FORECASTING METHODOLOGY INFORMATION PAPER

National Electricity Forecasting

2012

AEMO
AUSTRALIAN ENERGY MARKET OPERATOR

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CHAPTER 1 - INTRODUCTION

1.1 National Electricity Forecasting

AEMO has changed the way it develops and publishes annual electricity demand forecasts for the electricity industry, by developing independent forecasts for each region in the National Electricity Market (NEM).

Electricity demand forecasts are used for operational purposes, for the calculation of marginal loss factors, and as a key input into AEMO's national transmission planning role. This requires a close understanding of how the forecasts are developed to ensure forecasting processes and assumptions are consistently applied and fit for purpose. AEMO is ideally positioned to undertake this task and lead collaboration with the industry to ensure representative and reliable forecasts are consistently produced for each region.

Previously, AEMO developed demand forecasts for South Australia and Victoria, while the regional transmission network service providers (TNSPs) developed forecasts for Queensland, New South Wales (including the Australian Capital Territory), and Tasmania. These forecasts were published via a series of AEMO publications including the Electricity Statement of Opportunities (ESOO), the Victorian Annual Planning Report (VAPR), and the South Australian Supply and Demand Outlook (SASDO).

National electricity forecasting

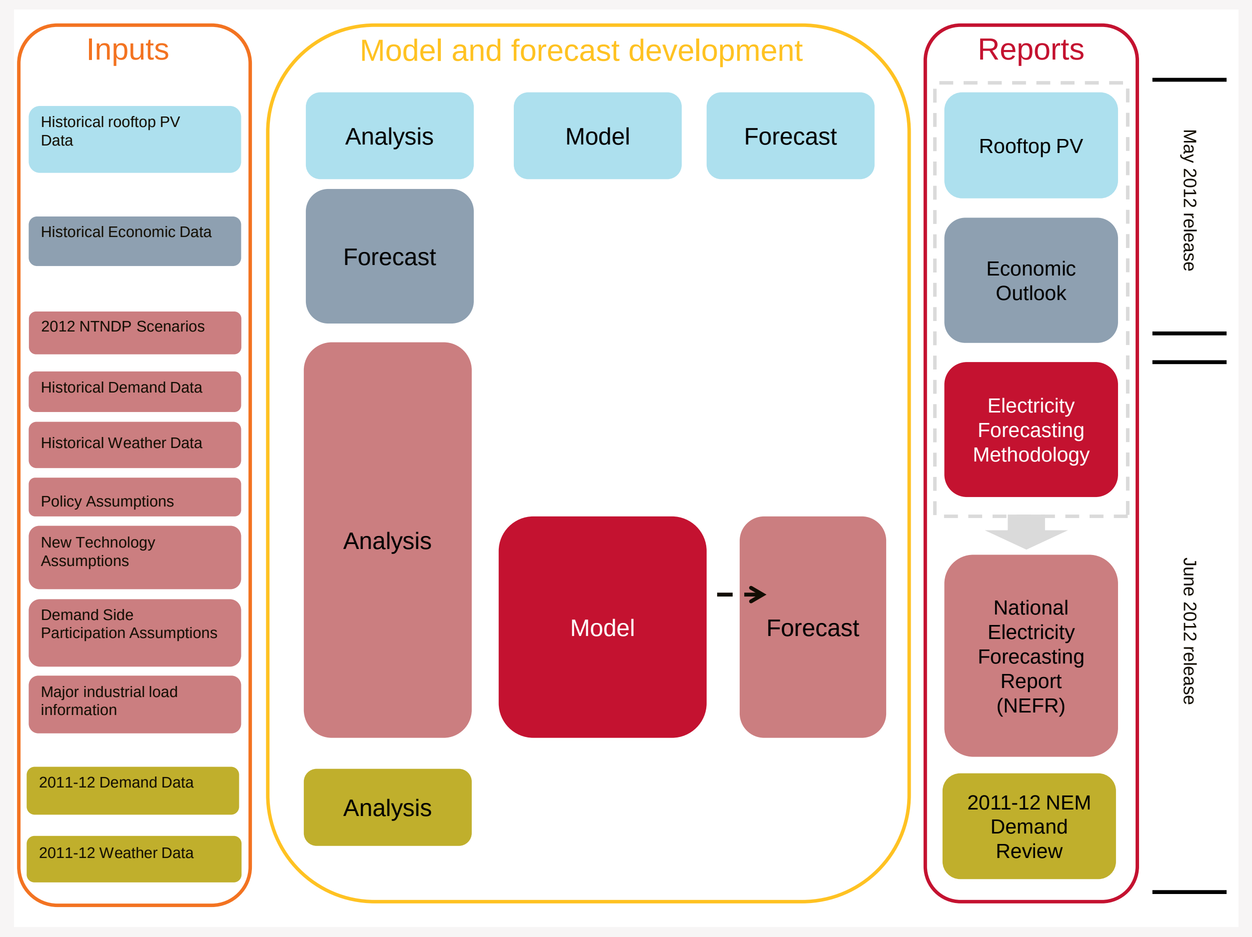
To facilitate greater forecasting transparency and stimulate discussion with the electricity industry, AEMO is now publishing the annual electricity demand forecasts via a series of separate information papers and reports:

- **Economic Outlook Information Paper** is AEMO's assessment of the work undertaken by the National Institute of Economic and Industry Research (NIEIR), published in May 2012.
- **Rooftop PV Information Paper** quantifies the impact of rooftop photovoltaics (PV) on the electricity market, published in May 2012.
- **2011–12 NEM Demand Review Information Paper** reviews 2011–12 NEM demand.
- **Forecasting Methodology Information Paper** describes the modelling process underpinning the demand forecast development.
- **2012 National Electricity Forecasting Report (NEFR)** presents the electricity demand forecasts for the five NEM regions.

Figure 1-1 illustrates the inputs, the modelling and forecast development processes, and the subsequent reports underpinning AEMO's new approach to national electricity forecasting.

This is first time AEMO has developed forecasts for the NEM, so more work still needs to be done, and AEMO will continue to improve the underpinning data, modelling, and interpretation, as well as engaging with industry on an ongoing basis to ensure an open and transparent process.

Figure 1-1 — AEMO's National Electricity Forecasting



1.2 Content of paper

Chapter 1, Introduction, provides the background to AEMO's National Electricity Forecasting project, the context for the remainder of this paper, and possible future work to improve the forecasting process.

Chapter 2, Measuring and forecasting electricity demand, defines what is being forecast and where these forecasts fit in the overall scheme.

Chapter 3, Modelling non-large industrial consumption, discusses the data and modelling approach for the annual energy forecasts.

Chapter 4, Modelling maximum demand distribution, discusses the modelling of half-hourly demand and the simulation of maximum demand probability distributions.

Chapter 5, Energy modelling example, provides some empirical results using the approach described in Chapter 3 and based on data for New South Wales.

Chapter 6, Comparison of forecasting models across regions, describes the energy forecasting models developed by AEMO for each region that were actually used to produce the 2012 energy and maximum demand forecasts.

Appendix A, Estimation of long run coefficients and forecasting models, presents estimation output related to the example in Chapter 5.

Appendix B, References, lists the sources used when developing the paper.

1.3 Future work

Modelling and forecasting energy and maximum demand is an evolving process. As well as the choice of model type, there are elements of trade-off and judgement involved in assessing alternative model estimations. A number of possibly contradictory measures may be employed to gauge how well a model fits the data and the likely accuracy and bias of the forecast. In addition, the chosen model will change with each historical data update and associated model re-estimation.

This paper describes a general approach to modelling regional energy which may not perfectly reflect the particular process that was followed to produce AEMO's 2012 forecasts. This is partly due to the particular nature of the data for each region and partly due to the time constraint. AEMO's 2012 forecasts were produced to a timetable using the best approach available at that time.

A number of aspects of the modelling approach discussed in this publication are already under review, with the aim of improving the modelling approach for 2013:

- Developing the dynamic ordinary least squares (DOLS) approach.
- Improving measurement of historical retail energy prices.
- Better measurement of transmission losses and generator auxiliary loads.
- Refining the data for large industrial loads to segregate a larger number of customers.
- Further energy segmentation into residential, business and distribution losses.
- Producing simulated future energy forecasts using different temperature projections, rather than assuming mean temperatures.
- Improving integration of the energy and demand models by allowing for changing load factors in the demand models.
- Refining the half-hourly energy data by developing more accurate half-hourly photovoltaic (PV) series.
- Integrating all demand components–comprising large industrial loads (LIL), power station auxiliaries (AUX), transmission losses (TX), rooftop photovoltaics (PV) and all non-large industrial consumption (NLIC) – to run simulations that produce the most accurate overall probability of exceedence (POE) levels of maximum demand as generated.

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CHAPTER 2 - MEASURING AND FORECASTING ELECTRICITY DEMAND

Electricity is consumed as a consequence of millions of individual decisions to utilise various electrical appliances at any moment in time. Some of these decisions are investments in new electrical appliances, decommissioning of old ones, or changes from electrical appliances to non-electrical appliances (for example a switch from electrical to solar water heating). Other decisions are operational, for example turning on a light at night or turning on an air-conditioner on a hot afternoon. Fortunately, a great many of these decisions represent habitual behaviour which is reasonably predictable in aggregate. The core modelling task is therefore to effectively capture the relationship between electricity consumption in homes, factories and commercial centres and key economic drivers such as population, income, energy prices and the weather.

The measurement of electricity use in the National Electricity Market (NEM) includes several considerations other than bulk, end-use consumption:

- Large industrial loads that do not respond in the same manner to the bulk consumption drivers.
- Power station auxiliaries needed to operate coal powered generation.
- Transmission and distribution network losses, which vary with different generation sources and levels of consumer demand.

At the same time, significant behind-the-meter generation, for example by rooftop PV, appears as a fall in consumption.

2.1 Defining demand

AEMO's objective in defining demand is to isolate the underlying use of the bulk of end-use consumers, so it can be modelled and forecast. Basic measures of regional energy and demand generally derive from two areas:

- Generating unit output metered at the generator terminals.
- Interconnector flows metered at regional boundaries.

The measures include generating units registered with AEMO as scheduled or semi-scheduled and all non-scheduled units for which metered data is available, and generally exclude smaller generating systems, such as industrial cogeneration and rooftop PV.

The basic measures of regional energy and maximum demand have been subdivided by AEMO using supplemental data for large industrial loads (LIL), power station auxiliaries (AUX), transmission losses (TX) and roof-top photovoltaic generation (PV), which form the components of overall electricity generation load.

Equation 2-1 — Historical energy and maximum demand

$$\boldsymbol{electrical\ generation} = \boldsymbol{AUX} + \boldsymbol{TX} + \boldsymbol{LIL} - \boldsymbol{PV} + \boldsymbol{NLIC}$$

In Equation 2-1, NLIC is general mass market sales of electricity plus PV and including distribution losses. It therefore represents the underlying demand for electricity as closely as possible, which can be modelled using economic drivers.

In forecasting energy and maximum demand, as well as projecting past trends in non-large industrial consumption, several other factors are also considered:

- The extent to which appliance efficiency will accelerate.
- The extent to which consumers will switch from using electricity to using other sources of energy.

This also accounts for important policy decisions and measures that accelerate increasing trends in energy efficiency (EE).

