25 year forecast view using this technique is deemed appropriate given the need for indicative forecasts to service medium to long term network planning requirements.

It should be noted that maximum demand forecasts for all zone substations are updated annually. So any emerging changes in forecasting trends should be readily identified and communicated to network planning in a timely manner so that any emerging issue can be planned for and mitigated accordingly.

8.4 Assumptions not explicitly incorporated in the long term forecasts

Western Power is actively considering the following issues such as electricity storage systems. This issue as well as the long-term effects of adding more solar PV to the network feature in the 2017 forecast review to some degree:

[9] 3% for households (A1) and small businesses (L1) from 1 July* see Source: http://www.finance.wa.gov.au/cms/Public_Utilities_Office/Energy_in_Western_Australia/Electricity/Electricity_pricing.aspx

[10] Citation: Energy Operators (Electricity Generation and Retail Corporation) (Charges) By-laws 2006 (03-e0-00) see Source: https://www.slp.wa.gov.au/legislation/statutes.nsf/main_mrtitle_1378_currencies.html.

[11] Log linear regression modelling suppresses forward trends (inclining or declining) towards a flat-line/horizontal state.

- The long-term accumulation of solar photovoltaic power systems. In relation to maximum demand, these systems should cease to have any measurable impact on the trend component of maximum demand beyond summer-time sunset.
- Complementary widespread adoption of electricity (or energy) storage systems. This outcome could lead to effective time-shifting of demand as customers that have solar photovoltaic power systems could choose to store energy for use later in the day. Assuming appropriate financial incentives, this could help slow long-term growth in summertime maximum demand trends.
- Widespread adoption of electric vehicles. The advent of autonomous vehicles in recent years suggests that electric vehicles may eventually become commonplace. However, it is not clear why this would impact on maximum demand trends because time of use tariffs would encourage off-peak charging. Western Power believes that this innovation would impact more on average demand than maximum demand. The impact on maximum demand would depend on the adoption rates of decentralised electricity generation and storage systems.
- Increasing industrial demand for network-delivered electricity. The Western Power Network has continued to experience robust growth in demand from industrial customers. The next round of industrial demand increase would likely result from downstream processing of bulk raw materials such as iron ore, alumina etc. This would be more likely if Western Australia was able to become internationally competitive in capital formation, energy and labour costs.

It is important to note that the impact of battery storage systems on the future maximum demand of the Western Power network has been incorporated at the network level only as information is largely based on sentiment and conclusions are conceptual.

With regard to electric vehicles (EVs) Western Power conducted an investigation in to the emergence and impact of EVs on the Western Power network. It was concluded that EVs will have no impact within the 5 year forecast view and believe that they will have immaterial impact in the 5 – 10 year forecast view. Therefore, the impact of EVs on the Western Power network has been excluded in the 2017 forecast review. However, Western Power is committed to monitor and re-evaluate the network impact of this emerging technology regularly throughout future forecast years and adjust our assumptions accordingly.

9. Block load forecasts

Key messages:

- Western Power employs a multi-criteria framework to forecast block loads
- This approach is designed to ensure that a consistent, systematic and evidence-based approach is applied to large customer connection applications that can be vastly different from each other
- The block load evaluation criteria also assists in articulating the changes in forecasters' assessment of specific block loads over time

