2015 VICTORIAN ELECTRICITY DISTRIBUTION PRICING REVIEW:

AN ASSESSMENT OF THE VIC DNSP'S DEMAND FORECASTING METHODOLOGY

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1. Introduction

As part of their submissions for the 2015 Victorian electricity distribution pricing review, the Victorian distribution businesses have submitted forecasts of future peak demand. These forecasts of future demand are an input into the regulatory reset process. In particular, these forecasts are used to inform the assessment of future capital expenditure requirements.

The Victorian distribution businesses have each used different methodologies to forecast future peak demand. But all of the Victorian distribution businesses forecast material growth in peak demand over the next five-ten years. This contrasts with the AEMO Connection Point Forecasts[1], prepared late last year, which forecast little or no growth in peak demand in aggregate for each of the DNSPs.

This note examines the issues involved in forecasting peak demand in the current market environment. It also assesses each of the methodologies used by the DNSPs for their strengths and weaknesses.

Forecasting inevitably involves a degree of crystal-ball gazing – that is, speculation about what will occur in the future. Amongst other things, forecasting inevitably requires assumptions about what relationships between peak demand and key drivers that we observe in the past will remain the same and what will change. For example, if we observe that a certain increase in economic growth was associated with a given increase in the growth of electricity demand in the past, will this relationship continue in the future? Or will this relationship evolve over time? Or be affected by other new drivers, such as changes in the structure of electricity tariffs? These assumptions cannot be derived from the data but must be imposed by the modeller, drawing on knowledge of engineering, economics, and the factors affecting the industry. Judgment is required.

Moreover, forecasting of *peak* demand inevitably involves forecasting of events which are, by their nature, rare and only occur in extreme conditions. The POE10 level of demand is only expected to arise once in every ten years. Even a very long time series of data is only likely to record a few instances of such events, and these are not likely to be in the recent past, so may not be representative of what may happen in the future. In addition, the drivers of electricity demand under these extreme conditions may be different to the drivers under more moderate conditions. For these reasons, forecasting of peak demand is inherently uncertain. We should be careful not to rely too heavily on peak demand forecasts. This point is made quite clearly by NIEIR in their report for United Energy:

[1] AEMO, "Transmission Connection Point Forecasting Report for Victoria", September 2014.

> "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 or 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 reinforce the need to use a range of information when making important decisions. … Modelling is an important tool in developing our understanding of a process or event, it cannot (should not) make decisions for us".[2]

As we will see, in the last few years the path of electricity demand seems to be changing. In particular, both total electricity demand and peak demand in Victoria seem to be declining after a sustained period of material growth. This raises fundamental questions for the modeller: Is this an aberration? Will we soon see a return to historic growth rates, or will growth continue to be zero or negative in the near future? Can this growth be explained as solely due to changes in a few economic drivers, such as income, population, or electricity prices?

There is room for legitimate doubt and dispute on these matters. However, in my view there there is evidence to suggest demand patterns in Victoria are being affected by factors other than these basic economic drivers (such as GSP and electricity prices). In particular, it appears that electricity demand in Victoria is being affected by factors such as the changing composition of the Victorian economy, the changing stock of electricity consumption assets (i.e., replacement of older, less efficient devices and appliances with newer, more energy efficient devices), building code requirements which are improving the energy efficiency of the building stock, investment in solar PV, and changing tariff structures. To an extent the decline in demand is part of a worldwide long-term trend towards increasing energy efficiency. Moreover there are new developments in the industry which are likely to affect peak demand going forward, such as the proposed move to demand-based network tariffs in Victoria. These factors were not, to my knowledge, incorporated in the modelling carried out by the network businesses.

The DNSPs have all put substantial resources into, and have substantial expertise in, forecasting the future path of electricity demand. I do not question that the DNSP forecasts have been prepared in good faith, using tools which have proven robust and effective in other contexts in the past. However, I observe that many of the DNSPs have sought to estimate a single fixed relationship between demand and key factors (such as weather, and economic variables) over a period of the past ten years. I am concerned that the estimated relationships do not and cannot adequately capture these factors which might explain the recent decline in demand and changes

[2] NIEIR, "Energy, Demand and Customer Number Forecasting for United Energy to 2025: Part A", A report for United Energy Distribution, August 2014, page 122.

in demand which can be anticipated in the near future, such as the impact of energy efficiency, solar PV, deindustrialisation, and tariff changes.

There is substantial commentary in the industry press that the electricity industry is at a crossroads. Rapid technological growth and pressure for decarbonisation of the energy sector has led to the development of a large range of devices and appliances (known collectively as distributed energy resources) over the past decade. There has been substantial investment in Australia in some of these devices and appliances (particularly solar PV) in the past few years, and there is substantial potential for more such investment (particularly in residential battery storage) in the future. The role of electricity networks in this transformation is uncertain. On the one hand, the increase in distributed generation should reduce the demand for network services, but it is possible that the role of distribution networks will change to facilitate a two-way flow of trade in electricity. The key point here is that the future path of the electricity industry is more uncertain than at any time in the last 20 years.

In the light of the developments in the industry of the past few years, and the uncertainty about the future industry path, I am concerned that the modelling approaches used by the network businesses, which are based on historic relationships and a limited number of drivers, will not accurately reflect likely future market developments. On this basis it could be reasonable to argue that the DNSPs demand forecasts do not reflect a realistic expectation of demand over the upcoming period.

This note has two main sections. In the first section I seek to explain the issues involved in forecasting future demand, following the methodology proposed by ACIL Allen for AEMO. The purpose of this section is to help the reader understand the steps in the process and the judgements that must be made at each step. I show that, looking at the evidence for how demand has evolved in the recent past, there are a range of possible reasonable forecasts for how demand will evolve in the near future.

The second main part of this note looks in more detail at each of the approaches taken by the DNSPs. As we will see, the DNSPs have each chosen a different approach to forecasting peak demand. The aim of this section is to set out the strengths and weaknesses of each of the methodologies.

The appendix sets out evidence for a number of drivers which I believe have not been adequately captured in the modelling by the network businesses and which could explain both the historically-observed downturn in demand and which might lead to even lower levels of demand in the future.

2. Issues in the Forecasting of Peak Demand

As mentioned above, the different DNSPs have each chosen a somewhat different approach to forecasting peak demand. However, at a fundamental level there are basic similarities in the approaches. It is useful to understand the issues involved in forecasting peak demand and the judgements and decisions that have to be made. This assists us to understand the strengths and weaknesses of the various approaches chosen by the DNSPs.

In order to highlight the issues involved in forecasting peak demand in this section I carry out a simple exercise in peak demand forecasting. This exercise is based on the methodology proposed to AEMO by ACIL Allen.[3] ACIL Allen proposed their methodology as a tool for developing

[3] In 2013, at the time when AEMO was developing processes for connection point forecasts AEMO commissioned ACIL Allen to develop a nationally consistent methodology for forecasting maximum electricity demand at connection points. ACIL Allen (2013), "Connection Point Forecasting: A Nationally Consistent Methodology for Forecasting Maximum Electricity

forecasts of peak demand at each connection point.[4] For the purposes of illustration I will apply this methodology to forecasting demand for the VIC region as a whole.[5]

Demand for electricity can be thought of as a function of a number of drivers. Importantly, there are both short-term (or "high frequency") drivers and longer-term (or "low frequency" drivers). Conceptually the process of forecasting peak demand can be thought of as involving four steps: (1) removing the short-run drivers of demand to "weather normalize" the data, (2) determining a long-run relationship between underlying demand and key drivers, (3) adding back the short-run drivers to those forecasts to determine estimates of the historic POE10, POE50 and POE90 peak demand; and (4) forecasting those POE10, PEO50 and POE90 relationships forward.[6] The next sections look at each of these steps in more detail.

2.1 Weather normalisation

We will start by looking at the short-run drivers of electricity demand. In principle there are many potential short-term drivers of electricity demand. These include weather conditions, time of day, day of the week, wholesale electricity spot price, and the degree of solar radiation (which affects the degree of solar PV production). However, in practice, one of the most important drivers of electricity demand in the short-run is the ambient temperature. All of the DNSPs put substantial effort into determining a relationship between temperature and electricity demand. This process of establishing a relationship between weather and electricity demand is sometimes known as "weather normalisation" of the demand data.

The process of weather normalisation of the electricity demand data involves making choices over such as:

- The form of demand to model – the half-hour demand, or the peak daily demand?
- The nature of the weather drivers – such as the current temperature, the maximum and minimum daily temperature, average of the temperature of the last few hours, average of the last few days and so on. In addition choices must be made as to which weather station or stations to use.
- The time period to consider – such as just the summer period, or an entire year or longer, and whether to include all days, or to exclude weekends and public holidays, and whether to treat some days (such as Friday) differently to other days.

Demand", 26 June 2013. AEMO has made a number of improvements to the forecasting methodology since the methodology was first published. These improvements include: (a) adjustments to the underlying data to reflect estimated rooftop PV before weather normalisation; (b) the use of a non-linear rather than a linear time trend; (c) improved post-model adjustments for rooftop PV, including allowing the time of maximum demand to change as rooftop PV capacity increases; (d) the pooling of data to improve the stability of coefficients – specifically the use of a rolling three-year window to estimate the weather-demand relationship; (e) improved reconciliation between the connection point forecasts and the regional demand forecasts developed as part of the NEFR.

[4] A connection point is a point where a distribution network connects to the transmission network. The number of connection points of a distribution network depends on both the magnitude of the load served by the distribution network and the geographic spread of the network.

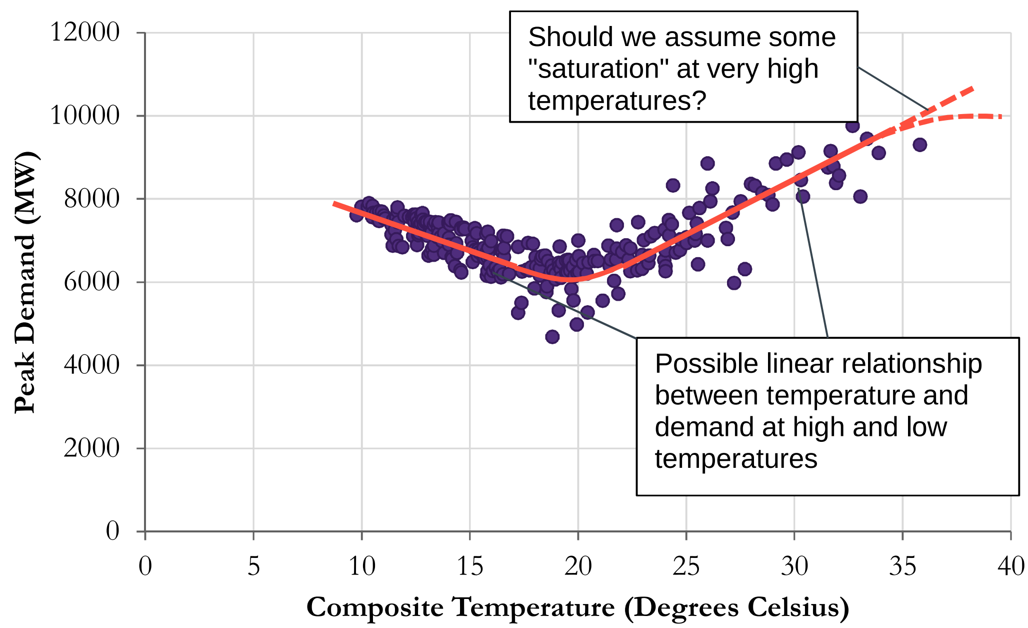
[5] There are some other minor differences between the methodology used here and the ACIL Allen methodology. Specifically, I have focussed on all weekdays in the relevant period with maximum demand above 25 degrees. In contrast, the ACIL Allen methodology focuses on all working days (excluding holidays) in the summer. In addition, in forecasting the POE10 levels of peak demand I have simulated historic weather conditions whereas the ACIL Allen methodology simulates historic weather conditions *and* a random error term.

[6] These steps are not always followed in a simple linear manner. It is also possible to combine steps one and two in one step (estimating the historic relationship) and then to combine 3 and 4 into one step (forecasting forward and using the forecasts to estimate future POEx levels).

For the purpose of illustration, Figure 1 below illustrates how the peak daily electricity demand in Victoria on weekdays during the 2012/13 fiscal year is related to a measure of temperature consisting of 75% of the peak daily maximum temperature and 25% of the peak daily minimum temperature. This composite temperature measure was chosen as it reflects a better fit of the data than just maximum or minimum temperature alone. The temperature data is taken from the Bureau of Meteorology weather station readings at Moorabbin Airport.

Figure 1 illustrates the typical U-shaped or V-shaped curve that relates ambient temperature to electricity demand.

Figure 1: VIC Peak daily demand versus composite temperature weekdays 2012/13



The process of weather normalisation involves choosing how to represent this V-shaped relationship in a small number of variables. For example, one possible approach would be to divide the graph up into regions, and seek to approximate each region with a simple function, such as a linear or polynomial curve. For example, we could observe that in the region 18-22 degrees, the electricity demand seems to be broadly insensitive to temperature. Below 18 degrees there seems to be a linear relationship between temperature and demand (with lower temperature corresponding to higher demand) and above 22 degrees there seems to be something of a linear relationship between temperature and demand (with higher temperature corresponding to higher demand). These lines are illustrated on figure 1 above.