Equation 2-2 shows the components of forecast energy and maximum demand.

Equation 2-2 — Forecast energy and maximum demand

$$\textit{electrical generation}\ (\textit{forecast}) = AUX + TX + LIL - PV + NLIC - EE$$

The forecasting process begins with modelling each of the components on the right hand side of Equation 2-2 for each NEM region.

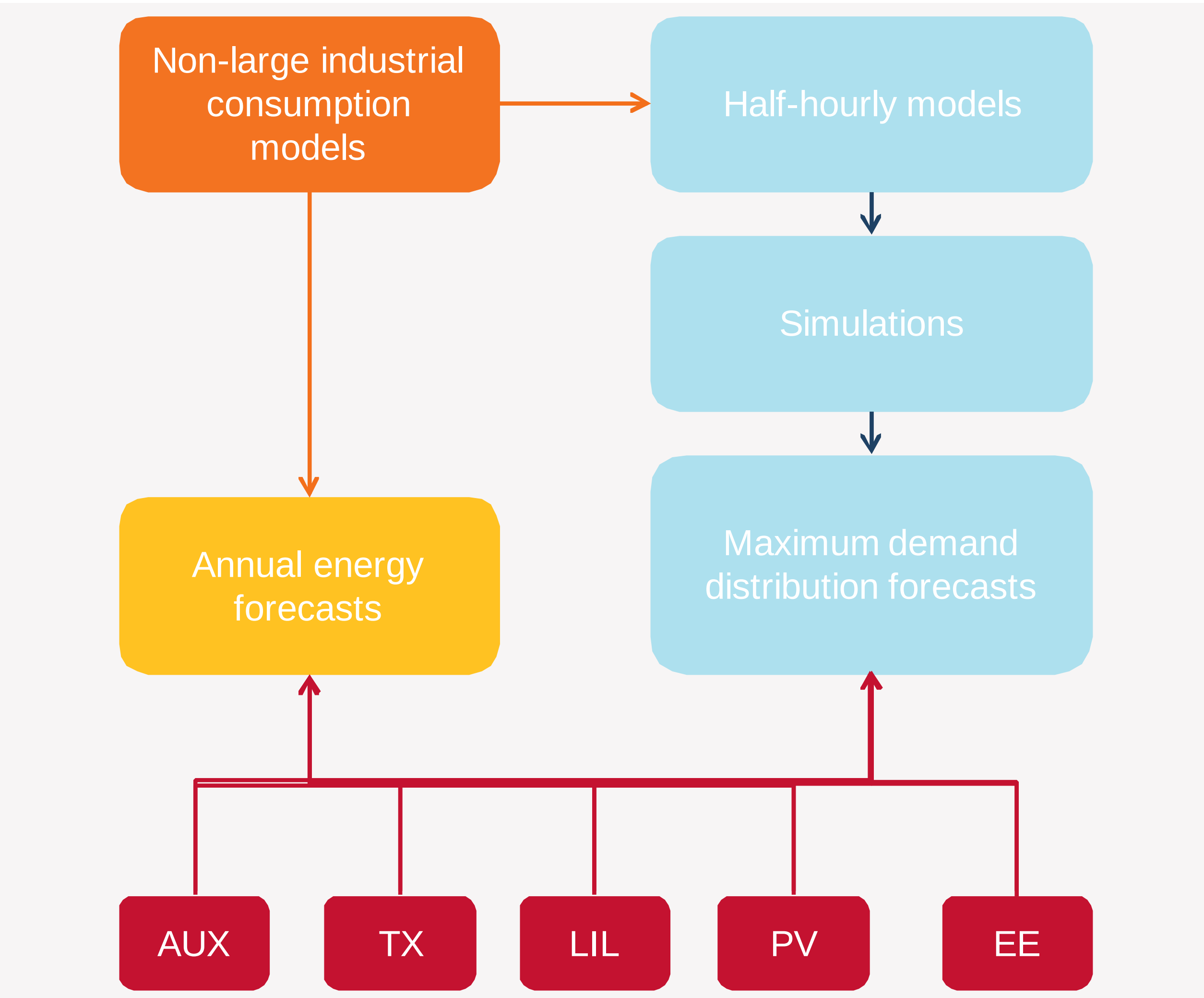
2.2 Forecasting process overview

The annual energy and maximum demand forecasts are interconnected, since annual energy forms an average level of demand around which half-hourly variations are modelled.

Figure 2-1 shows an overview of the forecasting process.

Forecasts for each region are prepared separately, and combined to create the NEM-wide forecasts.

Figure 2-1 — Forecasting process overview



2.2.1 Models for non-large industrial consumption

Non-large industrial consumption was generally modelled by AEMO as a function of regional income, energy prices and weather. The development of the non-large industrial models is described in detail in Chapter 3.

2.2.2 Half-hourly models and simulations

Half-hourly models were used to develop simulated maximum demands for both winter and summer by Monash University's Business and Economic Forecasting Unit.[1] The model development and simulation process is described in detail in Chapter 4.

2.2.3 Power station auxiliaries (AUX)

AEMO prepared estimates of future power station auxiliary consumption based on known historical measures and assumptions about future power station operations.

2.2.4 Large industrial loads (LIL)

The large industrial loads are generally transmission-connected customers, with electricity consumption that varies because of major investment or decommissioning decisions and is not weather-sensitive. AEMO developed projections of future LIL using a combination of TNSP information and public announcements in the short term, and assumptions based on long-term trends in the longer term.

2.2.5 Rooftop photovoltaic generation (PV)

Data for installation and self-generation from rooftop PV was collected with the assistance of DNSPs in each region. AEMO developed the forecasts based on assumptions about future installed capacity and generation models that project historical sunlight exposure. For more information about the collection of historical PV data and forecast development, see AEMO's Rooftop PV Information Paper.[2]

2.2.6 Energy efficiency (EE)

The overall energy efficiency impact of recent initiatives was assessed by AEMO and an average allowance was developed for each region for each future year, in terms of replacement generation. For more information about specific EE allowances, see the 2012 National Electricity Forecasting Report.

[1] Monash University, available http://www.buseco.monash.edu.au/units/forecasting. Viewed June 2012.
[2] AEMO, available http://www.aemo.com.au/Electricity/Forecasting. Viewed 20 June 2012.

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CHAPTER 3 - MODELLING NON-LARGE INDUSTRIAL CONSUMPTION

This chapter describes AEMO's energy forecasting model development for regional non-large industrial consumption (NLIC). NLIC includes mass market electricity sales plus distribution losses plus PV (see Chapter 2).

A number of basic approaches to electricity forecasting were described in AEMO's Electricity Forecasting Framework Paper. Fiebig (1997) provides a survey of energy modelling techniques, and a range of approaches suitable for maximum demand forecasting is described in Contreras (2012). Forecasting models generally vary according to the type of forecasts required. Four broad categories of models could be considered, including econometric models, computable general equilibrium (CGE) modelling, time series (TS) techniques and neural networks (NN). However, AEMO has chosen to develop econometric models for each NEM region due to the features of this type of modelling:

- They are suitable for medium to long-run forecasts of the required timeframe.
- They can explain the separate contribution to growth of each demand driver.

Other categories of models either require a high resource investment to establish and maintain, involve difficulty in aligning model energy measures with the available data, or are unable to provide intuitive explanations for what drives the forecast.

3.1 Data sources and selection

AEMO has constructed several demand measures for each NEM region to act as a specific forecasting database. Historical and projected demographic, income, production and price data was compiled for AEMO for this modelling exercise by the National Institute of Economic and Industry Research (NIEIR), which provided the economic scenarios. Weather data was interpolated Bureau of Meteorology records supplied via Telvent. Specific variables considered in constructing the regional energy models and their original sources are as follows:

- Non-large industrial electricity consumption in kWh per capita (AEMO and ABS 3101.0).
- Real gross state product (GSP) per capita in $/person (ABS 5206.0/ABS 3101.0).
- Real state final demand (SFD) per capita in $/person (ABS 5206.0/ABS 3101.0).
- Real average household electricity price inc/kWh (NIEIR/ESAA/ABS 6401.0).
- Real average price of 'other household fuels', index 1989-90=100 (ABS 6401.0).
- Real standard variable mortgage interest rate, % per annum.[3]
- Heating degree days, using region-representative weather stations, daily average temperatures and region-specific change points, degree Celsius days (Bureau of Meteorology).
- Cooling degree days, using region-representative weather stations, daily average temperatures and region-specific change points, degree Celsius days (Bureau of Meteorology).
- Average air-conditioning ownership, ratio of number in regular use to total number of households.[4]

The final variable selection was determined by the best statistical fit for each region.

[3] RBA, available http://www.rba.gov.au/statistics/tables/index.html#interest_rates Table F5. Viewed 9 May 2012.
[4] Australian Government, available http://www.energyrating.gov.au/resources/program-publications/?viewPublicationID=1110. Viewed 9 May 2012.

3.2 Model options

Electricity demand is generally believed to be determined in the long run by the price of electricity, the price of relevant substitute sources of energy and income. In the short run, a lot of seasonal variation is evident in the data, which is mainly driven by the weather.[5] A traditional static energy model using these drivers was developed, for example, in Donnelly and Saddler (1984).

One deficiency with this approach is that much of the time series data is non-stationary, which can violate the assumptions of the ordinary least squares method of selecting best linear unbiased estimates of the coefficients. However, methods are available for testing long-run relationships in non-stationary data. In particular, if the data can be said to be cointegrated, then the estimated coefficients will converge quickly towards their true values in relatively small sample sizes.

This property of cointegrated variables is known as super-consistency. This is important because AEMO's data is characterised by relatively short samples, given consistent electricity data is only available for all regions since the first quarter of 2000.

Another disadvantage of a traditional static model is that it is not very accommodating to seasonal data. This is because the seasonality itself may be partially caused by the effects of past changes in the explanatory variables. As a result, AEMO's models place the true long-run relationships between the variables within a dynamic structure.

The concept and properties of cointegrating equations permit the long-run relationship to be analysed separately. The Engle and Granger (1987) method is one approach to doing this. Engle and Granger propose the estimation of a single long-run equation (see Equation 3-1) testing the residuals for cointegration and then using the coefficients in an error-correction form including lagged differences of the long-run variables. AEMO has not done this, however, due to small sample sizes.

Alternative approaches include the Johansen vector error-correction (VEC) method and dynamic ordinary least squares (DOLS). For more information about methods for determining long-run relationships, see Sections 3.2.1 to 3.2.4. For more information about selecting the dynamic structure of the energy forecasting equation, see 3.2.5.

3.2.1 Static demand equation

Electricity demand, y_t, can be related to a matrix of independent variables, X_t, via a static demand equation (see Equation 3-1), where α is a constant, β is a matrix of coefficient estimates, and u_t are independently and normally distributed residuals.

Equation 3-1 — Static demand equation

$$\boldsymbol{y_t = \alpha + \beta X_t + \mu_t}$$

If the variables in Equation 3-1 are non-stationary (in particular if the data are first order integrated) then the Engle-Granger approach may be invoked, involving testing of the relationship for cointegration by examining the residuals. However, in the presence of strong seasonality, this equation may still not produce viable estimates of the standard errors and may be unreliable. The absence of dynamics may introduce autocorrelation in the residuals, which produces additional bias in the standard errors.