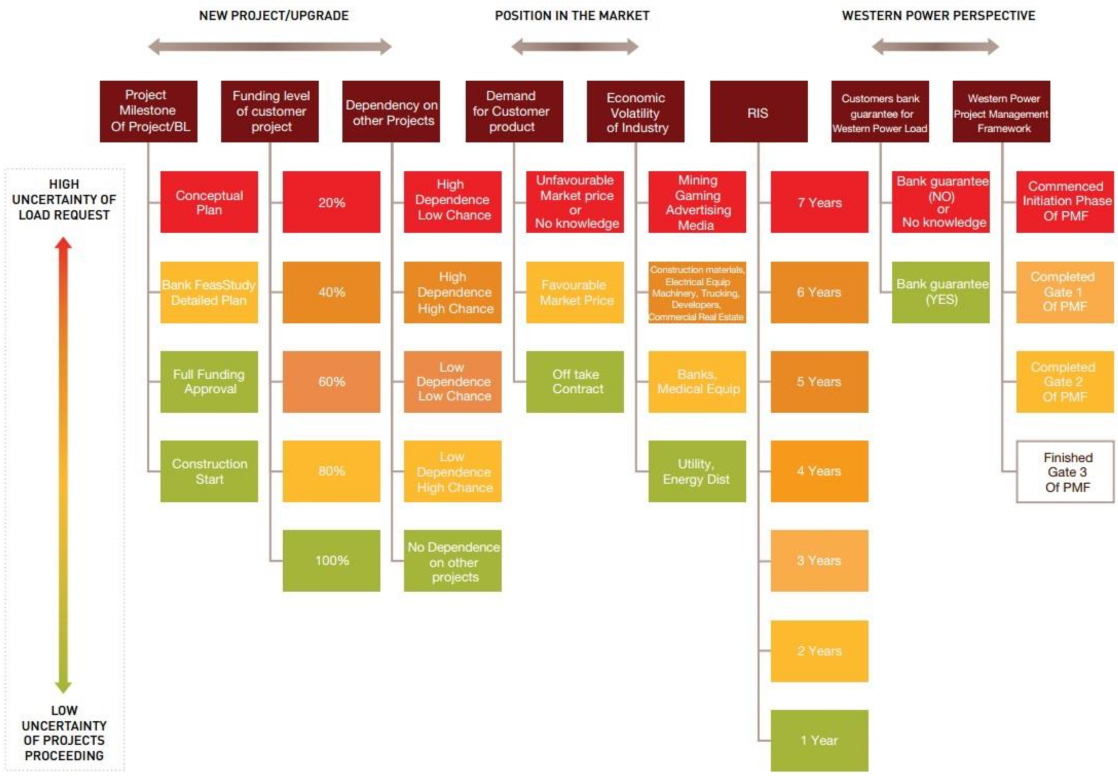
9.1 Prepare block load forecasts

Western Power connects many new customers every year. Most of these connections are small enough to be subsumed in the forecast of underlying growth in demand and do not need to be accounted for separately. Less frequently, Western Power is required to connect new customers that represent an increase in demand above the forecast underlying growth in demand. These new customers are collectively referred to as block loads. Once added to underlying demand growth, a block load introduces an often permanent step-change into an otherwise smooth trend.

Such step-changes occur infrequently and are not easily accommodated by most statistical methods.

Consequently, block load forecasts are developed within a judgemental forecasting framework, as indicated in Figure 10. The figure shows the criteria considered at the top (starting left and working to the right). The boxes under each criterion shows the choices available to the forecaster. Only one of these choices is selected for each criterion and a score is assigned based on the choice.

Figure 10: Block load evaluation criteria



The customer data required for the application of this framework is stored in an internal database named Sales Force. The Senior Forecast Analyst reviews the information in Sales Force and transfers customer application data to the Block Load evaluation tool for assessment.

The Block Load Evaluation Tool is embedded in an Excel template and imposes a linear step-by-step application of the framework. The outcome is a ranking of potential block loads with probability ratings of the block load actually taking electricity from the network implied in the ranking. These can be added to the underlying load growth trend under any arbitrary scenario.

10. Forecast reporting

Once produced, the energy, maximum demand and customer numbers forecasts are reviewed and distributed to: Revenue, Treasury and Risk; Regulation and Investment Management; and Network Planning.

The energy and customer numbers forecasts inform both the Annual Price Review and the financial year budget. The forecasts are presented in report form (e.g. the Energy & Customer Numbers Forecast - 2017).

Maximum demand forecasts are provided to network planners as text files for use in Digsilent; and in report form (e.g. 2017 Maximum demand forecasts (Summer) by zone substation).

In addition, the zone substation maximum demand forecasts are provided as an interactive map named the Network Capacity Mapping Tool (see: http://ncmt.westernpower.com.au/index.cfm).