Since we are interested in forecasting peak demand and since peak demand primarily occurs during hot periods in Victoria (primarily in summer), we will focus on forecasting the peak demand at times of higher-than-average temperatures. As noted above, this relationship has been represented as a straight line on this graph. NIEIR refer to the slope of this line as the "temperature sensitivity" of electricity demand.

The relationship between temperature and peak electricity demand is not necessarily a straight line. It is plausible that as temperatures continue to rise a point is reached where electricity demand does not continue to increase – that is, once all the relevant air-conditioning units are already operating, an increase in the temperature does not elicit any further increase in electricity demand. This is sometimes referred to as "saturation". Another possibility is that very high temperatures are associated with very high wholesale prices, which might elicit some demand response, dampening peak demand. Either way the temperature sensitivity at very high temperatures may not be as strong as at more moderate temperatures. This is represented on Figure 1 as a possible down-turn in the temperature sensitivity at very high temperatures.[7]

ACIL Allen are quite clear about the potential for saturation. They observe that "The relationship between demand and weather tends to follow the S-shape … [at high temperatures] there is a range where the relationship 'flattens out' under extreme conditions. This … is only observed during extreme weather conditions".[8]

AusNet is the only DNSP to allow for the possibility of saturation at very high temperatures. This could be simply because including the possibility of saturation significantly complicates the analysis. In any case, since very high (POE10) demands occur so rarely there is very little data to either confirm or deny the possibility of saturation. In practice the other DNSPs have simply ignored the potential for saturation. This may upwardly bias their forecasts of peak demand.

Figure 1 illustrates the relationship between peak demand and temperature for just one year (2012/13). Conceptually, this relationship can be summarised in two variables: (a) a constant term and (b) the slope or temperature sensitivity of the peak demand with respect to temperature.

A similar relationship can be estimated for each year of the sample period. This yields the same two variables (the constant term and the slope) for each year in the sample. The evolution of these two variables over time can be understood as describing the "long-term" or underlying evolution of electricity demand.

This approach of estimating the short-term relationship separately for each year in the sample allows for some flexibility in that it doesn't force, in advance, any particular relationship between these annual measures of underlying demand (here, the constant term and the temperature sensitivity) and other possible drivers such as time, economic growth, population growth and so on. This is both a strength and a weakness. The modeller must hypothesise *some* relationship between demand and key drivers in order to forecast into the future. But the approach illustrated here doesn't impose such a relationship at the outset. Instead, as set out below, we will examine the estimated historic path of peak demand and draw on knowledge of developments in the industry to infer a possible future path for peak demand in the future.

This approach is in contrast to the approach taken by most of the DNSPs. Several of the DNSPs (via their consultants) have chosen the approach of imposing a structural relationship at the outset. This is not necessarily problematic – as long as the assumed relationship accurately reflects fundamental long term trends. This is an issue which we will discuss further below.

2.2 Deriving a longer-term relationship

Once we have "weather normalized" the annual data we can start to examine the longer-term relationship between demand and its longer-term drivers. Let's assume that we have estimated a short-run relationship between peak demand and peak daily maximum and minimum temperatures for each year in our sample of data. Table 1 below presents the results of

[7] It is also possible to make a case that the temperature sensitivity might increase at very high temperatures – this might occur if homes or businesses had more than one air-conditioning unit and they preferentially used their more efficient unit first and, only when the capacity of that unit is exhausted do they bring on line the less efficient unit.

[8] ACIL Allen, "Connection Point Forecasting", 26 June 2013, page 22.

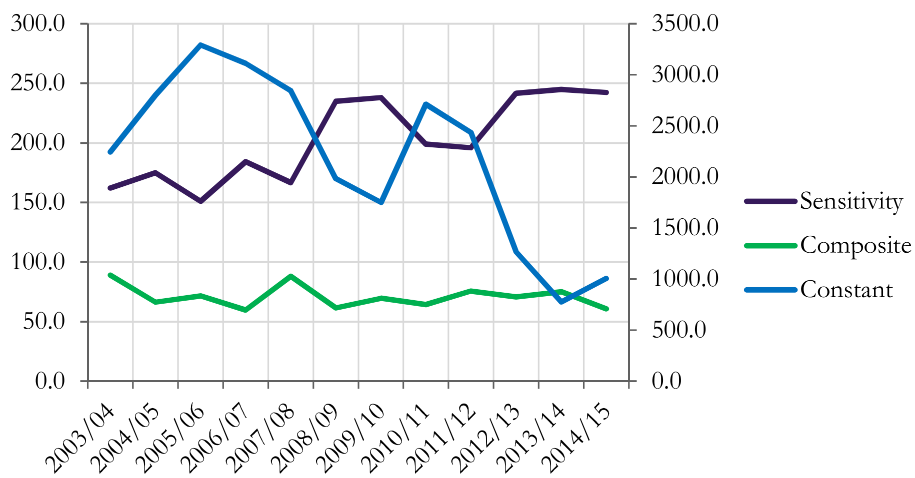
estimating such a relationship back to 2003/04. In this table, "composite" refers to the make-up of the composite temperature variable.[9]

Table 1: Relationship between temperature and peak demand weekdays[10] by fiscal year

Year	Constant	Sensitivity	Composite
2003/04	2243.7	162.0	89.1%
2004/05	2798.5	174.9	66.4%
2005/06	3290.7	151.0	71.7%
2006/07	3109.7	184.3	59.9%
2007/08	2843.9	166.6	88.0%
2008/09	1983.0	234.8	61.5%
2009/10	1748.9	237.8	69.6%
2010/11	2711.9	199.0	64.3%
2011/12	2434.8	195.9	75.7%
2012/13	1269.1	241.6	70.9%
2013/14	775.8	244.8	75.1%
2014/15	1007.0	242.3	60.8%

There is a lot of "noise" in the variables presented in Table 1, but we can discern certain broad trends over time. This is illustrated in Figure 2. As Figure 2 shows, the constant term appears to have reduced over time, while the sensitivity term seems to have increased. Put another way, it appears that the "base" level of electricity demand in Victoria is declining, while the sensitivity of demand to temperature is increasing.

Figure 2: Evolution of the temperature-demand relationship over time weekdays VIC



[9] The composite temperature variable is determined by the coefficients given in the regression for the daily maximum temperature and daily minimum temperature. For example, in 2004/05 the composite is given as 66.4% - this means that in that year the best-fit temperature variable involves a 66% weighting on the maximum temperature and a 34% weighting on the daily minimum temperature. In all of these regressions the maximum daily temperature is statistically significant and in nearly all of the regressions the minimum daily temperature is statistically significant.

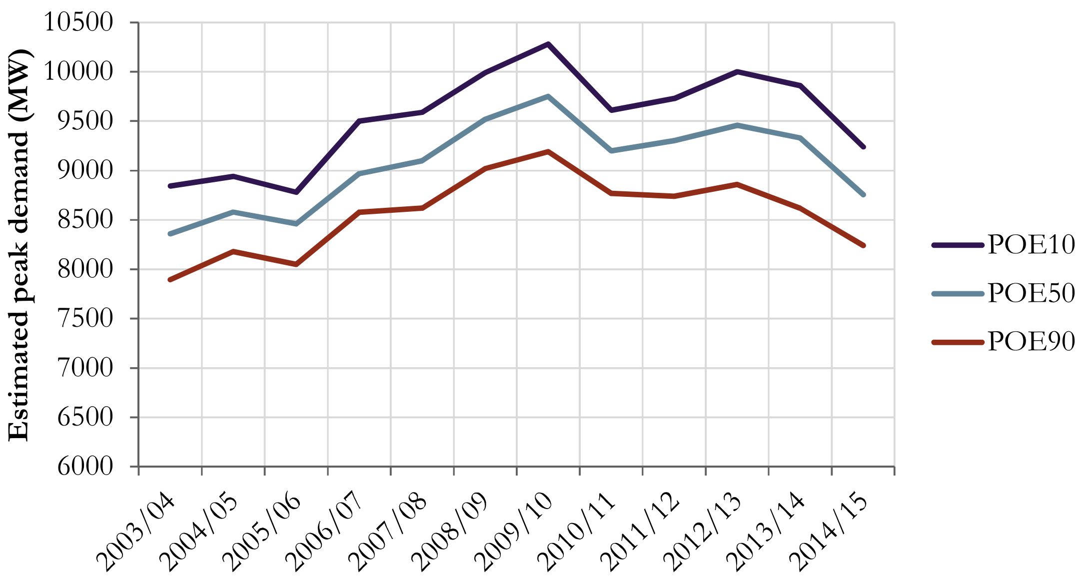
[10] In this simple analysis weekends were excluded but not public holidays or the December/January holiday period.

The decline in the base or average level of electricity demand could be due to factors such as deindustrialisation, energy efficiency, rising average electricity prices, and investment in local generation (solar PV). The increase in the temperature sensitivity of demand could be due to factors such as increasing penetration of air-conditioning, and increasing investment in solar PV coupled with a lack of availability of solar PV at the extreme demand peak events.

The next step in the process is to use this information to infer the historic POE10, POE50 and POE90 levels. This is often carried out using "Monte Carlo" simulation to estimate the distribution of peak demand. This involves sampling from blocks of historic weather conditions and random errors, and using the relationship derived in the previous step to form a distribution over peak demand. From this distribution it is, in principle, possible to read off the 10%, 50% and 90% of the distribution.

In the simple illustrative model I am using here, using the structural relationship between temperature and demand for each year set out in Figure 2, I simply applied the historic weather conditions (going back 45 years) to each of these relationships and then found the demand level which occurred as an annual peak more than 90 per cent of the time (between 40 and 41 times) for the POE90, more than 50 per cent of the time (between 22 and 23 times) for the POE50 and more than 10 per cent of the time (between 4 and 5 times) for the POE10.[11] The resulting estimated historic evolution of the POE10, POE50 and POE90 levels is illustrated in Figure 3 below.

Figure 3: Evolution of VIC POE10, POE50 and POE90 peak demands



Although the precise details of the graph in Figure 3 are specific to the data and assumptions I have chosen, the broad "hump" shape shown in Figure 3 is reflected in several other demand forecasting studies (see, for example, figure 5 and figure 11 below).[12] In other words, there seems to be something of a consensus that estimates of peak demand increased up until 2009 or 2010

[11] I have not included simulation of the residual or regression error. Including this component would probably increase the estimated POE10, POE50 and POE90 levels by a small amount.

[12] See, for example, NIEIR, "Energy, Demand and Customer Number Forecasting for United Energy to 2025: Part A", Figure 9.3, page 85.

and have been broadly declining since. Understanding the drivers of this relationship is very important for forecasting the future path of the POE10, POE50 and POE90 demand levels.

2.3 Using the past to forecast the future

The next step in the process is to use the longer-term relationship illustrated in Figure 3, to inform us about the path of the POE10, POE50 and POE90 demand levels in the future.

The standard approach, used by many of the DNSPs, is to assume that there is a fixed structural relationship between peak demand levels (or average demand levels) and certain key long run drivers. This relationship is typically assumed to be linear. Once the drivers, and how they enter the relationship is assumed, techniques such as regression are used to estimate the parameters in the model (typically the coefficients on each driver) using a data set reflecting the historic outcomes many years into the past.

Provided certain conditions are satisfied, that is, provided:

- There is a fixed, underlying relationship between peak demand and the key drivers that extends into the past and continues into the future; and
- That relationship has been correctly captured in the model; and
- The parameters in the model have been correctly estimated,

then forecasting the future POEx demand levels is primarily a matter of forecasting those same economic drivers into the future.

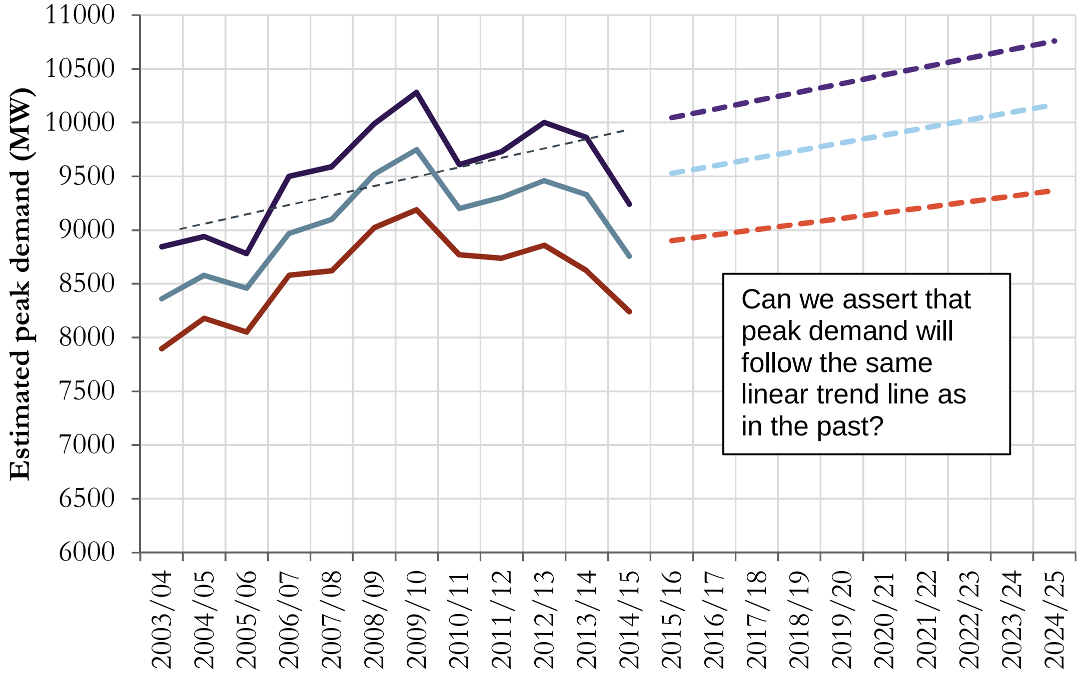
However, as noted above, I am concerned that the structural models proposed by the DNSPs do not fully capture the factors which are driving the recent downturn in demand, or the factors affecting demand in the future.