3.2.2 Auto-regressive distributed lag model

An alternative representation of Equation 3-1 with dynamics may be termed an auto-regressive distributed lag (ARDL) model (see Equation 3-2). Cointegration between y and X variables may be tested using the bounds testing approach of Pesaran Shin and Smith (2001).

[5] Some researchers have also emphasised changes in the stock of electrical appliances as a more immediate long-run driver of electricity demand. See, for example, Silk and Joutz (1997) who seek to partly explain US retail electricity demand by weighting temperature variables with appliance stocks and interest rates (reflecting the propensity to bring forward spending on major appliances and housing).

Equation 3-2 — Auto-regressive distributed lag (ARDL) equation

$$y_t = \alpha + \sum_{i=1}^{n} \rho_i y_{t-i} + \sum_{i=0}^{n} \sigma_i X_{t-i} + \mu_t$$

While Equation 3-2 may be estimated in a single step, small sample bias remains a significant issue for the available data, and the simultaneous estimation of the long-run component with the lag structure could result in misspecification of the dynamics.

3.2.3 Vector error-correction model

An alternative method of estimating β is to use the Johansen (1988) likelihood method, based on a vector error-correction representation. A general representation, which may consist of several equations determined by the number of cointegrated variables, is shown in Equation 3-3 for a two-variable system in y and x, with n lagged differences.

In this equation, the terms in brackets represent the lagged residual from the long-run equation, and the terms δ_1 and δ_2 determine the speed of adjustment towards the long-run growth path. These terms should be between zero and minus one for the system to be stable. In this representation, it is not assumed a priori, either that y is dependent on x, or vice versa. In the case of energy demand, however, it is clear that, for example, if y is electricity demand and x is GSP, then it is likely that GSP causes electricity demand but not the other way round. Therefore for the purpose of forecasting electricity demand we would select only the single equation in Δy and discard the other equation.

Equation 3-3 — Vector error-correction two-equation demand system

$$\Delta y_t = \delta_1(y_{t-1} - \alpha_1 - \beta_1 x_{t-1}) + \sum_{i=1}^{n} \rho_{1,i} \Delta y_{t-i} + \sum_{i=1}^{n} \sigma_i \Delta x_{t-i} + \mu_{1,t}$$

$$\Delta x_t = \delta_2(x_{t-1} - \alpha_2 - \beta_2 y_{t-1}) + \sum_{i=1}^{n} \rho_{2,i} \Delta x_{t-i} + \sum_{i=1}^{n} \sigma_{2,i} \Delta y_{t-i} + \mu_{2,t}$$

Any of the single equations in Equation 3-3 may be represented using the Bewley transformation[6] by an ARDL model, as represented in Equation 3-2. Alternatively, an ARDL may be regarded as an ‘unconstrained’ version of one line of Equation 3-3.

Like the Engle-Granger approach to determining cointegrating relationships, the Johansen method requires pre-testing of the variables for their order on integration, but it does not suffer from small-sample bias and is applicable to situations where there is more than one cointegrating equation. Therefore, to obtain valid results on the assumption of one cointegrating relationship, the following conditions are necessary:

- The cointegrating variables must be prior tested to be integrated of order one, or I(1).
- Tests for cointegration must reject the hypothesis that there are no cointegrating equations and not reject the hypothesis that there is at least one cointegrating equation.
- The estimated speed of adjustment coefficient δ must be between zero and minus one.
- The long run coefficients β must have the expected signs.
- The standard errors associated with estimates of δ and β should be small enough for the coefficients to be statistically different from zero.

[66] Bewley, R.A. (1979) “The Direct Estimation of the Equilibrium Response in a Linear Dynamic Model”, Economics Letters, 3, 357-361.

3.2.4 Dynamic ordinary least squares

The short-comings of both the Engle-Granger and ARDL models still may not be overcome with the Johansen method unless the data conform to all the necessary conditions. However, under these circumstances the procedure often referred to as dynamic ordinary least squares (DOLS) is available.

Saikkonen (1991) suggested DOLS as a way of alleviating the problem of small-sample bias that arises from the Engle-Granger procedure for estimating the long-run relationships.

The first step of DOLS involves estimating the long-run relationship in the presence of the current first-difference of the variables, 'sufficient' lags of these differences, and (importantly) by adding the leads of these differences, as shown in Equation 3-4.

Testing for cointegration between the y and X variables is based on the null of no cointegration and the residuals from Equation 3-4, following Shin (1994).

Equation 3-4 — Dynamic ordinary least squares

$$y_t = \alpha + \beta X + \sum_{i=-n}^{n} \sigma_i \Delta X_{t+i} + \mu_t$$

Once estimated, the long-run coefficients β may be placed within an error-correction structure (as in the second step of the Engle-Granger procedure) with the inclusion of contemporaneous independent variables, as set out in Equation 3-5.

This is the second step of the DOLS procedure. The remaining coefficients ρ_i and σ_i can be estimated after determining the most suitable lag structure.

Equation 3-5 — Error-correction model with prior estimates of long-run coefficients

$$\Delta y_t = \delta(y_{t-1} - \alpha - \beta X_{t-1}) + \sum_{i=1}^{n} \rho_i \Delta y_{t-i} + \sum_{i=0}^{n} \sigma_i \Delta X_{t-i} + \mu_t$$

While Equation 3-5 represents a general form of the energy forecasting equation, a similar form may be estimated by one of the methods described in the previous sections (in particular the Johansen method).

The selection of the best approach for each region is determined by testing the data for each region.

3.2.5 Lag length selection

After determining the long-run coefficients for each region's energy model, the number of lags included in the forecasting equations may be determined by starting with the largest practical number of lags (four) and then eliminating the longest lagged coefficients for all variables until the lowest Akaike Information Criteria (AIC) or Schwartz criteria is achieved.

3.2.6 Model testing

Some common diagnostic tests for the forecasting equations are as follows:[7]

- The adjusted R^2 shows the proportion of energy demand 'explained' by the data.
- The standard error (S.E.) of regression is a measure of the variance of the errors.
- The equation F-statistic tests the strength of the statistical relationship between the dependent variable and all the independent variables jointly (the larger the F-statistic, the stronger the relationship).

[7] See Beggs (1988).

- The AIC is the distance from the 'true' underlying model and may be used to determine model improvements such as the correct lag length (smaller is closer to the 'true' model).
- The Durbin-Watson statistic is a measure of first order serial correlation, which is unreliable for equations containing lagged dependent variables (a value close to two is indicative of the absence of such serial correlation).
- The Lagrange multiplier (LM) test can be used for higher orders of serial correlation (associated probabilities are that serial correlation is not present).
- The forecast root mean square error (RMSE) measures the accuracy of a forecast, without regard to direction (smaller is better).
- The associated bias proportion is an indication of the persistent tendency of the forecast to depart from the actual value in a particular direction (zero would indicate the complete absence of bias).

3.3 Summary of the energy forecasting approach

The conceptual energy model chosen by AEMO relates energy to a number of independent long-run drivers, which specify a long-run path around which actual energy fluctuates. Estimates of the long-run coefficients on their own (the Engle-Granger method) are likely to be biased, both due the limited amount of data available and also due to the strong seasonality in the energy data.

Estimates of the long-run drivers simultaneously with the lagged effects of these drivers and any other short-run drivers, such as temperature-related variables (an unconstrained ARDL), may also result in biased estimates of the long-run drivers and misspecified dynamics if there is any significant co-linearity between the independent variables.

One way to overcome these problems is to use the Johansen method to estimate a vector error-correction (VEC) system and use the estimates of the long-run coefficients from this system to inform a single equation including dynamics. However, a number of conditions must be fulfilled to ensure the estimated VEC is valid.

Dynamic ordinary least squares (DOLS) is an alternative to both the Engle-Granger and the Johansen methods. DOLS consists of a relatively unbiased prior estimation of the long-run coefficients, followed by the estimation of a single equation containing both the long and short-run variables where the long-run coefficients are constrained to their prior values.

The actual method employed and the form of the resulting forecasting equation for each region is determined by results obtained with the actual data. A range of standard statistical tests are also used to inform the fit and performance of the final models. For an example of how to proceed, see Chapter 5.

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CHAPTER 4 - MODELLING MAXIMUM DEMAND DISTRIBUTION

The maximum demand distribution forecasts are prepared by Monash University's Business and Economic Forecasting Unit (for more information, see Hyndman and Fan, 2010). For each region, a semi-parametric model of half-hourly demand is developed as a series of daily models relating to each period— p $(p = 1, \ldots, 48)$—of the day. The models include daily calendar-dependent and weather effects, as well as quarterly demographic, economic and weather effects, where the system of daily equations is separated from the quarterly model. The daily models are developed by Monash and the quarterly models (which were also used by AEMO to prepare the energy forecasts) were supplied to Monash by AEMO. The models are used together by Monash with simulated temperatures and residual re-sampling to predict both historical and future demand distributions.

4.1 Maximum demand model

Equation 4-1 demonstrates how the model for each half-hour period can be written. The model is described in detail in different publications for each region, for example, Hyndman and Fan (2008a). Large industrial loads, transmission network losses and the generator auxiliary loads are subtracted, rooftop PV is added and the remaining demand (non-large industrial consumption, equivalent to NLIC in Figure 2-1) is modelled using the driver variables.

Equation 4-1 — Short and long-run demand model

$$y_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + g\left(\sum_{j=1}^{J} c_j z_{j,t}\right) + \mu_t$$

Where:

- $y_{t,p}$ (in logs) denotes half-hourly demand on day t (measured in megawatts).
- $h_p(t)$ models all calendar-dependent effects.
- $f_p(w_{1,t}, w_{2,t})$ models all temperature effects using two locations within each region.
- $z_{j,t}$ is a quarterly demographic, economic or weather variable at time t and its impact on half-hourly demand is measured via the coefficient c_j (these terms do not depend on the period p).
- μ_t denotes the demand which is left unexplained by the model (the model residuals) at time t.

Equation 4-2 represents the split in the model between daily effects for each period p and long-run quarterly effects.

Equation 4-2 — Normalisation of half-hourly demand

$$y_{t,p} = y^*_{t,p} \times \bar{y}_i$$

Where:

- $\bar{y}_i$ is quarterly average demand for quarter i in MW (equal to quarterly energy in GWh multiplied by $h/1{,}000$ where h is the number of hours in quarter i).
- $y^*_{t,p}$ is the standardized demand for day t and period p.

The quarterly model for $\overline{y}_i = g\left(\sum_{j=1}^{J} c_j z_{j,t}\right)$ is built by AEMO. Equation 4-2 in effect normalises the daily movements in demand for period p so that the short-run model is reduced to the form shown in Equation 4-3. The fixed relationship between half-hourly demand and average demand, however, means that forecasts generated with these models will reflect historical average load factors.[8]

Equation 4-3 — Half-hourly demand model

$$y_{t,p}^{*} = h_p(t) + f_p\left(w_{1,t}, w_{2,t}\right) + \mu_t$$

For half-hourly demand $y_{t,p}^{*}$, the data are modelled by Monash in natural logarithms, as this resulted in the best fit to the available data. The model is also easier to interpret as the temperature and calendar variables have a multiplicative effect on demand. Some specific features of the model are as follows.

- Variable selection followed a stage-wise process using groups of input variables to determine the model with the lowest mean square error.
- Calendar effects are modelled using dummy variables and include day-of-week, time-of-year and public holidays, including days immediately before and after public holidays.
- Temperature effects $f_p\left(w_{1,t}, w_{2,t}\right)$ are modelled using additive regression splines.
- Temperatures from the last three hours and the same period from the last six days are included, as are the maximum and minimum temperature in the last 24 hours and the average temperature in the last seven days.
- The daily temperature data, using the same locations, was shared by both AEMO and Monash, and the same warming trends based on CSIRO, Department of Climate Change and Energy Efficiency, and the Bureau of Meteorology (2009) were applied to simulated future temperatures to allow for climate-change impacts.

The selected model was used to predict historical demand and the residuals were compared to predicted demand. From this procedure an evident bias for large demand predictions was subsequently used to adjust forecasts using this model.

4.2 Simulation of maximum demand distribution

Producing forecasts using the half-hourly demand model requires future values for the temperature variables as well as the fixed calendar effects. Temperature is not random but cannot be predicted on a daily basis more than a few days into the future. As a result, Monash use a seasonal block re-sampling approach to simulate numerous temperature patterns based on historical data. For more information about this re-sampling process, see Hyndman and Fan (2008b).

As well as temperature variations, the model itself involves a random element that does not follow a normal distribution pattern when observing only seasonal maximum demands. To capture this random element, Monash also re-sample the historical model residuals to simulate numerous small adjustments to the modelled demand outcomes.

The simulation process consists of running the half-hourly model 1,000 times over the same simulation period, each time using a different set of simulated temperature inputs and re-sampled model residuals. Each simulation contains a particular maximum demand for any particular season, so that any percentile of maximum demand may be extracted from all the simulated maximum demands for that season.

By re-constituting the half-hourly demand with the underlying quarterly average demand (as in Equation 4-2), the 10%, 50% and 90% probability of exceedence (POE) maximum demand forecasts can be calculated for any future demographic and economic scenario. A 10% POE maximum demand forecast has a 1-in-10 chance of being met

[8] A new transformation allowing for varying future load factors is under consideration by Monash for future forecasting exercises.

or exceeded in any year. A 50% POE forecast has a 50-50 chance of being met or exceeded, and a 90% POE forecast has a chance of being met or exceeded in 9 times out of 10.

The distributions of maximum demand calculated this way derive from measures of non-large industrial consumption after removing LIL, AUX and TX, and after adding in rooftop PV. The forecasts include EE. As a result, no account was taken in this process of random variability in these elements. However, random variability of large industrial loads will be taken into account in future forecasting exercises.

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CHAPTER 5 - ENERGY MODELLING EXAMPLE

This Chapter provides an example of the approach AEMO has used to model energy demand by working through an example for the New South Wales region (including the Australian Capital Territory).

5.1 Variable selection and future scenarios

From the data described in Section 3.1, the variables selected for this exercise are as follows:

- $y =$ non-large industrial electricity consumption in kWh per capita.
- $i =$ real State Final Demand (SFD) per capita in $ per capita.
- $p =$ real average household electricity price in c/kWh
- $hdd =$ heating degree days, equal to the sum of the daily differences between the change-point temperature and the average temperature below the change-point.
- $cdd \cdot (1 + ac) =$ cooling degree days, equal to the sum of the daily differences between the average temperature and the change-point temperature above the change-point, multiplied by one plus average air-conditioning ownership, expressed as the ratio of the number of units in regular use to total number of households.

For the demographic and economic variables, future scenarios consistent with AEMO's high scenario descriptions were supplied with the historical data by NIEIR. Future average temperature variables were supplied by Monash consistent with CSIRO modelling of future climate warming.

5.2 Data and data testing

Figure 5-1 shows the selected data plotted over the period from the quarter ended March 2001 to the quarter ended December 2011, and the following observations:

- The persistent downward trend in energy consumption in New South Wales since 2008, even after adjusting for the rise in rooftop PV installation, appears to be primarily driven by price increases (sharp increases in p coincide with the downswing in y, although there was an initial fall in i).
- Strong seasonal movements in y, while i is constructed from seasonally adjusted data.
- p follows a step function because it is based on annual movements only (this may be realistic for the earlier periods when the average price was subject to greater tariff regulation but becomes a more restrictive assumption as time progresses).
- The weather variables hdd and $cdd \cdot (1 + ac)$ have a large variance but no noticeable trend.

From a basic understanding of electricity demand, a long-run correlation is expected between y, i and p with causation running from i and p to y. That is, a permanent increase in income or decrease in price should permanently cause an upward shift in electricity consumption. Weather variables should have strong contemporaneous impacts, but the effect of any one quarter of extreme temperatures should not have lasting effects on consumption.

Figure 5-1 — Variables used in the forecasting model

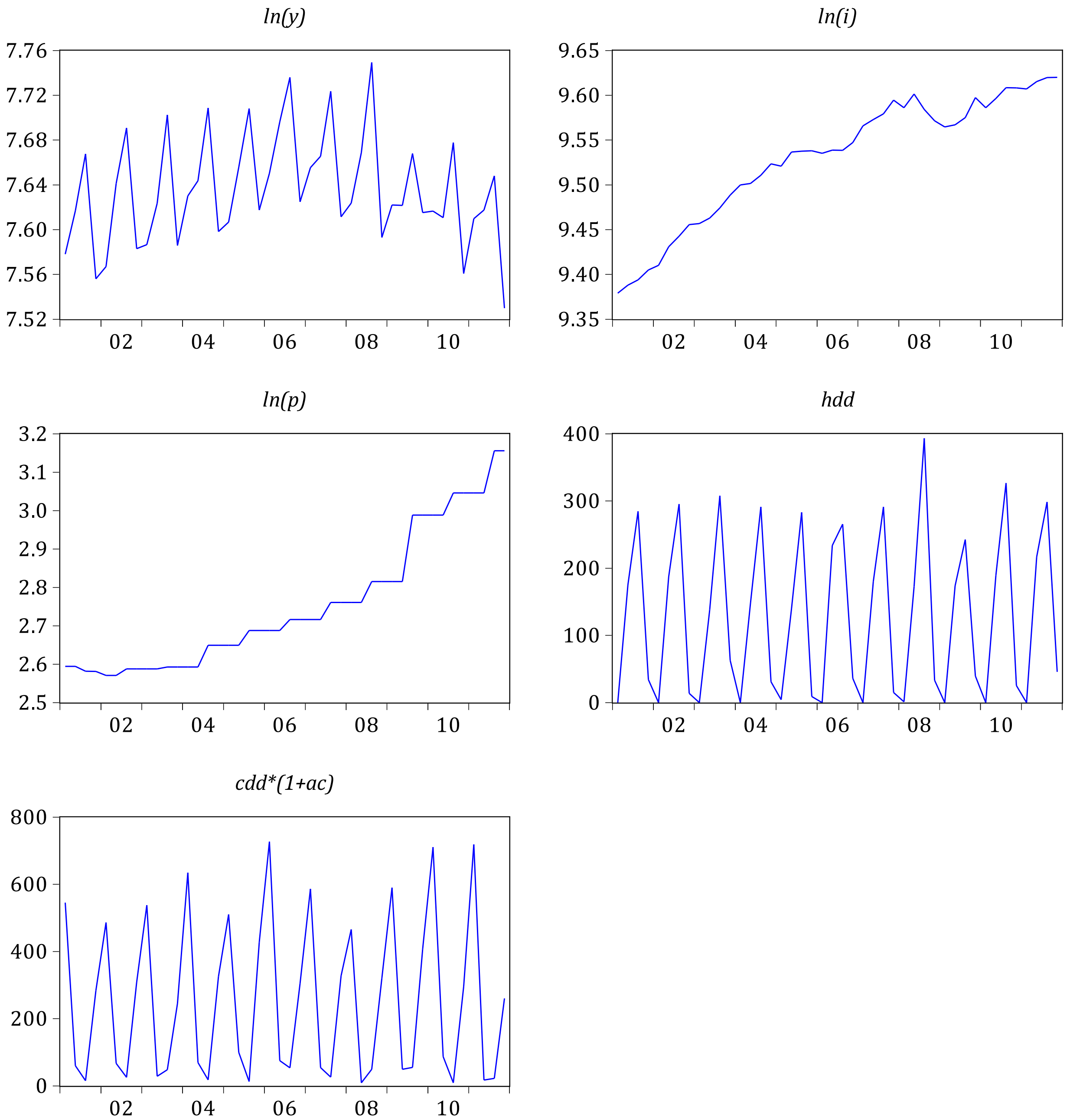


Table 5-1 lists the correlation matrix, which shows greater than 10% correlation of the other variables with y. However, $cdd \cdot (1 + ac)$ has the wrong sign and it also appears that i and p are strongly correlated with each other.

Table 5-1 — Correlation matrix

	y	i	p	hdd	cdd*(1+ac)
ln(*y*)	1.000	0.133	-0.111	0.784	-0.508
ln(*i*)	0.133	1.000	0.812	0.057	0.002
ln(*p*)	-0.111	0.812	1.000	0.082	-0.001
hdd	0.784	0.057	0.082	1.000	-0.857
cdd(1+ac)*	-0.508	0.002	-0.001	-0.857	1.000

Unit root tests were conducted on each of the variables individually using an augmented Dickey-Fuller (1979) method, using the Schwartz criterion to determine lag length in the test equation, and a maximum of eight lags.

Table 5-2 shows the results for each variable in both levels and first differences, with a constant but no trend in the test equations.

Table 5-3 shows the results when a linear trend is also included in the test equations. The underlying critical values and the probabilities shown in the tables are from MacKinnon (1996).

Table 5-2 — ADF tests, constant and no trend in test equation

Variable	Test statistic: levels	Lag length (Schwartz)	Probability*	Test statistic: differences	Lag length (Schwartz)	Probability*	Conclusion
ln(*y*)	-0.921	4	0.772	-21.353	2	0.000	I(1)
ln(*i*)	-1.998	0	0.287	-7.476	0	0.000	I(1)
ln(*p*)	0.944	8	0.995	-0.921	7	0.772	I(2)
hdd	-3.165	3	0.029	-6.146	6	0.000	I(0)
cdd(1+ac)*	-2.943	8	0.050	-33.281	2	0.000	I(0)

Table 5-3 — ADF tests, constant and trend in test equation

Variable	Test statistic: levels	Lag length (Schwartz)	Probability*	Test statistic: differences	Lag length (Schwartz)	Probability*	Conclusion
ln(*y*)	0.129	3	0.997	-23.323	2	0.000	I(1)
ln(*i*)	-1.441	0	0.835	-7.655	0	0.000	I(1)
ln(*p*)	-0.312	8	0.988	-2.445	7	0.353	I(2)
hdd	-4.573	6	0.004	-6.158	6	0.000	I(0)
cdd(1+ac)*	-3.462	8	0.058	-32.987	2	0.000	I(0)

Table 5-2 and Table 5-3 show that y and i are strongly I(1), while $cdd \cdot (1 + ac)$, although I(0) at the 10% level, is borderline I(1). This result may be due to the limited amount of data available for testing. Meanwhile, p shows up as I(2). This result, however, appears to be caused by the large rise towards the end of the test period. Since it is unlikely that this series has previously or will in future rise indefinitely at recent rates, it is considered reasonable to regard p as an I(1) variable.