The potential problems that can arise when the assumed model does not capture all of the relevant drivers (or does not capture the manner in which the drivers affect peak demand) can be illustrated using simple examples. The DNSPs and their advisors have, in practice, used much more sophisticated models. However I believe that the potential problems with the more sophisticated models can be illustrated using the simple examples below.

To begin, let's suppose that we take the simplest possible approach of using the entire sample period to estimate a simple linear relationship between peak demand and time. We might then assume that this relationship continues into the future. This results in POE10, POE50 and POE90 forecasts which are illustrated in Figure 4.

As can be seen, the forecasts that emerge from a simple linear extrapolation are both extremely high (relative to the most recent estimated POE10, POE50 and POE90 levels) and growing over time. This approach essentially assumes that *all* of the down-turn in peak demand in recent years is purely statistical noise. This assumption does not seem credible, for reasons which are discussed further below.

Figure 4: Forecasting VIC POE10, POE50 and POE90 levels by extrapolating a straight line



Internal validity checks on the modelling

Clearly, for the forecasts to be accurate, it is fundamentally important that the estimated long-run relationship correctly reflects a fixed relationship between peak demand and the key drivers which will continue unchanged into the future. But how can we tell whether or not this is the case? The preferable way is to rely on knowledge of the industry and industry developments. This is discussed further below. However we might also ask whether there are any simple modelling tests that might shed light on whether or not the model is accurately capturing a fixed long-term relationship?

One possible approach is to simply divide the time period into two parts and estimate the structural model on each time period separately. If the model is accurately capturing a fixed long-term relationship, the parameters of the model should be similar across the two time periods.[13] This is a relatively simple test. In the simple model above, if we divided the past ten years into two periods of five years we would find that the model forecast very substantial growth in peak demand in the first five years and a substantial decline in peak demand in the second five years. This seems to clearly imply that there is no fixed relationship between peak demand and time, and therefore we cannot use time (as the sole or primary driver) to accurately forecast peak demand in the future.

A second possible approach to assessing the reliability of the model is to examine the distribution of the "error" or "residual term" (that is, the difference between the actual and the estimated value). If the model is accurately capturing an underlying relationship this error should not vary in a systematic way with any of the drivers. In the simple linear model above we see that the residual or error (the difference between the estimated linear trend and the actual POE10 value) is negative in the early and later years of the past decade, and is positive in the middle

[13] Technically, a statistical test should be performed to determine if the differences in the estimated models are due to chance.

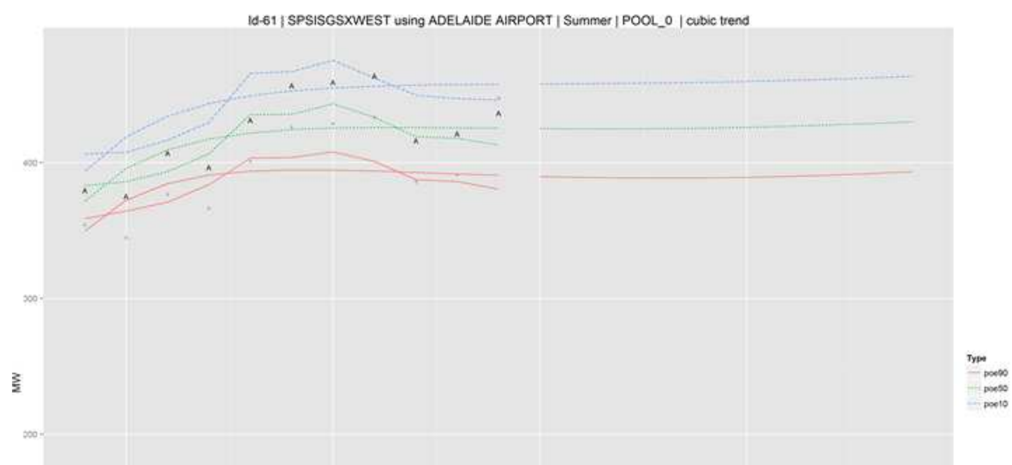
years. It would be unlikely for such a relationship to arise by pure chance. Again, it seems unlikely that the assumption that there is a simple fixed relationship between peak demand and time is not likely.

Another, related approach is to use a statistical test to determine whether or not the model is reliable. For example, in the example above we could perhaps use a statistical test to determine whether or not a simple linear time trend is accurately capturing the underlying relationship. Frontier, in their critique of AEMO's approach note that:

> "Frontier provided a statistical test to determine when use of the linear time trend model for producing forecasts was inappropriate due to nonlinearity. In cases where the statistical test rejected the use of the linear trend model for producing the forecasts, Frontier recommended using judgement to determine an appropriate alternative trend to use".[14]

Ideally the assumed relationship between demand and its drivers would be based on knowledge of the engineering and economics of the industry. AEMO have proposed that, instead of fitting a linear relationship, we might fit a polynomial curve such as a cubic.[15] The result of this approach is illustrated in Figure 5. The problem here is that the choice of a cubic polynomial is arbitrary in the sense that it is not justified on the basis of knowledge of the underlying economic phenomena or industry drivers. The use of a cubic time trend provides a better statistical fit to the data but raises the question why it is reasonable to assume that this cubic relationship will continue into the future?

Figure 5: AEMO has proposed extrapolating from a cubic equation fitted to the peak demand curves



The off-the-point versus off-the-line issue

Figure 4 reflects a simple extrapolation of a linear trend in which the estimated historic relationship is simply extended into the future. ACIL Allen refer to this as the "off-the-line"

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14 Frontier, "High Level Review of Transmission Connection Point Forecasts: Victoria", Report for AEMO, September 2014, page 14.

15 More specifically AEMO's view is that if the historical data suggests a non-linear trend then a non-linear trend line will provide a better indication of future demand than a linear trend. They also note that there are a number of physical drivers that may cause a non-linear trend, including changing solar PV uptake rates, energy efficiency effects on maximum demand, and saturation of air-conditioning uptake.

approach. However, as noted above, this results in forecasts which start well above the most recent estimates and therefore appear unrealistic.

An alternative approach is to use the growth rates (the slope) implied by the linear estimation of the historic data, but to start the line at the location of the *most recent value*. ACIL Allen refer to this as the "off-the-point" approach. If we applied this to the model in Figure 4 we would find peak demand forecasts which are much lower but still have quite high growth rates.

As discussed further below, ACIL Allen use the "off-the-point" approach for the connection point forecasts for Jemena.

One problem with the "off-the-point" approach is that it is theoretically inconsistent with the assumptions that underlie the use of a linear extrapolation in the first place. The use of a linear extrapolation essentially assumes that all departures from the long term linear trend reflect pure temporary statistical noise. If this is the case the use of the most recent point (which is itself assumed to be just a temporary departure from the long term trend) as the starting point for the future forecasts cannot improve those forecasts. Frontier, in their critique of AEMO's methodology, express it this way:

> "From a statistical point of view, 'off the point' should only be used as the starting point if the linear time trend regression model is not well specified, and hence does not provide a good indication of future maximum demand".[16]

There are alternative assumptions about the underlying relationship in which it might make sense to start the forecast trend from the most recent point. This would be the case, for example, if peak demand followed a random walk with a long-term trend. However in this case it would not be consistent to estimate the long-term trend with a simple linear regression.

GHD, in their critique of the AEMO methodology, also focus on the use of the "off-the-point" approach. They observe that AEMO are apparently using this technique "to compensate for a perceived structural break". They go on to emphasise that rather than using an ad hoc adjustment it would be preferable to reconsider the formulation of the model to ensure that it is capturing all the relevant drivers:

> "If the energy model cannot fully explain the recent downturn in electricity demand, then a considered response might be to review the specification of the model, including whether the log-log form is the most appropriate and additional drivers that should perhaps be included … The fact that energy growth has flattened since 2008 to a greater extent than can apparently be explained by reduced economic growth and rising electricity costs implicitly means that the energy intensity of economic growth is falling. … Without further investigation it is difficult to determine what the appropriate remedy might be. The first step may be to investigate drivers that may be significant but that are not included in AEMO's current models to explain a falling recent trend in demand growth".[17]

AEMO accept that if the trend line lies significantly above the most recent weather normalised historical value it is likely that the model hasn't captured a structural change. At the connection point level this could be due, for example, to large loads coming on-line or off-line. AEMO's approach is to attempt to correct for this structural change, generally through reviewing and

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[16] Frontier, "High level review of transmission connection point forecasts: Victoria", A report prepared for the Australian Energy Market Operator, September 2014. Frontier propose that a statistical test should be used to determine whether a linear trend is a good approximation.

[17] GHD, "Review of AEMO Demand Forecasting Methodology", January 2015, page 17.

cleaning the historical data, and only to forecast "off the point" if there is a strong reason to believe this will provide a more robust forecast.

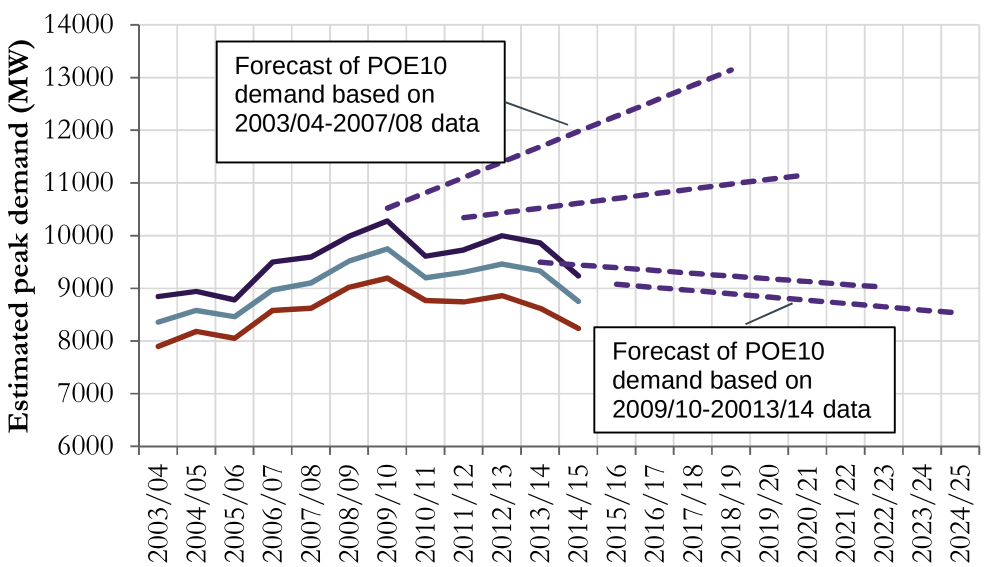
The choice of "off the point" versus "off the line" forecasting is likely to remain a controversial issue.

Even if we recognise that the assumed structural relationship does not fully capture all of the drivers of demand, we might nevertheless assume that the factors which are not captured in the model change slowly. If the un-modelled factors are changing slowly enough a structural relationship which is estimated using *recent* observations might yield reasonable forecasts for the near future.

Let's explore the implications of this assumption using the simple model discussed above. The problem, as we will see, is that when this approach is applied to the historic evolution of peak demand, it yields vastly different forecasts depending on the immediate recent past.

This is illustrated in Figure 6. Figure 6 illustrates the future forecasts of POE10 demand based on a simple linear extrapolation of the past five years of data. In 2008/09 POE10 levels had been growing rapidly. On the basis of the most recent five years of experience it might have been reasonable to forecast continued strong growth, as shown below. But, by 2014/15 the most recent five years of data show declining POE10 levels. If it is reasonable to forecast growth in 2008/09 on the basis of the most recent data, is it reasonable to forecast a decline in POE10 levels in 2014/15?

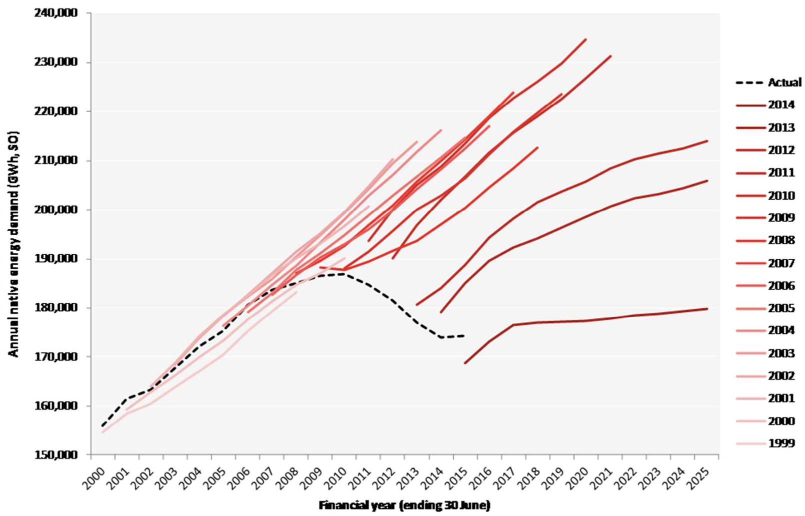
Figure 6: Illustration of future forecasts of POE10 levels based on the most recent five years of data



To an extent, AEMO's forecasts of future demand (in this case energy, not peak demand) have evolved in this way over time. Specifically, as illustrated in Figure 7, in recent years AEMO's forecasts of future demand have reflected both a lower starting point and a lower slope.[18]

[18] AEMO's 2015 forecasts, which are not shown in figure 7, reflected a slightly higher starting point and slightly higher slope than 2014.

Figure 7: Evolution of AEMO forecasts of NEM-wide demand for energy



Source: Frontier analysis of AEMO forecasts

2.4 Post-modelling adjustments

There may also be other steps in the process of estimating peak demand levels which are not discussed here in this simple example. For example, several of the DNSPs go to some length to discuss “post-modelling adjustments”. These post-modelling adjustments include changes in the forecasts in the light of (a) known policy developments or (b) market developments which are not fully reflected in the historic trends. Examples might include changes in the carbon price, or further policy initiatives encouraging take-up of solar PV or energy efficiency.

The DNSPs (and AEMO) typically carry out forecasts of peak demand at different levels of geographic granularity – specifically, DNSPs typically forecast peak demand both at the level of each transmission connection point (typically one to two dozen points), and at the level of the network as a whole. In principle these two forecasts should be consistent with each other. Therefore both the DNSPs and AEMO carry out a further step in their forecasting process which involves reconciling the forecasts at the connection point level with the forecasts at the network-wide level.

This reconciliation process involves (a) determining diversity factors and loss factors between connection points and the system-wide demand, to place the forecasts on the same footing; and (b) scaling either the connection point forecasts or the system wide forecasts (depending on which is viewed as being the more reliable).

ACIL observes that the system-wide forecasts usually take into account a wider variety of economic information (including prices, economic growth, population growth and so on), whereas the connection point forecasts take into account local factors and local knowledge. ACIL suggest that the scaling of the connection points should be proportional unless specific local knowledge suggests that a particular connection point should be scaled more or less than average. This reconciliation step is an area of concern for DNSPs – if the regional level forecast is not reflective of current demand conditions the associated connection point forecasts will also suffer credibility. I have not focused on differences between connection point forecasts and network-wide forecasts in this review.

2.5 Summary

This section used a simple forecasting model, based on the approach recommended by ACIL Allen, to illustrate the issues that arise in forecasting peak demand. Amongst other things, this section illustrated the impact of assuming a structural relationship which does not fully and accurately capture the recent downturn in demand. In this case, the model treats some or all of that downturn in demand as statistical noise and forecasts a return to a higher level of demand, and a growth rate reflecting average trends over the previous ten years. This section also discussed the impact of estimating the model using a shorter, more recent time period and showed the impact of this approach on recent forecasts of demand.

A key message of this paper is the importance of the choice of the functional form for the estimated equation – that is the selection of drivers and the way those drivers influence peak demand. It is important to draw on industry knowledge and experience to inform the application of the statistical forecasting techniques. Although the network businesses have included a range of drivers, including measures of electricity prices and income, I am concerned that these drivers do not capture a range of effects including both long-term trends and more recent developments in the industry. As a result I am not confident that the models proposed by the network businesses will accurately forecast peak demand in the near future. In particular, as explained further in the appendix, I am not confident that the models used by the businesses have fully captured:

- Energy efficiency trends (both increasing efficiency of houses and appliances)
- The rapid growth in solar PV
- Slowing of the rate of penetration of air-conditioners
- The impact of changing tariff structures; and
- De-industrialisation of the Victorian economy.

In addition, the models used by the businesses, which are based on historical experience, do not take into account the potential for rapid growth in distributed energy resources, such as energy storage, which could have a material impact on peak demand in Victoria in the future.

I also observe that many (or all) of the DNSPs are proposing to introduce a demand-based tariff in the near future. A demand-based tariff has the specific intention of reducing peak demand. Jemena explains this in their regulatory proposal as follows:

> "We propose to update our network tariff structures to encourage more informed customer decision making and to put downward pressure on our costs and average prices over the long-term by: Introducing a new 'maximum demand charge' for all residential and small business customers to more clearly signal the higher costs of using our network during periods of peak demand, and thus encourage these customers to reduce or spread out consumption".[19]

To my knowledge, none of the network businesses have included the impact of new tariff structures in their demand forecasts. These issues are discussed further in the appendix.

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[19] Jemena, Regulatory Proposal, page 105

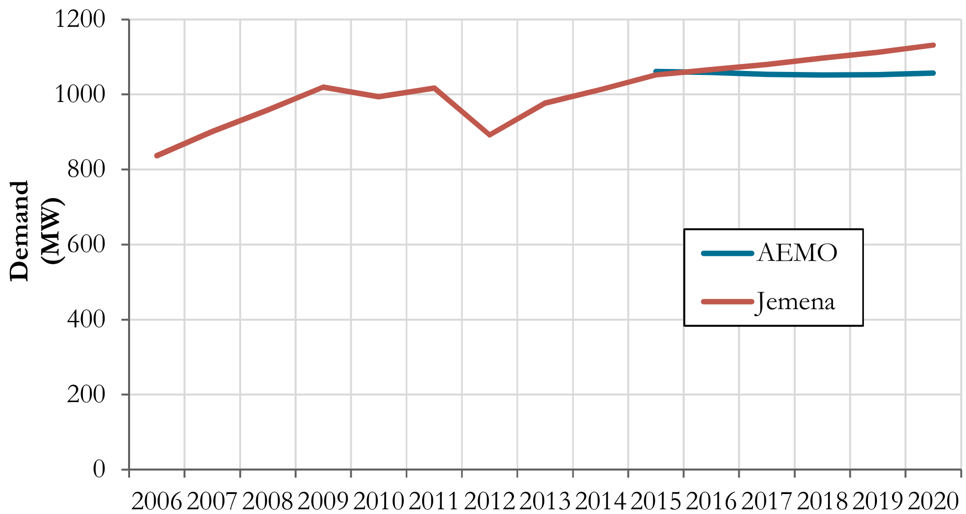
3. Assessment of the methodologies used by the DNSPs

Let's turn now to look in more detail at the methodologies used by each of the VIC DNSPs to forecast peak demand on the network. We start with Jemena because Jemena's approach most closely reflects the methodology set out above. We then look at the approach of United Energy, who draw heavily on the work of NIEIR, followed by CitiPower/Powercor, who rely on a model developed by CIE. We will conclude with an examination of the approach used by AusNet, which appears to be slightly different to all of the others.

3.1 Jemena

Like other DNSPs, Jemena has forecast growth in POE10 levels of peak demand which is somewhat faster than the growth forecast by AEMO (Figure 8).

Figure 8: Comparison of Jemena and AEMO POE10 demand forecasts



Jemena has submitted two documents relevant to the forecasting of peak demand:

- ACIL Allen, "Electricity Demand Forecasts", Report to Jemena Electricity Networks, 20 November 2014, submitted as Jemena, "Attachment 3-1: Electricity demand forecasts report", 30 April 2015
- Jemena, "Attachment 3-5: JEN Demand Summary Report", ELE RP 0001, 30 April 2015

Jemena's approach to forecasting peak electricity demand follows the approach recommended by ACIL Allen. In fact, Jemena has engaged ACIL Allen to prepare peak demand forecasts for the Jemena network. ACIL Allen has prepared peak demand forecasts (POE10, POE50 and POE90) at both (a) the system (network wide) level and (b) the connection point level. The approaches used by ACIL Allen to estimate peak demand levels at the system level and the connection point level are slightly different. The two different sets of forecasts are reconciled in the second phase.

Jemena's connection point forecasts

In regard to the connection point forecasts, ACIL Allen followed the methodology they recommended to AEMO. Specifically, this approach involves the following steps:

- For each connection point and for each year, the temperature-demand relationship was estimated assuming a simple linear relationship between demand, weather and other calendar variables.
- This temperature-demand relationship was then used in a simulation to determine a distribution over demand levels in each year. This simulation was used to estimate the POE10, POE50 and POE90 demand levels for each historic year.
- A line was then drawn through the POE10, POE50 and POE90 for each connection point (using a simple regression, as was illustrated above).
- The forecast of peak demand growth (at each of the POE10, POE50 and POE90 levels) was assumed to be a simple linear extrapolation of the historic growth, using the "off-the-point" approach. Specifically, the *slope* of the regression line was used as the best estimate of the slope of the growth rate of the forecast peak demand in the forecast years. However, the starting point of the line of forecasts was chosen to be the point of the most recent POE10, POE50 and POE90 forecasts. This was explained by ACIL Allen as follows:

  "ACIL Allen compared the 'point' with the 'line' at each termination station for summer and winter. In the summer models, the 'line' was above the point in all cases whereas in the absence of a statistical basis the distribution should be even more. For this reason ACIL Allen has chosen to take all of the terminal station forecasts off the point". (page 41).

  As noted above, this off-the-point approach has been criticised by Frontier who point out that it is not internally consistent.

Jemena's network-wide forecasts

ACIL Allen also prepared peak demand forecasts for the entire network. This was achieved by estimating a single structural model for peak demand for all the years of the sample. In effect ACIL Allen assume that a single linear relationship between peak demand and the other variables (temperature, calendar variables, electricity price and GSP) applies for the entire sample period (and for the period over which forecasts are made).

Specifically, I understand that Jemena has sought to find a relationship between daily maximum demand and a set of driver variables on all non-mild days (i.e., excluding weekends, public holidays, and days of mild temperature) in summer during the sample period 2004/05 to 2013/14. The driver variables include various measures of temperature, Gross State Product (GSP), electricity price, and the product of GSP and measures of temperature. [20]

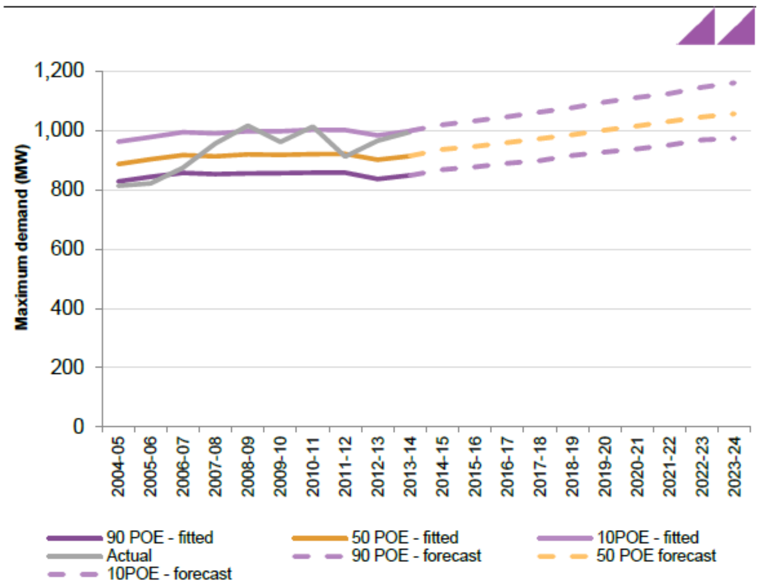
[20] This model expresses daily maximum demand as a function of the following ten factors: GSP_t: gross state product; Min_t*GSP_t: minimum daily temperature, multiplied by gross state product; Max_t*GSP_t: maximum daily temperature, multiplied by gross state product; Max_{t-1}: maximum daily temperature on the previous day; Max_{t-2}: maximum daily temperature on two days prior; Maxgt34: indicator variable set to 1 when maximum temperature (max_t) is greater than 34 C; $Price_t$: retail electricity price; $February_t$: indicator variable, equal to '1' if month is February, '0' otherwise; $Monday_t$: indicator variable, equal to '1' if day is Monday, '0' otherwise; $Friday_t$: indicator variable, equal to '1' if day is Friday, '0' otherwise.

The output of this model was used, along with forecasts for electricity price and GSP, to simulate future peak demand in a range of weather scenarios and with a range of error terms (regression residuals). This yielded forecasts of POE10, POE50 and POE90 levels of demand.

In the final stage the connection point peak demand forecasts were scaled up to make them consistent with the system-wide peak demand forecasts.

The outcome of this process can be set out in Figure 9 below.

Figure 9: JEN system level maximum summer demand - actual and forecast, 2004-05 to 2023-24



Source: ACIL Allen Consulting

Assessment of Jemena's approach

Jemena's forecasting approach has the advantage that it is relatively clear and transparent, and uses the methodology that ACIL Allen have recommended for AEMO.

One of the advantages of the ACIL Allen connection point methodology is that it allows for a separate relationship between temperature and demand to be estimated in each year of the sample. In other words, it doesn't force or require a particular long-term structural relationship between temperature and demand over time. However, in the process of estimating the system-wide peak demand ACIL Allen have adopted the conventional approach of assuming a fixed relationship between underlying economic drivers and peak demand over time. This system-wide forecast of peak demand is used to adjust the connection point forecasts.