5.3 Long-run estimators

5.3.1 Engle-Granger process

An Engle-Granger test for cointegration may be performed after estimation using fully modified ordinary least squares (FMOLS) in Eviews (more more information see Table A-1). This estimation method modifies ordinary least squares to account for serial correlation effects and for endogeneity in the regressors that result from the existence of a cointegrating relationship.

This procedure was performed using logarithmic values of the long-run variables y, i and p and including hdd, $cdd \cdot (1 + ac)$ and seasonal dummies s_1, s_2 and $s_3$as deterministic variables (and not part of the cointegrating regression). The residuals were then tested for cointegration using the Schwartz criterion (SC) with a maximum lag length of nine to determine the lag length in the test equation.

The long-run coefficient estimates are derived from Table A-1.

Table 5-4 shows elasticities and. Table 5-5 shows the cointegration tests (tau and z-statistics).

The associated probabilities firmly reject the hypothesis of no cointegration and so as a final step, the long run coefficients may be placed within an error-correction form of forecasting equation.

Table 5-4 — Engle-Granger long run elasticity estimates

Variable	Elasticity	Std. Error	t-Statistic	Prob.
Income (i)	0.497	0.0603	8.25	0.000
Price (p)	-0.224	0.0238	-9.41	0.000

Table 5-5 — Engle-Granger cointegration test results

	Value	Prob.[a]
Engle-Granger tau-statistic	-4.192	0.0292
Engle-Granger z-statistic	-24.78	0.0261

a. MacKinnon (1996) p-values.

5.3.2 Unconstrained ARDL estimation

Prior to estimating the unconstrained ARDL, a differenced form of the equation (see Table 5-6) was estimated for the purposes of calculating an F-statistic to test redundancy of the levels variables, which was then compared with non-standard critical values to test for cointegration. The results are shown in Table 5-7, where upper and lower critical bounds are shown at three significance levels for the case where there are four regressors (k=4) with the values taken from Table CI(iii) in Pesaran, Shin and Smith (2001). Calculated F-statistics are shown for test equations in zero to five lags. The highest critical bound is 5.06 (99% critical level) and the lowest F-statistic is 4.78. The calculated values are generally above the critical bounds, providing strong evidence of cointegration.

Table 5-6 — F-statistics for cointegrating relationship

	90% critical level		95% critical level		99% critical level	
k	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
4	2.45	3.52	2.86	4.01	3.74	5.06
Calculated F-statistics						
ARDL(0) fy(y|i,p,hdd,cd*(1+ac)) = 12.55						
ARDL(1) fy(y|i,p,hdd,cd*(1+ac)) = 13.89						
ARDL(2) fy(y|i,p,hdd,cd*(1+ac)) = 12.22						
ARDL(3) fy(y|i,p,hdd,cd*(1+ac)) = 9.56						
ARDL(4) fy(y|i,p,hdd,cd*(1+ac)) = 4.86						
ARDL(5) fy(y|i,p,hdd,cd*(1+ac)) = 4.78						

Table 5-7 lists the long run elasticities derived from the complete estimated forecasting ARDL (for more information see Table A-3), where three lags were selected via the process described in Section 5.4. The long-run elasticities are slightly higher than the values calculated by the static Engle-Granger method and have relatively high standard errors.

Table 5-7 — Unconstrained ARDL estimation of long-run elasticities

Variable	Elasticity	Approximate std. error	t-Statistic
Income (*i*)	0.510	0.339	1.50
Price (*p*)	-0.284	0.119	-2.39

5.3.3 Johansen procedure

The Johansen procedure was used to generate vector error-correction systems with a constant but no trend in both the cointegrating equations and the error correction terms. Up to five lagged differences were included in the error-correction terms and some results are shown in Table 5-8 for the equation in $\ln(y)$ (unless stated otherwise).

The following conclusions are based on Table 5-9:

- The system minimum AIC selects the number of lagged difference terms as five, whereas the Schwartz criterion selects zero lags.
- The number of identified cointegrating equations varies with the number of lags. For the systems with zero, one and three lags both the Trace statistic and the maximum Eigen value select one cointegrating equation at the 5% probability level. At other lag lengths the number of cointegrating equations is two.
- The coefficients on the cointegrating equation for the term in $\ln(y)$ are not viable (between zero and minus one) for the system with four lags.
- The long-run coefficients for $\ln(i)$ and $\ln(p)$ (equal to the long-run elasticities) vary in magnitude and degree of significance, but are generally of the expected signs.

These results signify that the error-correction results based on the system with zero or one lags should be used (the three-lag system has an insignificant income coefficient estimate). It was decided to use the no-lag system for its lower Schwartz criterion and slightly greater significance for the long-run coefficients (0.472 for income and -0.219 for price). These values are lower but not too dissimilar to the values estimated previously.

Table 5-8 — Johansen VEC estimation results

No. lags	0	1	2	3	4	5
AIC	-16.86	-16.94	-16.75	-17.07	-17.44	-17.49
Schwartz	-15.89	-15.60	-15.04	-15.00	-14.98	-14.63
Trace 5%	1	1	2	1	2	2
Eigen 5%	1	1	2	1	2	2
CointEq	-0.828	-0.608	-0.580	-0.186	0.226	-0.459
Std error	0.12	0.09	0.10	0.04	0.22	0.12
t-statistic	6.74	6.90	5.93	4.79	1.00	3.78
ln(*i*)	0.472	0.439	0.475	0.151	0.723	0.585
Std error	0.05	0.07	0.07	0.23	0.05	0.11
t-statistic	9.30	6.31	6.56	0.64	16.02	5.36
ln(*p*)	-0.219	-0.274	-0.298	-0.444	-0.224	-0.350
Std error	0.02	0.03	0.03	0.12	0.02	0.05
t-statistic	9.94	8.53	8.67	3.83	10.74	7.37

5.3.4 DOLS estimation

DOLS was employed to account for small-sample bias and seasonality in the data and the poor significance levels sometimes encountered in the Johansen estimation. As a result, the long-run coefficients in Table 5-9 are likely to be the least biased. In this case, the temperature and seasonal variables are included in the error-correction term to account for seasonality. The estimated long-run elasticities for income (0.563) and price (-0.241) estimated in this fashion are higher in absolute value than the previous estimates.

Table 5-9 — Long-run coefficients estimated using DOLS

Variable	Coefficient	Std. error	t-Statistic	Prob.
ln(*i*)	0.563	0.112	5.05	0.000
ln(*p*)	-0.241	0.0292	-8.25	0.000
hdd	0.000298	0.0001	3.82	0.001
cdd(1+ac)*	0.000186	0.0000	5.83	0.000
s_1	-0.0169	0.0120	-1.42	0.168
s_2	0.0644	0.0152	4.23	0.000
s_3	0.0914	0.0228	4.01	0.000

Section 5.4 details the use of these long-run coefficients and the selection of lag length in the forecasting equation.

5.4 Lag length selection

Each of the long-run coefficients estimated in the previous section from the Engle-Granger, Johansen and DOLS approaches may be placed within a dynamic, error-correction forecasting model. The unconstrained ARDL may be used as is. A general strategy for selecting the lag length in each forecasting model is as follows:

a) Construct models with varying lag lengths and examine the AIC and Schwartz criteria for each. The lowest test statistic indicates the optimum lag length. It is possible that each criterion may give contradictory results.

b) For error-correction models, the coefficient on the cointegrating equation should be significantly between zero and minus one. If it is not, the model is rejected as it will not perform sensibly.

c) Check the significance of the coefficients on the longest lagged variables. If none are significant, drop to the model with the next shortest lag length.

This strategy does not allow for general removal of equation terms on the grounds that they fail to exceed some significance level. Rather, it is accepted that the lag structure may only be an unbiased influence if it remains intact.

The following tables show AIC and Schwartz statistics for zero to five lags for each type of model so far discussed. The minimum values in each table for each respective test statistic are highlighted in bold.

Table 5-10 shows that the most efficient lag length for the Engle-Granger model is three. However, none of these models with the five alternative lag structures were able to be estimated with a coefficient on the cointegrating equation that was significantly between zero and minus one. As a result, the best model that could be adopted using this method was the long-run model (for more information, see Appendix 1, Table A-1).

Table 5-10 — Lag length selection for Engle-Granger OLS model

Lags	0	1	2	3	4	5
AIC	-5.133	-5.198	-5.161	**-5.837**	-5.815	-5.702
Schwarz	-4.768	-4.711	-4.553	**-5.107**	-4.955	-4.709

Table 5-11 shows contradictory results between the two tests for lag length using the unconstrained ARDL model. Since the model with zero lags (as chosen by the Schwartz criterion) is effectively the same as the Engle-Granger model, the longer lag length as chosen by the AIC was accepted. However, since none of the fourth lags were significant in this model, the chosen lag length was actually three (see Table 5-11).

Table 5-11 — Lag length selection for unconstrained ARDL model

Lags	0	1	2	3	4	5
AIC	-5.841	-5.835	-5.912	-5.891	-6.213	**-6.278**
Schwarz	**-5.517**	-5.389	-5.344	-5.201	-5.402	-5.336

Table 5-12 shows contradictory test results for the choice of lag length for the model derived from a Johansen estimation of a VEC. The model with three lags was chosen as providing more information, the third lag being significant for at least two variables and the coefficient on the cointegrating equation well-behaved.

Table 5-12 shows the chosen model.

Table 5-12 — Lag length selection for Johansen VEC model

Lags	0	1	2	3	4	5
AIC	-5.923	-5.911	-5.848	**-6.192**	-6.139	-6.036
Schwarz	**-5.558**	-5.424	-5.240	-5.462	-5.279	-5.043

Table 5-13 shows that the most efficient lag length is four for the DOLS error-correction model (with temperature and seasonal variables included in the cointegrating equation). To offset any long-run bias from the seasonal variables, lags of the temperature variables are also included in the error-correction model in the form of differenced temperature variables. On the evidence of the Akaike criteria, the chosen model was the one with four lags (for more information see Table A-7).

Table 5-13 — Lag length selection for DOLS error-correction model

Lags	0	1	2	3	4	5
AIC	-6.075	-6.047	-5.982	-6.317	**-6.368**	-6.366
Schwarz	**-5.710**	-5.561	-5.374	-5.587	-5.508	-5.373

5.5 Model testing

The models so far discussed are represented by 'FMOLS' (static model estimated by fully modified least squares), 'ARDL3' (unconstrained ARDL with 3 lags), 'JEC3' (Johansen method-derived error correction model with 3 lags), 'DOLSEC0' (DOLS-derived error correction model with zero lags) and 'DOLSEC4 (DOLS-derived error-correction model with four lags). Since many comparable statistical tests are unavailable within Eviews for FMOLS, additional results are shown for a similar equation estimated by ordinary least squares (OLS).