As emphasised throughout this report, this approach is appropriate as long as the assumed relationship effectively captures all of the key drivers and has captured them in the correct way. It is not clear that ACIL Allen's model has achieved this. In particular, it appears that ACIL Allen's model treats all of the recent down-turn in demand as due to an increase in electricity prices or a decrease in GSP. If there is some other change in the market (such as permanent, long-term trends in energy efficiency or investment in solar PV which has had a permanent change on electricity demand) it is not clear that this would be adequately captured in ACIL Allen's model.

The model also does not account for the potential effects of the change in tariff structure which has been proposed by Jemena. As noted elsewhere in this report, Jemena argue that a primary rationale for the introduction of a demand-based tariff is that such a tariff will reduce peak demand, thereby reducing network costs. If the tariff acts as Jemena intends it will have a further impact on peak demand which is not captured in ACIL Allen's modelling.

It would also be worth exploring further whether the ACIL Allen model is sensitive to the time period to which it is applied. As noted earlier, if this model is adequately capturing all of the long-term trends in the market, it should not matter which time period it is applied. For example, it would be possible to separate the sample period into two time periods and estimate the relationship separately for each time period. If the underlying model is robust the estimates should remain broadly the same across the two time periods.

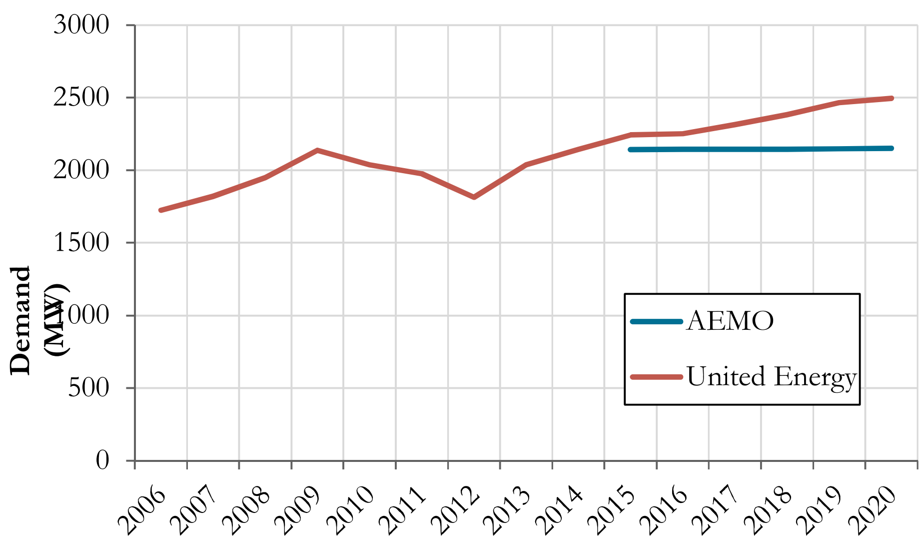
Finally, I observe that the ACIL Allen report for Jemena was prepared in November 2014, without the benefit of one further year's experience of summer demand. From the analysis set out in the previous section it appears that if the summer of 2014/15 was included in the analysis it would further confirm and reinforce the decline in demand that has been observed in recent years.

The electricity industry in Victoria is currently in a phase of quite material change. This change increases the uncertainty about the future path of peak demand and increases the importance of capturing all of the relevant factors which may drive peak demand in the future. There are grounds for concern about the methodology used by Jemena and therefore I am concerned that the estimates put forward by Jemena are not a realistic expectation of future demand.

3.2 United Energy

Like other DNSPs, United Energy has forecast growth in POE10 levels of peak demand which is somewhat faster than the growth forecast by AEMO (Figure 10).

Figure 10: Comparison of United Energy and AEMO POE10 demand forecasts



Like the other DNSPs, United Energy have put significant resources into developing demand forecasts. The United Energy approach to maximum demand forecasting is set out in several documents:

- United Energy, *Maximum Demand Overview Paper*, 30 April 2015
- United Energy, *Maximum Demand Forecasting Method*, Document No. UE PR 2200
- NIEIR, *Energy, Demand and Customer Number Forecasting for United Energy to 2025*, Part A and B, August 2014

In forecasting maximum demand United Energy relies primarily on forecasts which were prepared by NIEIR using their "PeakSim" model (described further below). In order to validate the NIEIR forecasts United Energy commissioned AECOM to prepare an independent top-down maximum demand econometric forecasting model. This model uses the eViews software package and is referred to by United Energy as the "eViews model". The next sections describe each of these approaches in turn.

The NIEIR PeakSim Model

As noted above, United Energy have relied heavily on forecasts prepared by the National Institute of Economic and Industry Research (NIEIR) using their "PeakSim" model. This model is apparently proprietary in nature and is not described in full detail in the submitted documents. However the model is described in general terms in the reports submitted by NIEIR. The description here is based on my inferences using the material in the NIEIR reports.

The PeakSim model appears to estimate the historic temperature sensitivity of demand for each historic summer separately (here referred to as the "weather coefficient"). The PeakSim model apparently uses forecasts of half-hour by half-hour demand for each summer, based on key drivers – in particular weather factors. This historic temperature sensitivity is, apparently, assumed to be linear. NIEIR explain the model as follows:

> "The half-hour models … 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. A change in the intercept from one year to the next is indicative of a change in the stock of electrical equipment associated with weather insensitive demand activities. Similarly, a change in the weather coefficient is indicative of a change in the stock of electrical equipment associated with weather sensitive demand activities (such as air conditioning equipment)" (page 126).

Once this linear relationship between demand and weather has been estimated for each year of the sample, NIEIR use the historic long-term probability distribution of temperatures to infer POE10, POE50 and POE90 levels of temperature. These temperature levels are used to directly infer the corresponding historic POE10, POE50 and POE90 peak demand levels for each summer independently.[21] (In other words, there appears to be no separate simulation of weather blocks or residuals as described earlier).

The resulting historic estimates, as presented by NIEIR, are set out in Figure 11:

[21] Specifically, NIEIR state: "NIEIR's PeakSim model infers the underlying probability distribution of maximum demand for each historical summer". NIEIR (2014), Part A, page 84.

Figure 11: Implied POE level and observed summer maximum demand (MW) – United Energy, as estimated by NIEIR

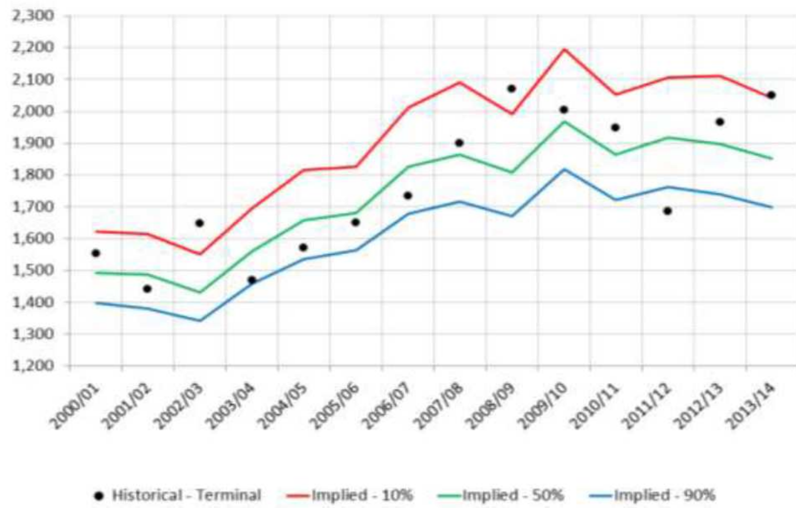


Figure 11 appears, at least on the surface to be consistent with figure 3. That is, it appears that the growth in peak demand experienced in the early 2000s has moderated and reversed in recent years.

The next step in the process is to use this observed historic pattern of peak demand to forecast future peak demand. In forecasting future peak demand NIEIR use the following approach:

First, NIEIR observe that the movements in the "base" or temperature insensitive component of demand tracks relatively closely to the total annual energy sales. This is broadly plausible under the assumption that the annual energy volumes are primarily driven by the "base" demand – i.e., that very hot days are relatively rare and therefore contribute relatively little to the annual volume of energy consumed.

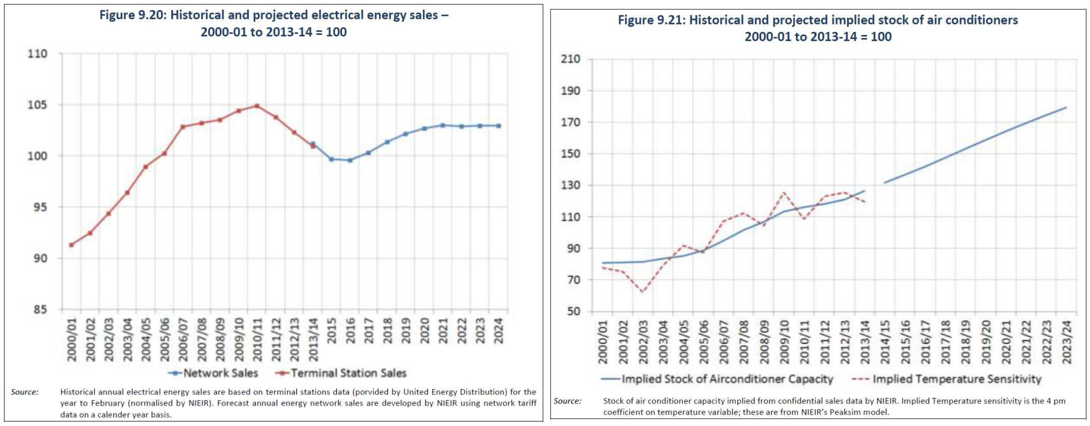
Second, NIEIR make an argument that historically there has been an increase in the temperature sensitivity of electricity demand, and that this increase in temperature sensitivity broadly tracks the penetration of air-conditioning units in Victoria. They therefore make the argument that the temperature sensitivity of electricity demand in Victoria is primarily driven by the penetration of air-conditioning load.

Third, NIEIR forecast weather-normalised energy sales into the future using a different (unspecified) model.[22] This model forecasts energy volumes no longer dropping, but recovering to around 2008 levels before levelling off. See figure 12a below.

Fourth, NIEIR forecast continuing increasing penetration of air-conditioners, increasing at the rate of 3 to 4 per cent per annum. See figure 12b below.

[22] NIEIR does not describe this model. It merely notes that "Forecast annual energy network sales are developed by NIEIR within a separate model using network tariff data on a calendar year basis".

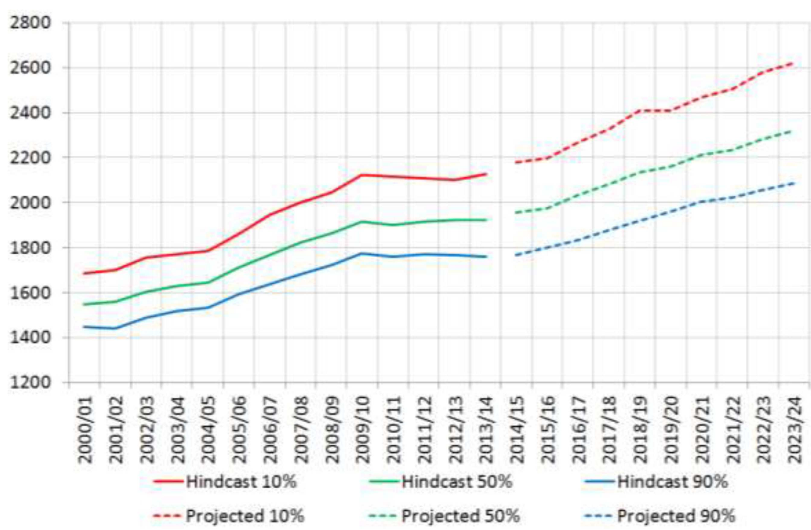
Figure 12: NIEIR forecasts of future electricity demand and air-conditioner penetration (United Energy region)



Fifth, combining these two effects, NIEIR forecast that base (temperature insensitive) electricity demand will recover and the temperature sensitivity will increase. This yields a forecast increase in the POE10, POE50 and POE90 projections of maximum demand. See Figure 13.

Finally, NIEIR go on to make various post-modelling adjustments, for changes in electricity prices, energy efficiency programs, and small-scale embedded generation. Collectively these adjustments are quite small (a few percentage points).

Figure 13: Forecasts of POE10, POE50 and POE90 demand, United Energy region



In assessing the NIEIR model, I make the following points:

- NIEIR's approach to forecasting the POE10, POE50 and POE90 levels into the future relies on a model of future demand which is not described in the reports that I have. This model predicts a recovery of demand levels in the future. The reason for this forecast is not clear. Further explanation of this model seems to be required.
- Furthermore, I understand that NIEIR's predictions about future peak demand levels depend primarily on assumptions about air-conditioner penetration. It is plausible that other factors, such as energy efficiency, and solar PV investment are also having an impact on both base level demand and temperature sensitivity, but these factors do not

appear to be taken into account. The Victorian government has on-going energy efficiency programs designed to increase the average efficiency of the stock of household appliances. It is also not clear to me why NIEIR have used a "hindcasting" approach, which again seems primarily based on air-conditioner penetration, to revise the historic estimates of peak demand levels.

- There is relatively little justification of the forecasts of future air-conditioning penetration put forward by NIEIR. To the extent that new air-conditioner purchases are being used to replace older, less efficient models, an increase in air-conditioner purchases might be expected to reduce (rather than increase) the temperature sensitivity. It would be useful therefore to determine the extent to which air-conditioner purchases are replacement rather than new installations. In addition, no account is taken of the possibility of an "S-curve" effect in penetration, where penetration eventually levels off. The evidence set out in the appendix suggests that growth in the rate of air-conditioning has slowed in recent years. This point is also made by GHD in their critique of modelling by AEMO:

  > "Australian data on air-conditioners shows that rapid uptake in the early 2000s was followed by more recent slowing approaching saturation levels and also possibly reflecting higher efficiency standards for newer models. This would partly explain the generally slower growth in peak electricity demand in recent years".[23]

- Finally, as was observed with the ACIL Allen report for Jemena, the NIEIR report for United Energy was prepared in August 2014 so it is now almost one year old. In particular, NIEIR were not able to take into account the experience of the most recent summer. From the earlier analysis it appears that if the summer of 2014/15 was included in the analysis it would further confirm and reinforce the decline in demand that has been observed in recent years.

In short, while NIEIR's approach to estimating historic peak demand levels seems to be sound, there are questions about their approach to forecasting future peak demand levels.

The AECOM eViews Model

United Energy also set out an econometric model which they use to "validate" the NIEIR results. This model follows the approach suggested by two academics at the Monash Business and Economic Forecasting Unit (Hyndman and Fan, 2008). The model apparently estimates a structural (linear) relationship between electricity demand, weather, calendar variables, and economic variables such as GSP, electricity prices, income, and AC and PV penetration. United Energy report the regression coefficients from the model in Table 3 (page 15-17) of the "Maximum Demand Overview Paper", but the variables themselves are not defined.

Once the relationship has been estimated, UE forecast the key economic variables into the future and use simulations of temperature variables and random regression errors to estimate the probability distributions of peak electricity demand in the future. The forecasts of GSP, electricity prices, income and AC and PV penetration are not described in the submission.

A strength of the eViews model is that it incorporates a wider range of potential drivers than the other similar models discussed above. However, as noted earlier, a weakness of these regression models is that they inevitably restrict both the possible drivers of peak demand and the way those drivers can affect peak demand. The UE eViews model does not allow for the possibility that these relationships might change over time (perhaps due to some unmodelled effects). Neither does the eViews model allow for interaction between the drivers – for example, the

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[23] GHD, "Review of AEMO Demand Forecasting Methodology", January 2015.

possibility that increasing AC or PV penetration might increase the sensitivity of demand to temperature over time.

The last few years have seen quite substantial change in the electricity industry with quite large price changes and major new developments such as investment in energy efficiency and solar PV (as described in the appendix). Furthermore, as noted elsewhere in this report, proposed tariff changes have the potential to have a material impact on peak demand in the future. It is not clear that the model is able to capture all of these past or future developments accurately.

As noted earlier, one possible test of the validity of the model would be to estimate the model over different (shorter) timeframes. If the assumed underlying structural form of the model is reasonably robust (that is, unchanging over time) the estimated coefficients should not change significantly (and neither should the forecasts).

To a certain extent, UE recognise these potential problems and note the following caveats of the eViews model:

> "It is important to note that the eViews model estimates demand based on existing trends (10-years of historical data) and relationships only. For example, the model considers the impact of solar generation and energy efficiency, but only insofar as those are reflected in the existing trends, which are correlated with the explanatory data used. Faster or slower growths in solar generation or energy efficiency programs which could result from policy changes are not included and are better described by the NIEIR and ACIL Allen models". (page 17).

United Energy internal demand forecasting approach

United Energy also submitted a document setting out their "Maximum Demand Forecasting Method" (Document No. UE PR 2200). This document goes into significantly more detail and is, in some respects, inconsistent with the NIEIR report. It is not clear what status this document has relative to the NIEIR report. My best guess is that this document describes the in-house policy for demand forecasting on a granular level used by United Energy.

This document describes a demand forecasting process which is much more closely tied to the engineering features of United Energy's network. Specifically, this report emphasises that part of UE's network, covering the Mornington peninsula, is subject to substantial inflows of population during the holiday periods. For this reason, unlike the rest of the network, peak demand in this part of the network can occur on holidays and weekends. The fact that part of the UE network is holiday-peaking is not mentioned in the NIEIR report. The UE report also describes the choice of the weather stations used for weather normalisation (Cerberus and Scoresby). Again, these weather stations are not mentioned in the NIEIR report.

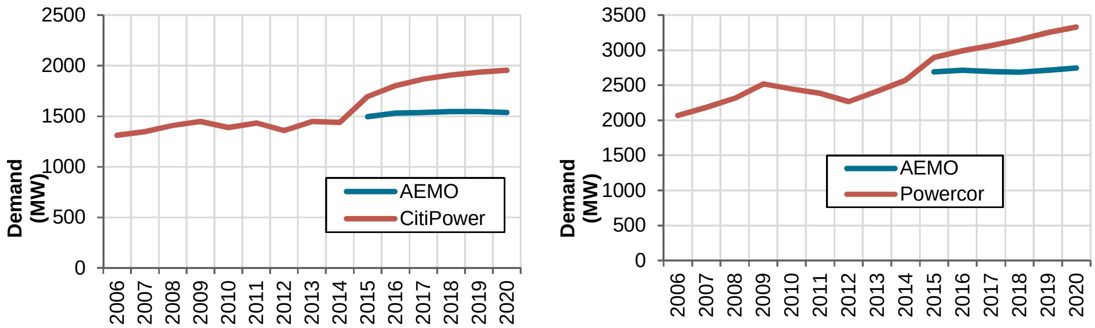
It is not clear how this document relates to the forecasts prepared by NIEIR. At this stage I have put this document to one side.

Overall, my impression is that UE has drawn on sophisticated tools, and has sought to validate their forecasting using a range of different approaches. However, as noted earlier, the electricity industry in Victoria is currently in a phase of quite material change. This change increases the uncertainty about the future path of peak demand and increases the importance of capturing all of the relevant factors which may drive peak demand in the future. There are grounds for concern about the methodology used by UE and therefore I am concerned that the estimates put forward by UE are not a realistic expectation of future demand.

3.3 CitiPower/Powercor

Like the other DNSPs, CitiPower and Powercor are forecasting materially higher levels and growth of peak demand than AEMO. See Figure 14.

Figure 14: Comparison of peak demand forecasts of CitPower/Powercor and AEMO



When it comes to forecasting peak demand CitiPower and Powercor have not chosen to use the methodology recommended by ACIL Allen. Instead CP/PC have engaged the Centre for International Economics (CIE) to prepare maximum demand forecasts for connection points in the CitiPower and Powercor regions. CIE describe their "overall approach" as "consistent with the best practice methodology described by ACIL Allen in their 2013 Report to AEMO". However, my impression is that CIE's approach is quite different to that of ACIL Allen.

The CIE approach (like the ACIL Allen approach) does not attempt to model peak electricity demand directly. Instead, they divide the task up into two parts corresponding loosely to models of (a) the "high-frequency" drivers of demand and (b) the "low-frequency" or longer-run drivers of base demand. Specifically CIE estimate two models:

- A model of peak demand relative to average demand. This model estimates a mathematical relationship between half-hourly peak and average demand which is assumed to hold over all ten years of the sample period.
- A model of average quarterly demand, as a function of economic drivers, population growth and so on, again over the ten years of the sample period.

In the CIE model, future forecasts of peak demand are estimated by applying the mathematical relationship derived from the first model to the long-run forecasts of electricity average demand derived from the second model. Both models are important for determining peak demand forecasts in this approach.

In more detail, the key features of the short-run model of peak-relative-to-average demand are as follows:

- CIE propose that there is a fixed relationship between the log of the ratio between actual and average demand and a few key drivers: weather (temperature), and so-called "calendar variables". These variables are estimated for 24 half-hour periods during the summer months.
- The calendar variables include dummy variables for each day of the week, weekday versus public holiday, a time trend, and a function representing the broad seasonal variation in demand over summer (represented as a cubic regression spline – that is 6 cubic functions joined at the ends).

- CIE include a range of weather variables, including current and recent temperatures, temperatures from 24 and 48 hours ago, temperature changes, minimum and maximum temperature of the current day, and average temperature of the current week.
- CIE also include a variable which allows for the temperature-dependence of demand to vary over time. This variable is the product of (a) the difference between the current temperature and 30 degrees (when that difference is positive); and (b) the number of years since 2004.

The longer-run model of quarterly demand estimates quarterly demand as a function of key economic drivers such as population, income per capita, electricity prices, gas prices, temperature (as reflected in heating-degree-days and cooling-degree-days), and the penetration rate of air-conditioning. A different relationship was estimated for each connection point using the most appropriate local government area statistics for population and economic growth, and the most appropriate local weather station data.

Once these relationships have been determined, CIE use simulation (using blocks of historic weather data and blocks of residuals from the estimation) to find the distribution of peak demand for each historic year, from which estimates of POE10, POE50 and POE90 values are be determined.

In order to forecast future peak demand CIE assume that the structural relationships estimated in these two models will continue to hold in the future. They forecast the future values of the economic factors to come up with a forecast of base or average demand using the long-run model. The short-run model is then used to find a distribution of peak demand above this base level. Again, simulation is used to determine a POE10, POE50 and POE90 levels of peak demand.

CIE also make post-modelling adjustments for embedded generation, solar PV investment, and industrial loads.

Assessment of CIE's approach

CIE's methodology is econometrically sophisticated. However, as noted earlier, this approach only yields reliable estimates where there is a stable underlying relationship between peak demand and the key drivers, where that relationship can be accurately estimated, and where that relationship persists into the future.

One question is whether the model can fully and accurately capture recent industry developments. CIE are aware of this possibility - in their modelling CIE was concerned that the original model proposed by Hyndman and Fan did not allow for the possibility for some of the key parameters to vary over time. To allow for this possibility CIE introduced a variable which allows the temperature sensitivity of demand is allowed to vary over time. This is a valuable extension of the Hyndman and Fan model however the specification chosen by CIE only allows the temperature sensitivity to vary in a particular linear way over the entire sample period.

It is not clear that recent developments in the market can be fully captured in the specification chosen by CIE. As noted in the appendix some of the recent developments in the market (such as energy efficiency or solar PV investment) have accelerated since around 2010. To the extent that these impacts have not been linear over the last ten years this could not be captured in the CIE model.[24]

CIE's model of long-run demand predicts that demand will grow strongly in the future. While this is possible it does not seem likely. The evidence such as that presented in the appendix suggests that, while there will continue to be pockets of demand growth[25], average demand growth has been falling in developed economies for decades and is likely to be low, zero or negative in the future. CIE's model does not allow for the possibility that the responsiveness of average demand to population and income factors will vary over time. There is also some suggestion that the trend towards energy efficiency has increased in recent years (see the appendix).

CIE, in their forecasting for CitiPower/Powercor have used what they call an "Error Correction Model". This has the effect of moving the forecast from "the point" (which they refer to as a short-run relationship) to "the line" (which they refer to as the long-run relationship) over a period of a few years. AEMO has used a similar technique in their Integrated Dynamic Model (IDM) used in the National Energy Forecasts. I note that the proposed "error correction" technique is purely statistical. It is not clear what assumptions this implies for the underlying behaviour of participants in the Victorian electricity industry.

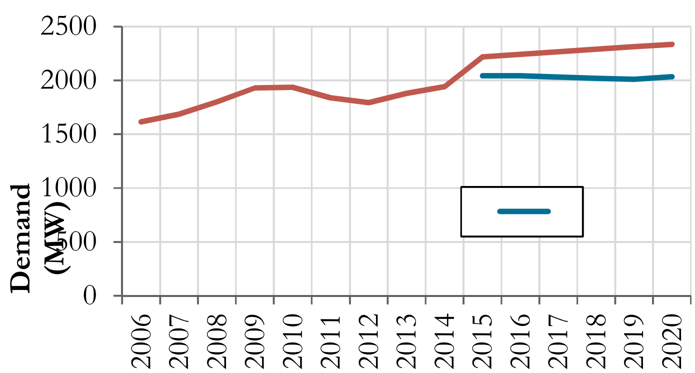
In addition, as noted above, CIE's forecasting report (dated July 2014) is now more than one year old and, in particular was prepared before the most recent summer. The addition of one more summer of data may yield different estimates.

Overall, CitiPower/Powercor have used sophisticated statistical techniques. But those techniques are only as valid as the underlying assumptions. As I have noted with the other DNSPs I am concerned that CIE's approach does not fully capture recent industry developments and therefore may not be a reliable forecast in the future. I am concerned that the estimates put forward by CitiPower/Powercor are not a realistic expectation of future demand.

3.4 AusNet Services

Like the other DNSPs, AusNet is forecasting a higher level of and faster growth in peak demand in the future compared with AEMO (Figure 15).

Figure 15: Comparison of AusNet and AEMO POE10 peak demand forecasts



[24] I understand that CIE have tried incorporating solar PV investment in the model but the signs of the relevant coefficients were unstable in different specifications and not always economically meaningful. For this reason CIE chose to incorporate solar PV through out-of-model adjustment.

[25] Such as, in CitiPower's region the Fishermen's Bend region.

AusNet Services' approach to peak demand forecasting is somewhat different to the other DNSPs. They have chosen an approach which differs in many important respects to the approach proposed by ACIL Allen. Helpfully, AusNet have commissioned ACIL Allen to carry out a comparison of their approach to ACIL's recommended approach. I draw on that comparison for much of the analysis in this section.