Table 5-14 shows the following:

- The goodness of fit of each model (R-squared and adjusted R-squared).
- The joint significance of all coefficients (F-statistic) and the probability that they are all equal to zero.
- Akaike and Schwartz criteria, used in model selection, where smaller is better.
- The Durbin-Watson statistic, which is an indication of first-order serial correlation if the value is not close to two, but which is unreliable in the presence of lagged dependent variables.
- Tests of the extent to which the residuals from each model are normal distributed (Jarque-Bera observations times R-squared) and the associated probabilities they are normally distributed (the probabilities are high that they all are).
- Breusch-Godfrey lagrange multiplier tests for first order serial correlation and the associated probabilities that no serial correlation is present (only the DOLS models pass this test at the 5% significance level).
- Breusch-Pagan-Godfrey tests for heteroskedasticity and the associated probabilities that it is not present (the probabilities are high that it is not).
- Chow breakpoint tests to examine the likelihood that there was a significant structural change from the June quarter 2007 and the associated probabilities of no structural change (the DOLS4 model is the only one that strongly rejects the proposal of structural change).

On the basis of these test results, the DOLSEC4 generally performs best across the range of measures, followed by DOLSEC0 and JEC3.

Table 5-14 — Statistical test results

	OLS	FMOLS	ARDL3	JEC3	DOLSEC0	DOLSEC4
R-squared	0.951	0.950	0.969	0.988	0.980	0.992
Adjusted R-squared	*0.942*	*0.941*	*0.951*	*0.981*	0.976	*0.984*
F-statistic	100.462	-	53.137	128.889	216.064	132.646
Prob(F-statistic)	*0.000*	-	*0.000*	*0.000*	*0.000*	*0.000*
Akaike info criterion	-5.841	-	-5.891	-6.192	-6.075	-6.368
Schwarz criterion	-5.517	-	-5.201	-5.462	-5.710	-5.5082
Durbin-Watson stat	1.113	1.155	1.437	1.405	2.012	1.963
Jarque-Bera obs[a]R-squared	2.922	2.520	0.422	1.390	0.099	2.26
Prob(Jarques-Bera)	*0.232*	*0.284*	*0.810*	*0.499*	*0.952*	*0.323*
Breusch-Godfrey obs*R-squared	8.227	-	5.594	4.980	0.100	0.000
Prob(Breusch-Godfrey)	*0.004*	-	*0.018*	*0.026*	*0.752*	*0.990*
Breusch-Pagan-Godfrey obs*R-squared	1.228	-	10.360	16.487	8.986	14.735
Prob(Breusch-Pagan-Godfrey)	*0.998*	-	*0.847*	*0.490*	*0.344*	*0.791*
Chow breakpoint F-statistic 2007(2)	4.397	-	2.684	2.439	3.528	3.561[a]
Prob(Chow F-statistic)	*0.002*	-	*0.058*	*0.100*	*0.006*	*0.398*[a]

[a] Test breakpoint 2006(3)

Figure 5-2 shows the results of the sum of recursive squared residuals (cusum-squared) tests, which are prepared by repeated estimation of each model using larger and larger data samples. Movement outside the 5% significance lines is indicative of the model's structural instability (meaning it may be especially unreliable for forecasting the future). This figure shows that each of the error-correction models (JEC3 and DOLSEC4 in particular) are more structurally stable than the static model or the unconstrained ARDL.

Figure 5-2 — Cusum squared tests

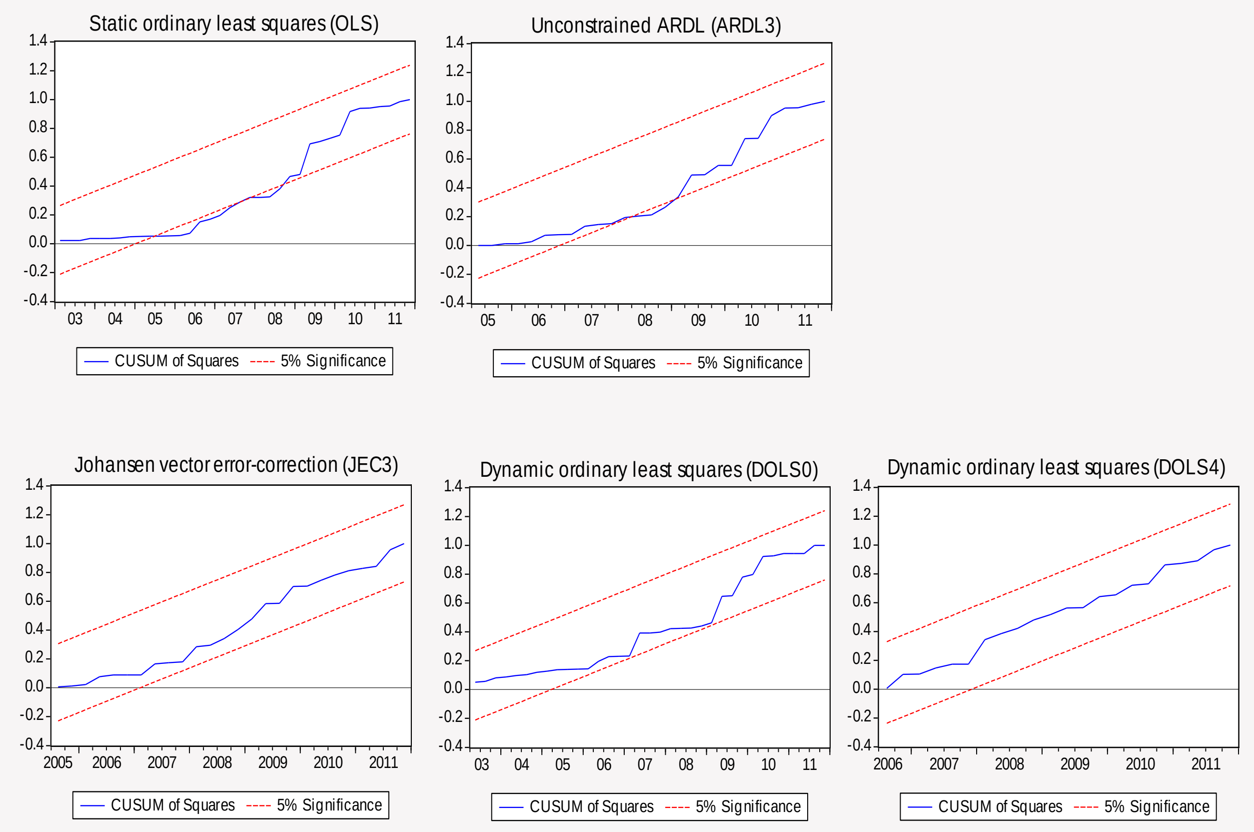


Table 5-15 shows the in-sample forecasting performance of each model. The lowest error measures (RMSE, MAE and MAPE) are attached to the DOLSEC4 model. Meanwhile the bias proportions are relatively low with the exception of the Johansen EC3 model. This appears to be caused by the failure to properly account for seasonal variables in the cointegrating equation.

Table 5-15 — Within-sample forecasts

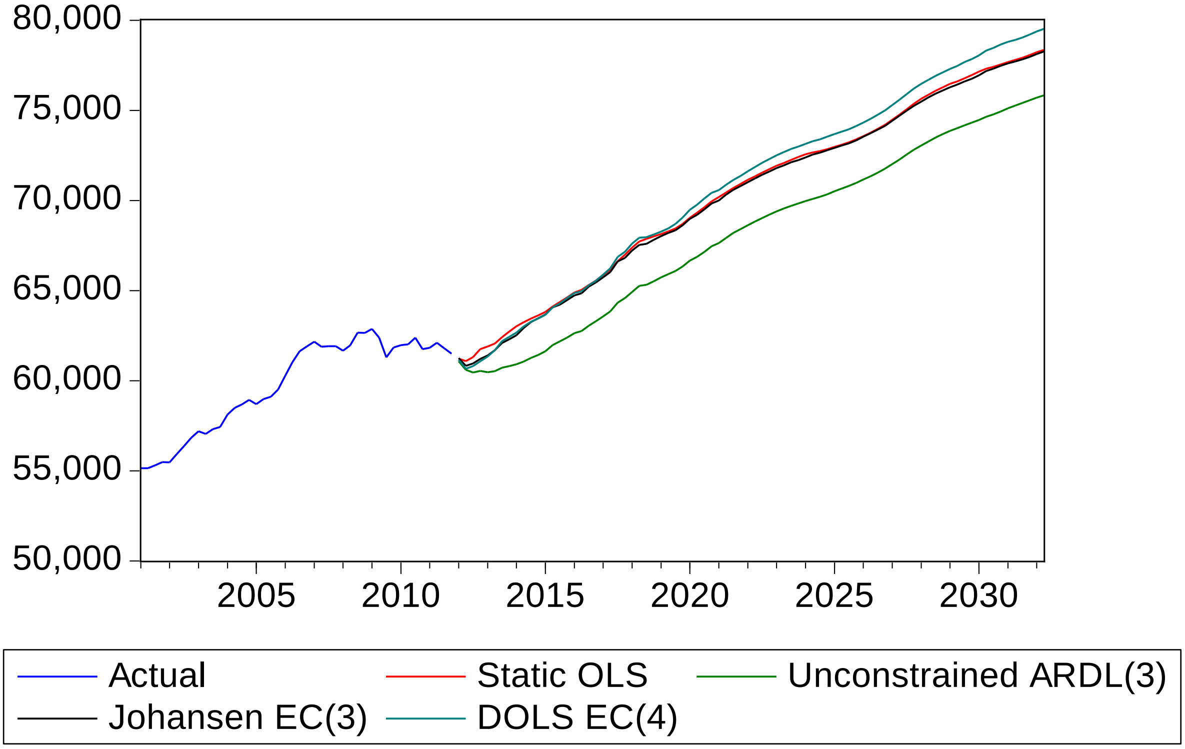
Forecast sample: 2001Q1 2011Q4	OLS	FMOLS	ARDL3	JEC3	DOLSEC0	DOLSEC4
Root Mean Squared Error	28.211	22.874	19.280	18.445	22.646	17.112
Mean Absolute Error	22.001	18.212	15.823	14.606	18.027	13.389
Mean Absolute Percentage Error	1.061	0.877	0.762	0.699	0.868	0.639
Theil Inequality Coefficient	0.007	0.006	0.005	0.004	0.005	0.004
Bias Proportion	0.000	0.001	0.000	0.005	0.0010	0.002
Variance Proportion	0.014	0.002	0.011	0.051	0.007	0.048
Covariance Proportion	0.986	0.997	0.989	0.944	0.992	0.950

5.6 Forecasting

Each of the static OLS, unconstrained ARDL, Johansen EC3 and DOLSEC4 models is used to predict quarterly non-large industrial consumption per head of population in kWh/capita to June 2032. This requires using a scenario for future income and price growth and average temperature trends. These measures are then converted to absolute GWh using a projection of population, and a moving sum is applied to generate annual energy quantities.

Figure 5-3 shows the results.

Figure 5-3 — Annual non-large industrial consumption forecasts



As anticipated, the ARDL performs differently from the other models, which is believed to be due to biased long-run coefficients and inappropriate dynamics. Meanwhile, the lack of dynamics in the static equation and the failure to properly account for seasonality in the Johansen model result in lower forecasts in the long run, compared to the model estimated by DOLS and eliminating the seasonal impact on the long-run coefficient estimates. Based on the reasoning that the DOLS procedure should produce the least biased long-run coefficient estimates, plus the performance displayed in Section 5.5, the DOLSEC4 forecasts should be the most reliable, subject to the underlying population and economic forecasts.