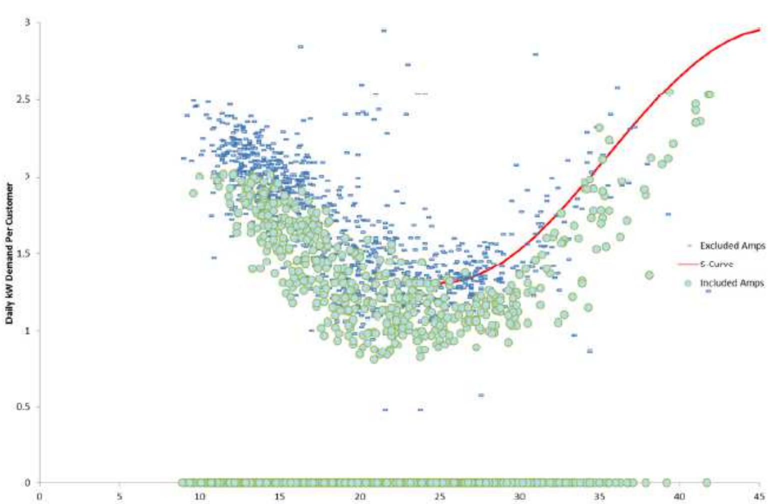
AusNet Services have submitted two documents related to maximum demand forecasting:

- ACIL Allen, "Distribution Demand Forecasting: Comparison of AusNet Services and ACIL Allen Methodologies", 17 April 2015 submitted as AusNet Services, *Appendix 4A: Distribution Demand Forecasting*, 30 April 2015
- AusNet Services, *Appendix 4B: Demand Forecasting Methodology*, 30 April 2015

AusNet's approach differs from other approaches to forecasting peak demand in several respects: First, it is based around forecasts of demand on a per-customer basis. This is combined with forecasts of customer growth rates at a local level to obtain forecast growth rates in demand for each feeder or connection point. AusNet assumes that customer growth rates on each feeder follow an "S-curve" shape, with initially slow growth, followed by rapid growth, followed by slow growth. AusNet seek to find the S-curve which best fits the historic growth rate, which then yields forecasts of the future customer growth rates into the future. AusNet also recognise that new buildings typically are more efficient than the stock of existing buildings, so new customers have a lower peak demand that existing customers.

Second, like other approaches AusNet estimates a relationship between temperature and peak demand. However AusNet's approach differs from other DNSPs in two respects: First, AusNet assumes that the relationship between temperature and (per customer) demand also follows an "S-curve" shape. This implicitly assumes that demand will become less responsive to temperature at very high temperatures – perhaps due to "saturation" (as illustrated in Figure 16 below). AusNet is the only one of the Victorian network businesses to make this assumption.

Figure 16: AusNet estimates the demand-temperature relationship using an S-curve



Once the temperature-demand response is estimated the POE10 and POE50 temperatures are determined by taking the highest and the middle of a sequence of peak annual temperatures for the last ten years (rolling forward over time). In other words, the POE10 temperature for 2004 is the highest temperature from 1995-2004 etc. This approach to determining the POEx temperature is questionable and is discussed further below.

The POE10 and POE50 forecasts are then formed by combining these factors: The customer growth forecasts and the POE10 and POE50 temperatures in the temperature-demand relationship, taking into account improvements in efficiency of new customers over time.

Assessment of AusNet's approach

AusNet's approach has certain strengths and weaknesses. The strengths of the AusNet approach include:

- The use of S-curves in modelling customer growth rates. This implicitly recognises that demand growth on a particular feeder slows as development reaches particular limits. This point is not explicitly drawn out in the methodology used by other DNSPs.
- The explicit recognition that new customers tend to be more energy-efficient than existing customers.
- Importantly, the assumption that the temperature-demand relationship also follows an S-curve. AusNet is the only distributor to acknowledge the possibility that the temperature-sensitivity of electricity demand may reduce at particularly high temperatures.

However, AusNet's approach also has certain unusual features:

- In determining the temperature-demand relationship AusNet seek to fit a curve to the "top" of the dataset – that is, they consider only the highest maximum demand ever recorded at each temperature. The highest maximum demand at a given temperature could have occurred many years in the past in quite different market conditions – in other words, could relate to a market scenario which is now out of date. ACIL Allen explains this as follows:

  > "Temperatures that are unusually high are, by definition, observed infrequently. Therefore, in AusNet Services' approach the S-curve is calibrated to data that are outdates. In practice, the very high temperature observations in the normalisation process are likely to have been observed in 2009, because temperatures that year were extremely high. This means that the AusNet Services methodology does not describe the relationship between very high temperatures and demand to the extent that there may have been changes since 2009. Those changes may be due to changing appliance efficiency or economic growth, for example".

  In effect, AusNet are estimating a relationship between per capita peak demand and temperature as it occurred in 2009. Earlier we suggested that the temperature-demand relationship has been declining since 2009. To the extent this is the case, the AusNet approach will tend to over-estimate the POE10 and POE50 forecasts.

- In estimating the POE10 and POE50 temperatures, AusNet take a rolling set of ten peak annual temperatures. The POE10 value is the highest of this set, and the POE50 value is the middle (median). The problem with this approach is that a set of ten consecutive years may easily have temperature outcomes which are above or below the long-term averages. This is particularly the case for the POE10 value which is based on only a single observation in the sample of ten values. As a result the AusNet approach may result in forecasts which are systematically above or below the true value. In fact, ACIL Allen suggests that in this case they are above:

> "The last 10 years contains the extreme weather events of 2009, which lie well above the POE10 level of demand using a longer time series of temperature data. … In our view this [AusNet approach] is likely to be biased upwards due to the extreme weather of 2009. To alleviate this bias, ACIL Allen recommends that a longer time series of at least 30 years is used to estimate the POE10 and POE50 maximum temperatures".

To conclude, AusNet's approach is probably strongest in regard to forecasting growth rates into the future. The use of S-curves should reduce the likelihood of over-estimating growth in regions which are approaching their natural growth limits. However some questions still remain. AusNet have not discussed their approach to forecasting customer numbers in regions which are experiencing a decline in population. Also AusNet have apparently assumed that all improvements in efficiency of new residential customers will cease in the next few years. It is not clear why this has been assumed to be the case.

AusNet's approach is probably weaker in determining the level of POE10 and POE50 demand. As noted, AusNet's approach to estimating the temperature-demand relationship combines data from many different years and therefore may not reflect a stable, robust relationship, especially since other evidence suggests that this curve has been shifting down over time.

As with the other DNSPs, in my view there are grounds for concern about the methodology used by AusNet and therefore I am concerned that the estimates put forward by UE are not a realistic expectation of future demand.

4. Conclusion

Forecasting future demand is not easy. It requires judgement about what relationships (if any) that have been observed in the past will continue into the future. The evidence set out in this note (and also in several of the consultant reports that were considered in the preparation of this note) suggests that peak demand levels in Victoria have recently been declining after several years of moderate growth. This raises fundamental questions about the drivers of that decline. Is this decline a temporary aberration? Or is the decline due to sustained, longer-term factors such as deindustrialisation, energy efficiency, or solar PV investment? If so, how far and for how long can those factors be expected to continue?

The electricity industry is in a period of unprecedented change, with rapidly increasing penetration of distributed energy resources such as solar PV and battery storage. New tariff structures proposed by the DNSPs in the future may significantly change demand patterns in future. In this context I have expressed concern about demand forecasting approaches which assume a rigid structural relationship between demand and key drivers in the past. Where this approach is adopted it is very important to ensure that the correct drivers are chosen and that the model accurately reflects the way that these drivers affect demand in the past (and will affect demand in the future). I have expressed concern that several of the models estimated for the purpose of forecasting peak demand do not allow for the potential changes that we may be observing the electricity market in Victoria. In my view, the detailed analysis of the forecasting approaches used by each of the businesses provides sufficient grounds for concluding that the forecasts put forward by the DNSPs are not a realistic expectation of future demand.

5. Appendix: Changing demand patterns in Victoria

As emphasised in the text, reliable forecasting involves determining a relationship which will remain stable over both the past (over which the relationship is estimated) and into the future (over the forecast period). I have expressed concern that the models used by the network businesses do not capture all of the factors which have affected peak demand both historically, in the recent past, and into the near future. This includes the following:

- Energy efficiency trends (both increasing efficiency of houses and appliances)
- The rapid growth in solar PV
- Slowing of the rate of penetration of air-conditioners
- De-industrialisation of the Victorian economy
- Changing network tariff structures
- The potential for rapid growth in distributed energy resources, such as battery storage.

Each of these issues is discussed further in this appendix.

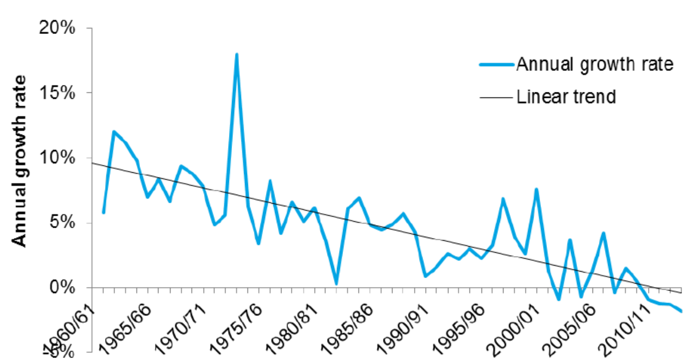
Energy efficiency trends

There appears to be a long-term trend in Australia towards a slowing of the growth rate of electricity consumption, despite economic growth and population growth. This is explained by the AEMC as follows:

> "Over the long term, the annual growth rate of electricity consumption in the NEM has been declining since the 1960s, with negative growth first experienced in 2002/03, as shown in Figure 2.3. This is indicative of a structural change in the Australian economy away from its agricultural and manufacturing origins, to one based on less energy intensive services, as well as gains in energy efficiency."[26]

Figure 2.3 is reproduced below:

Figure 2.3 Annual energy consumption growth rate for the NEM jurisdictions



Data source: BREE, Australian Energy Statistics 2013, Table I; AEMO, National Electricity Forecasting Report 2014.

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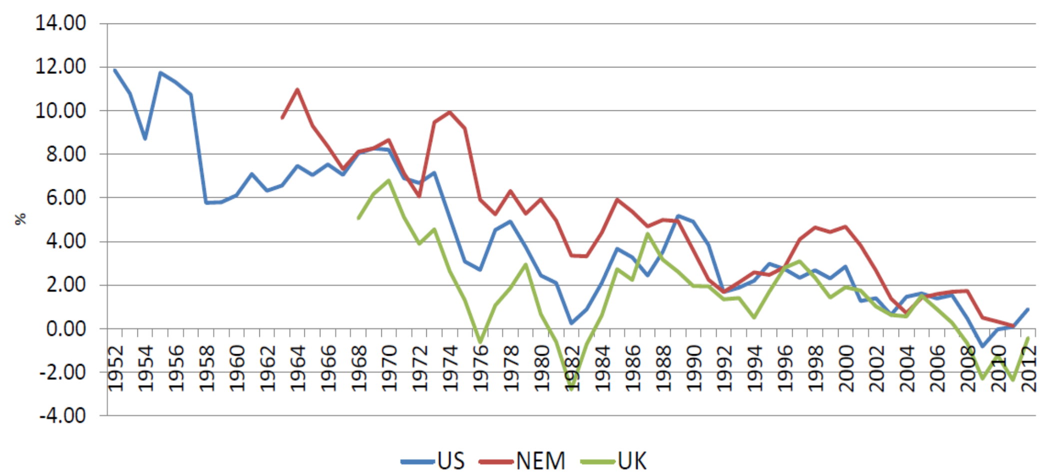
[26] AEMC, "Final Report: 2014 Residential Electricity Price Trends", report to COAG, 5 December 2014, page 13.

These factors are not unique to the NEM. This long-term trend towards decreasing growth in electricity demand was highlighted in a recent presentation by Matthew Warren of the ESAA. As shown in Figure 17, electricity demand is low or zero in many countries world-wide despite the existence of continued population growth and economic growth.

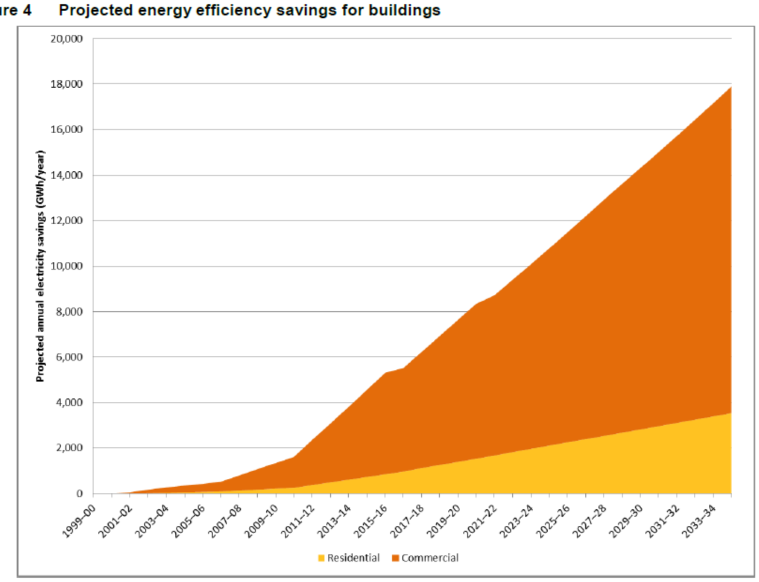
Figure 17: Long-term trends in electricity growth rates (three-year rolling average)



Sources: BREE, EIA, gov.uk

This reduction in electricity demand growth is, in part, due to increasing efficiency of energy use over time. There is some evidence that the trend towards energy efficiency is not constant over time, but has accelerated since around 2010, as suggested in the following graph by NIEIR:

Figure 4 Projected energy efficiency savings for buildings



Source: Pitt and Sherry (2013)

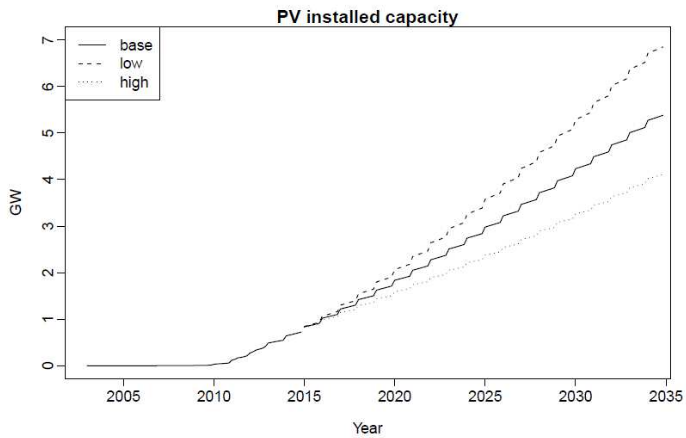
Source: NIEIR Part A, page 83

Of course, a reduction in average demand does not automatically imply a reduction in peak demand. Nevertheless there is likely to be some relationship between the two.

Growth in solar PV

In recent years there has been a dramatic increase in the volume of installed rooftop solar PV capacity in Australia. This change occurred around 2010, roughly in the middle of the ten-year sample period used by the network businesses. This is illustrated in Figure 18 below, which is drawn from a report prepared by Hyndman and Fan for AEMO.

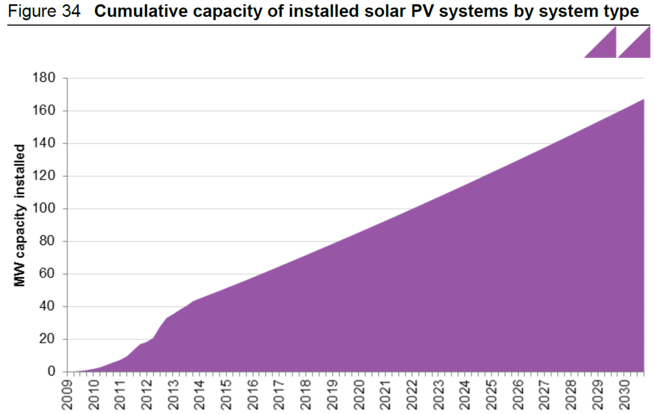
Figure 18: Three scenarios for installed capacity of rooftop PV cells



Source: Hyndman and Fan (2015), page 43.[27]

Other studies also show a rapid increase in the volume of installed solar PV, with the take-off occurring around 2010. The figure below is drawn from a report by ACIL Allen for Jemena and shows the projected capacity of solar PV systems in Jemena's region.[28]

Figure 34 **Cumulative capacity of installed solar PV systems by system type**



Source: ACIL Allen Consulting

[27] Professor Rob J Hyndman and Dr Shu Fan, "Forecasting long-term peak half-hourly electricity demand for Victoria", report for AEMO, 1 June 2015

[28] Jemena Electricity Networks, 2016-2020 EDPR, Attachment 3-1, Electricity Demand Forecasts Report

Another trend which appears to be occurring, but which does not seem to be captured in the models used by the network businesses, is a slowing of the rate of take-up of air-conditioning devices. This point is noted by GHD in their critique of the modelling approaches used by AEMO:

> "Australian data on air-conditioners shows that rapid uptake in the early 2000s was followed by more recent slowing approaching saturation levels and also possibly reflecting higher efficiency standards for newer models. This would partly explain the generally slower growth in peak electricity demand in recent years; however none of AEMO's current modelling can account for this phenomenon. One way to improve its capability in this regard would be to include air-conditioner stock data in the existing models' weather functions". [29]

There is some evidence for this in the following graphs from the AEMC and NIEIR:

Figure 2: Proportion of Australian Households with air conditioners 1990-2014[vii]

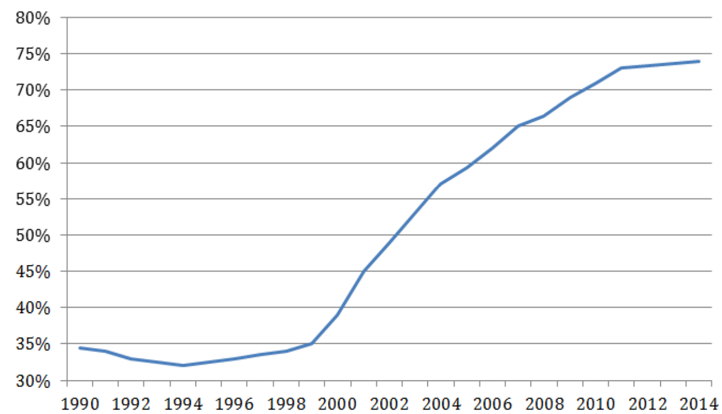
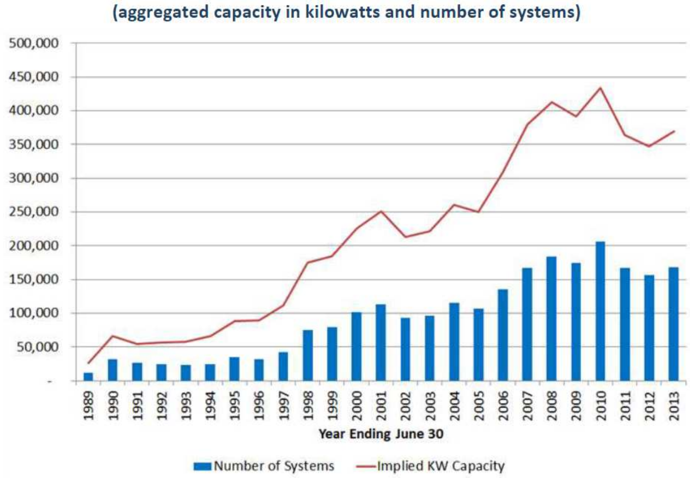


Figure 9.2: Annual sales of air conditioners in Victoria
(aggregated capacity in kilowatts and number of systems)



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[29] GHD, "Review of AEMO Demand Forecasting Methodology", January 2015.

Another factor which is driving demand (and peak demand) in Victoria is the changing patterns of industrialization – in particular the closure of large industrial loads. The AEMC notes that one of the drivers of the recent decline in electricity consumption is the "reduction in large industrial loads, such as aluminium smelters, due to the structural shift in the Australian economy away from energy intensive industries". They go on to observe:

> "A recent step-change in energy consumption has occurred in the NEM with the closure of major industrial electricity users. Between October 2011 and September 2012, the Port Kembla steelworks, the Kurri Kurri aluminium smelter and the Clyde oil refinery were partially or completely shut down. This removed around 3,600 GWh of annual Key trends in prices and cost components electricity consumption from the NEM. More recent closures include the Point Henry smelter and the Kurnell oil refinery, which both ceased operations in 2014."[30]

Many of these large loads will be directly connected to the transmission network. The closure of a large industrial load connected to the transmission network does not necessarily affect the peak demand on a distribution network. However, these large industrial enterprises often create clusters of associated economic activity. The closure of a large aluminium smelter will have an impact on local economic activity that will likely be reflected in demand patterns on the local distribution networks.

In addition, this pattern of deindustrialisation may continue to occur in the future. Hyndman and Fan (2015) forecast (in at least one scenario) a further decline in large industrial loads:

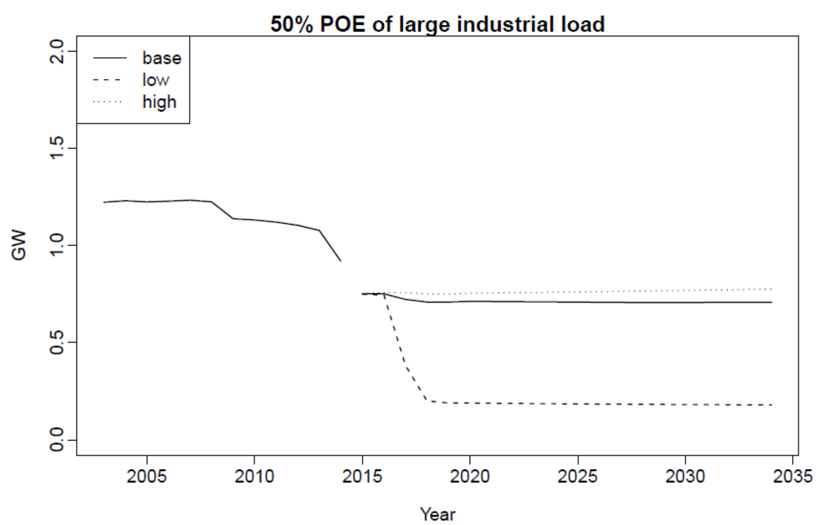

Figure 46: *Three scenarios for major industrial loads.*

Source: Hyndman and Fan (2015).[31]

[30] Citation

[31] Professor Rob J Hyndman and Dr Shu Fan, "Forecasting long-term peak half-hourly electricity demand for Victoria", report for AEMO, 1 June 2015

Changing tariff structures

Another factor which is likely to have a substantial impact on future demand is changing tariff structures. Again, this does not seem to have been fully taken into account in the models put forward by the network businesses. Changes in tariff structures can have (and are often designed to have) a material impact on peak demand. The AEMC observes:

> "In summer 2011, Victorian distributor SP AusNet restructured its commercial and industrial network tariffs to better reflect the network's costs and to target reductions in demand during peak times on critical peak days. The critical peak demand tariff resulted in a significant customer response, with a reduction of 88MW in summer peak demand".[32]

Importantly, over the next few years many of the distributors in Victoria are planning to implement what is the potentially the largest change in residential tariff structures in the history of the electricity industry. Specifically, the distributors in Victoria are planning to move to a residential tariff with a "peak demand" component in which the amount of revenue paid by each customer depends (in part) on their historic peak demand during the previous month. The potential impact of this change in tariff does not appear to be reflected in the peak demand forecasts put forward by the network businesses.

As an example, Jemena, in their regulatory proposal, point out that they plan to introduce a demand charge. Importantly, this demand charge is designed with the specific intent of reducing peak demand on the network.

> "We propose to update our network tariff structures to encourage more informed customer decision making and to put downward pressure on our costs and average prices over the long-term by: Introducing a new 'maximum demand charge' for all residential and small business customers to more clearly signal the higher costs of using our network during periods of peak demand, and thus encourage these customers to reduce or spread out consumption".[33]

> "In particular, we propose to introduce a new 'maximum demand charge' for all residential and small business customers. The amount customers will pay for this bill component will depend on the maximum amount of electricity they draw from the network during the specified 'demand charging window'. This window is from 10am to 8pm on weekdays, when peaks on our network are most likely to occur. Building and maintaining the network to meet peak demand is relatively costly, and so has a significant influence on our capital expenditure program and ultimately on our network prices".[34]

Jemena are clear that under a flat rate tariff "customers do not consider this [network] cost when deciding to turn on (or off) their electric appliances. As a result, peak demand is likely to be higher than it might otherwise be, imposing higher costs on all customers."[35]

I understand that the other network businesses in Victoria are also proposing to introduce a demand tariff for small customers. If this proposal is taken up it could have a very material impact on peak demand in Victorian networks.

The extent to which the network businesses have taken into account future tariff structure changes in forecasting peak demand is not clear.

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[32] AEMC, Power of Choice, Final Report, page 204.

[33] Jemena, Regulatory Proposal, page 105

[34] Jemena, Regulatory Proposal, page 106

[35] Jemena, Regulatory Proposal, page 112.

Other factors

There is an increasing recognition that the electricity industry is at a crossroads. In recent years there has been rapid growth in the availability of and interest in a range of new devices and technologies known collectively as distributed energy resources. Around the world, governments are grappling with how to integrate large amounts of distributed energy resources (DER) into the electricity industry.

One of the greatest potential benefits of DER is the potential to smooth out peak demand, reducing the need for network capacity. The growth of DER has the potential to materially change the pattern of demand on the electricity networks including peak demand.

One of the more significant forms of distributed energy resources is battery storage. Many network businesses have announced an intention to install battery storage devices on their network. There is also substantial potential for residential customers to install battery storage. Tesla has recently announced that Australia will be one of the first countries in the world for the roll out of the Tesla Powerwall.[36] Such devices could, if used reasonably efficiently, have a material impact on the peak demand of household customers.

Conclusion

This appendix has set out evidence that the electricity industry in Victoria is changing – it has changed in the last five years and looks set to change further in the future. It is not clear that these changes have been fully captured in the structural models used by the network businesses.

[36] Guardian, 21 September 2015, "Tesla's Powerwall will give its first taste of disruption to Australia's energy market"