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CHAPTER 6 - COMPARISON OF REGIONAL FORECASTING MODELS

This chapter describes the models developed by AEMO to produce 2012 non-large industrial consumption forecasts and compares the differences between these models for each of the five NEM regions.

Table 6-1 shows that estimated long-run elasticities are significantly different from region to region. Therefore, a similar change in either real income or electricity price can have quite a varied effect on demand in different regions. There are two likely explanations for this:

- The modelled non-large industrial consumption for each region captures different proportions of residential versus non-residential customer loads.
- Residential customers in different regions have varying heating load requirements, which results in larger average bills (and therefore a greater response to income and/or price shocks) where the heating load is greater.

Table 6-1 — Estimated own price and income elasticities

	New South Wales	Victoria	Queensland	South Australia	Tasmania
Income	0.62	0.34	0.26	0.34	0.68
(Standard error)	(0.069)	(0.047)	(0.041)	(0.045)	(0.40)
Price	-0.29	-0.14	-0.18	-0.25	-0.69
(Standard error)	(0.032)	(0.085)	(0.025)	(0.037)	(0.15)

All models also include contemporaneous and transitory weather impacts on electricity consumption, as well as some lagged income and price effects (and generally suggest that electricity consumption adjusts gradually to any given income or price shock):

- The Queensland model also includes the significant negative effects of interest rates and the 2010/11 floods.
- The Tasmanian model also includes the significant positive effect of alternative heating fuel prices.

6.1 New South Wales (including the Australian Capital Territory)

The model adopted by AEMO to produce the 2012 New South Wales non-large industrial consumption forecast was based on a modified version of the VEC estimation in Table A-4 and Table A-5 and discussed in Section 5.3.3.

The model uses the first, third and fourth lags of the differenced dynamic terms, both the VEC to estimate the long-run coefficients and also in the forecasting equation. The adopted model is shown in Equation 6-1 and for the following reasons, a VEC approach was used:

- The alternative OLS and ARDL models were found to be inadequate in the absence of dynamics and in the recognition of possible small sample bias.
- In order to obtain a valid VEC model, various options for the inclusion of constant and deterministic trend terms and the number of lags required some compromise and balance.
- A valid model was produced to a timetable that did not allow for further experimentation with DOLS.

Equation 6-1 — New South Wales non-large industrial consumption forecasting model

$$
\begin{aligned}
d(\ln(y_t) = &-0.53[\ln(y_{t-1}) - 0.62\ln(i_{t-1}) + 0.29\ln(p_{t-1}) - 2.25] \\
&-0.28d(\ln(y_{t-1}) - 0.05d(\ln(y_{t-3}) - 0.08d(\ln(y_{t-4})) \\
&+0.21d(\ln(i_{t-1}) + 0.03d(\ln(i_{t-3}) - 0.23d(\ln(i_{t-4})) \\
&+0.15d(\ln(p_{t-1}) - 0.26d(\ln(p_{t-3}) - 0.26d(\ln(p_{t-4}) \\
&+0.0003hdd_t + 0.0002cdd_t(1 + ac_t) \\
&+0.0004s_{1,t} + 0.11s_{2,t} + 0.10s_{3,t}
\end{aligned}
$$

The adopted approach produces long run coefficients that are higher in absolute magnitude than those derived from Table A-4 and Table A-5 but which are within two standard errors of the alternative estimates produced by DOLS and shown in Table A-6. The forecasts produced with the adopted model are similar in the long run, but lower than in the short run, to the DOLS model forecast shown in Figure 5-3.

Interpreting the model produces the following observations about the first term (in square brackets) in the long run:

- Per capita consumption has a fixed component (2.25 kWh per person) and an own price elasticity of -0.29, implying that the long-run response to a 1% increase in electricity price is a 0.29% decrease in electricity consumption.
- Per capita consumption has an income elasticity of +0.62, meaning that the long-run response to an increase in state final demand per capita of 1%, is a 0.62% increase in electricity consumption (this estimated sensitivity to income in New South Wales is generally higher than for other mainland regions).

The transition to the long-run growth path following any short-run shock takes place at the rate of 53% each quarter (this is derived from the first coefficient in the model, and is known as the 'speed of adjustment').

The remainder of the model produces the following observations in the short run:

- Lagged differences in consumption, price and income continue to have temporary effects.
- Heating degree days (which determine the heating load) and cooling degree days (which determine the cooling load) along with air-conditioning ownership have contemporaneous [9] impacts on electricity consumption.
- Quarterly seasonal dummy variables correct for residual seasonality.

6.2 Queensland

The model adopted by AEMO to produce the 2012 Queensland non-large industrial consumption forecast was developed as an ARDL with insignificant terms removed and is shown in Equation 6-2. This model was adopted for the following reasons:

- The alternative OLS model was found to be inadequate in the absence of dynamics and in the recognition of possible small sample bias.
- It was not possible to meet all the constraints required to produce a valid model using the Johansen method to estimate a VEC.
- A valid model was produced to a timetable that did not allow for further experimentation with DOLS.

[9] Heating and cooling have separate effects on energy, but these effects are only felt at the time of each heating or cooling event.

Equation 6-2 — Queensland non-large industrial consumption forecasting model

$$\ln(y_t) = 5.53 + 0.26\ln(i_t) - 0.18\ln(p_{t-3}) - 0.03\ln(r_{t-1})$$
$$+0.00035cdd_t - 0.008w - 0.012s_{1,t} + 0.012s_{2,t} + 0.021s_{3,t}$$

Where r is the real standard variable mortgage interest rate and w is a dummy variable for the Queensland floods in 2010–11, equal to one in the December quarter 2010, and in March and June quarters 2011, and zero at other times.

Interpreting the model produces the following observations:

- Per capita consumption has a fixed component (5.53 kWh per person).
- The own price elasticity is -0.18 (with a three-quarter lag), implying that the long run response to a 1% increase in electricity price is an 0.18% decrease in electricity consumption (the relatively low price elasticity in Queensland may reflect relatively low residential electricity bills due to minimal heating loads).
- The income elasticity is +0.26, meaning that the long run response to an increase in gross state product per capita of 1%, is a 0.26% increase in electricity consumption.
- The real interest rate has a small negative effect on electricity consumption in the long run.
- The extensive floods had a significant negative but transitory effect on Queensland electricity consumption.
- Heating degree days (which determine the heating load) are not significant but cooling degree days (which determine the cooling load) have contemporaneous impacts on electricity consumption.
- Quarterly seasonal dummy variables correct for residual seasonality.

6.3 South Australia

The model adopted by AEMO to produce the 2012 South Australian non-large industrial consumption forecast was based on VEC estimation. The model uses the first and second lags of the differenced dynamic terms and is shown in Equation 6-3. This approach was undertaken for the following reasons:

- The alternative OLS and ARDL models were found to be inadequate in the absence of dynamics and in the recognition of possible small sample bias
- A valid VEC model was available
- The model was produced to a timetable that did not allow for further experimentation with DOLS.

The underlying non-large industrial consumption, however, was first stripped of the residential electric hot water load, as this is being phased out by the South Australian Government and would distort underlying consumption patterns.

Equation 6-3 — South Australian non-large industrial consumption forecasting model

$$d(\ln(y_t) = -0.82[\ln(y_{t-1}) - 0.34\ln(i_{t-1}) + 0.25\ln(p_{t-1}) - 7.10]$$
$$-0.12d(\ln(y_{t-1}) - 0.09d(\ln(y_{t-2})$$
$$+0.13d(\ln(i_{t-1}) + 0.08d(\ln(i_{t-2})$$
$$+0.13d(\ln(p_{t-1}) + 0.03d(\ln(p_{t-2})$$
$$+0.0004hdd_t + 0.0005cdd_t$$
$$+0.007s_{1,t} + 0.04s_{2,t} + 0.07s_{3,t}$$

Interpreting the model produces the following observations about the first term (in square brackets) in the long run:

- Per capita consumption has an own price elasticity of -0.25, implying that the long-run response to a 1% increase in electricity price is a 0.25% decrease in electricity consumption.
- Per capita consumption has an income elasticity of +0.34, meaning that the long-run response to an increase in state final demand per capita of 1%, is a 0.34% increase in electricity consumption.

The transition to the long-run growth path following any short run shock takes place at the rate of 82% each quarter (this is derived from the first coefficient in the model, and is known as the ‘speed of adjustment’).

The remainder of the model produces the following observations in the short run:

- Lagged differences in consumption, price and income continue to have temporary effects.
- Heating degree days (which determine the heating load) and cooling degree days (which determine the cooling load) along with air-conditioning ownership have contemporaneous[10] impacts on electricity consumption.
- Quarterly seasonal dummy variables correct for residual seasonality.

6.4 Tasmania

The model adopted by AEMO to produce the 2012 Tasmanian non-large industrial consumption forecast was based on VEC estimation. The model uses the first lags of the differenced dynamic terms and is shown in Equation 6-4. This approach was undertaken for the following reasons:

- The alternative OLS and ARDL models were found to be inadequate in the absence of dynamics and in the recognition of possible small sample bias.
- A valid VEC model was available.
- The model was produced to a timetable that did not allow for further experimentation with DOLS.

Equation 6-4 — Tasmanian non-large industrial consumption forecasting model

$$
\begin{aligned}
d(\ln(y_t) = {} & -0.58[\ln(y_{t-1}) - 0.68\ln(i_{t-1}) + 0.69\ln(p_{t-1}) - 0.13\ln(g_{t-1}) - 2.85] \\
& -0.17d(\ln(y_{t-1}) + 0.24d(\ln(i_{t-1}) + 0.21d(\ln(p_{t-1}) + 0.13d(\ln(g_{t-1}) \\
& +0.0004hdd_t \\
& +0.005s_{1,t} + 0.16s_{2,t} + 0.16s_{3,t}
\end{aligned}
$$

Where g is the ABS index of gas and other household fuels, representing the cost of alternative energy sources (e.g. firewood, kerosene and gas, particularly for residential space heating).

Interpreting the model produces the following observations about the first term (in square brackets) in the long run:

- Per capita consumption has an own price elasticity of -0.69, implying that the long-run response to a 1% increase in electricity price is a 0.69% decrease in electricity consumption.
- Per capita consumption has an income elasticity of +0.68, meaning that the long-run response to an increase in state final demand per capita of 1%, is a 0.68% increase in electricity consumption.

The relatively high estimated sensitivity to both price and income for Tasmania, compared to other regions, is likely due to the non-large industrial consumption in Tasmania, which includes a relatively higher proportion of residential load.

[10] See note 9.

The transition to the long-run growth path following any short-run shock takes place at the rate of 58% each quarter (this is derived from the first coefficient in the model, and is known as the 'speed of adjustment').

The remainder of the model produces the following observations in the short run:

- Lagged differences in consumption, electricity and alternative fuel prices and income continue to have temporary effects.
- Heating degree days (which determine the heating load) have contemporaneous impacts on electricity consumption.
- Quarterly seasonal dummy variables correct for residual seasonality.

6.5 Victoria

The model adopted by AEMO to produce the 2012 Victorian non-large industrial consumption forecast was developed as an ARDL with insignificant terms removed and is shown in Equation 6-5. This model was adopted for the following reasons:

- The alternative OLS model was found to be inadequate in the absence of dynamics and in the recognition of possible small sample bias.
- It was not possible to meet all the constraints required to produce a valid model using the Johansen method to estimate a VEC.
- A valid model was produced to a timetable that did not allow for further experimentation with DOLS.

Equation 6-5 — Victorian non-large industrial consumption forecasting model

$$\ln(y_t) = 4.54 + 0.34\ln(i_t) - 0.04\ln(p_t) - 0.05\ln(p_{t-2}) - 0.04\,6\ln(p_{t-3}) - 0.096\ln(p_{t-4})$$
$$+0.00032hdd_t + 0.00037cdd_t - 0.0026s_{1,t} + 0.023s_{2,t} + 0.03s_{3,t}$$

Interpreting the model produces the following observations:

- Per capita consumption has a fixed component (4.54 kWh per person).
- The own price elasticity is -0.14 (sum of -0.04,-0.05,+0.046 and -0.096), implying that the long-run response to a 1% increase in electricity price is a 0.14% decrease in electricity consumption (the relatively low price elasticity may be due to the fact that average residential electricity bills in Victoria do not traditionally include a large space heating component).
- The income elasticity is +0.34, meaning that the long-run response to an increase in gross state product per capita of 1%, is a 0.34% increase in electricity consumption.
- Heating degree days (which determine the heating load) and cooling degree days (which determine the cooling load) both have the same impact on electricity consumption.
- Quarterly seasonal dummy variables correct for residual seasonality.

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APPENDIX A - ESTIMATION OF LONG RUN COEFFICIENTS AND FORECASTING MODELS

This appendix presents a summary of the EViews estimation of the models discussed in Chapter 5.

Table A-1 lists the static estimation of long-run coefficients using fully modified least squares (FMOLS).

Table A-1 — Static estimation of long-run coefficients using FMOLS

Dependent Variable: LOG(Y)
Method: Fully Modified Least Squares (FMOLS)
Date: 20/06/12 Time: 12:06
Sample: 2001Q1 2011Q4
Included observations: 44
Cointegrating equation deterministics: C HDD CDD*(1+AC) S1 S2 S3
Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(I)	0.496912	0.060258	8.246430	0.0000
LOG(P)	-0.224475	0.023848	-9.412846	0.0000
C	3.387764	0.521782	6.492687	0.0000
HDD	0.000337	0.000102	3.287453	0.0023
CDD*(1+AC)	0.000230	4.60E-05	5.010350	0.0000
S1	-0.030046	0.014368	-2.091182	0.0436
S2	0.059055	0.019034	3.102650	0.0037
S3	0.089893	0.029272	3.070985	0.0040

R-squared	0.950404	Mean dependent var	7.635542
Adjusted R-squared	0.940760	S.D. dependent var	0.049851
S.E. of regression	0.012133	Sum squared resid	0.005300
Durbin-Watson stat	1.154658	Long-run variance	0.000256

Table A-2 lists the ARDL bounds test equation using 4 lags.

Table A-2 — ARDL bounds test equation

Dependent Variable: DLOG(Y)
Method: Least Squares
Date: 27/06/12 Time: 17:14
Sample (adjusted): 2001Q2 2011Q4
Included observations: 43 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(Y(-1))	-0.144061	0.247968	-0.580969	0.5705
LOG(I(-1))	0.029264	0.145970	0.200479	0.8440
LOG(P(-1))	-0.082403	0.054160	-1.521467	0.1504
DLOG(Y(-1))	-0.221157	0.371041	-0.596044	0.5607
DLOG(Y(-2))	-0.277997	0.287192	-0.967985	0.3495
DLOG(Y(-3))	-0.391302	0.284372	-1.376021	0.1904
DLOG(Y(-4))	-0.383530	0.274327	-1.398076	0.1838
DLOG(I(-1))	0.157065	0.438283	0.358366	0.7254
DLOG(I(-2))	-0.040358	0.316655	-0.127451	0.9004
DLOG(I(-3))	0.363258	0.263646	1.377822	0.1899
DLOG(I(-4))	0.021786	0.275366	0.079117	0.9381
DLOG(P(-1))	0.240217	0.144859	1.658278	0.1195
DLOG(P(-2))	0.014109	0.129007	0.109368	0.9145
DLOG(P(-3))	-0.161385	0.118620	-1.360515	0.1952
DLOG(P(-4))	0.053672	0.148345	0.361803	0.7229
C	0.864637	0.905121	0.955273	0.3556
HDD	0.000333	0.000111	3.009820	0.0094
D(HDD(-1))	-0.000112	0.000128	-0.876771	0.3954
D(HDD(-2))	4.79E-05	0.000122	0.392906	0.7003
D(HDD(-3))	8.34E-05	0.000135	0.619603	0.5455
D(HDD(-4))	5.14E-05	0.000129	0.397577	0.6969
CDD*(1+AC)	0.000165	4.52E-05	3.657802	0.0026
D(CDD(-1)*(1+AC(-1)))	-0.000113	5.60E-05	-2.017142	0.0633
D(CDD(-2)*(1+AC(-2)))	-1.55E-05	6.25E-05	-0.248456	0.8074
D(CDD(-3)*(1+AC(-3)))	-3.07E-05	6.35E-05	-0.482824	0.6367
D(CDD(-4)*(1+AC(-4)))	4.94E-05	6.95E-05	0.711095	0.4887
S1	0.061864	0.068864	0.898354	0.3842
S2	0.204235	0.089515	2.281563	0.0387
S3	0.111566	0.078279	1.425232	0.1760

R-squared	0.990835	Mean dependent var	-0.001123
Adjusted R-squared	0.972505	S.D. dependent var	0.068624
S.E. of regression	0.011379	Akaike info criterion	-5.887397
Sum squared resid	0.001813	Schwarz criterion	-4.699611
Log likelihood	155.5790	Hannan-Quinn criter.	-5.449378
F-statistic	54.05537	Durbin-Watson stat	2.255212
Prob(F-statistic)	0.000000		

Table A-3 lists the dynamic estimation of long-run coefficients using an unconstrained ARDL with 3 lags.

Table A-3 — Dynamic estimation of long-run coefficients using ARDL

Dependent Variable: LOG(Y)
Method: Least Squares
Date: 20/06/12   Time: 12:06
Sample: 2001Q1 2011Q4
Included observations: 44

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(I)	0.679763	0.269257	2.524587	0.0178
LOG(P)	-0.138426	0.089530	-1.546133	0.1337
LOG(Y(-1))	0.176523	0.135731	1.300537	0.2044
LOG(Y(-2))	0.165566	0.137028	1.208265	0.2374
LOG(Y(-3))	0.047357	0.139342	0.339860	0.7366
LOG(I(-1))	-0.461666	0.367153	-1.257420	0.2194
LOG(I(-2))	-0.086787	0.307411	-0.282315	0.7799
LOG(I(-3))	0.180015	0.226812	0.793676	0.4343
LOG(P(-1))	0.137228	0.107993	1.270718	0.2147
LOG(P(-2))	-0.046571	0.115344	-0.403753	0.6896
LOG(P(-3))	-0.125855	0.097219	-1.294552	0.2064
C	2.036614	0.648369	3.141132	0.0041
HDD	0.000330	8.30E-05	3.977191	0.0005
CDD*(1+AC)	0.000187	3.76E-05	4.968708	0.0000
S1	-0.005085	0.026779	-0.189888	0.8508
S2	0.075812	0.023720	3.196166	0.0035
S3	0.100564	0.024753	4.062740	0.0004

R-squared	0.969220	Mean dependent var	7.635542
Adjusted R-squared	0.950980	S.D. dependent var	0.049851
S.E. of regression	0.011037	Akaike info criterion	-5.890702
Sum squared resid	0.003289	Schwarz criterion	-5.201356
Log likelihood	146.5955	Hannan-Quinn criter.	-5.635060
F-statistic	53.13705	Durbin-Watson stat	1.436988
Prob(F-statistic)	0.000000		

Note:

$$Long\ run\ income\ elasticity = \frac{\sum_{j=0}^{-3} coef\left(\ln\left(i_j\right)\right)}{1-\sum_{j=-1}^{-3} coef\left(\ln\left(y_j\right)\right)}$$

= 0.510

$$Long\ run\ price\ elasticity = \frac{\sum_{j=0}^{-3} coef\left(\ln\left(p_j\right)\right)}{1-\sum_{j=-1}^{-3} coef\left(\ln\left(y_j\right)\right)}$$

= -0.284

where $coef$ is for the coefficient value on the respective variable.

Table A-4 lists the Johansen estimation of long-run coefficients using vector error correction (VEC) estimates with 0 lags.

Table A-4 — Johansen estimation of long-run coefficients using VEC

Vector Error Correction Estimates
Date: 20/06/12 Time: 12:06
Sample: 2001Q1 2011Q4
Included observations: 44
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
LOG(Y(-1))	1.000000		
LOG(I(-1))	-0.471754 (0.05073) [-9.29984]		
LOG(P(-1))	0.218824 (0.02201) [9.94366]		
C	-3.742478		
Error Correction:	**D(LOG(Y))**	**D(LOG(I))**	**D(LOG(P))**
CointEq1	-0.827804 (0.12285) [-6.73853]	-0.157084 (0.07449) [-2.10888]	-0.226940 (0.24079) [-0.94248]
C	-0.126877 (0.01374) [-9.23369]	0.018454 (0.00833) [2.21500]	0.009197 (0.02693) [0.34146]
HDD	0.000289 (8.6E-05) [3.37001]	-4.63E-05 (5.2E-05) [-0.89246]	-0.000144 (0.00017) [-0.85925]
CDD*(1+AC)	0.000200 (3.8E-05) [5.22824]	3.96E-06 (2.3E-05) [0.17094]	3.26E-05 (7.5E-05) [0.43634]
S1	-0.006497 (0.01955) [-0.33234]	-0.027810 (0.01185) [-2.34614]	-0.038915 (0.03832) [-1.01559]
S2	0.074064 (0.01954) [3.78976]	-0.004976 (0.01185) [-0.41991]	0.009388 (0.03831) [0.24507]
S3	0.092131 (0.02651) [3.47595]	0.000234 (0.01607) [0.01458]	0.085211 (0.05195) [1.64017]

Table A-4 — (continued)

R-squared	0.967039	0.284274	0.488445
Adj. R-squared	0.961694	0.168210	0.405491
Sum sq. resids	0.006538	0.002404	0.025120
S.E. equation	0.013293	0.008060	0.026056
F-statistic	180.9235	2.449294	5.888092
Log likelihood	131.4805	153.4941	101.8689
Akaike AIC	-5.658204	-6.658822	-4.312221
Schwarz SC	-5.374355	-6.374974	-4.028373
Mean dependent	-0.000571	0.005421	0.012950
S.D. dependent	0.067920	0.008838	0.033793
Determinant resid covariance (dof adj.)		5.39E-12	
Determinant resid covariance		3.20E-12	
Log likelihood		394.9735	
Akaike information criterion		-16.86243	
Schwarz criterion		-15.88924	

Table A-5 lists the error-correction model based on Johansen estimation.

Table A-5 — Error-correction model based on Johansen estimation

Dependent Variable: D(LOG(Y))
Method: Least Squares
Date: 20/06/12 Time: 12:06
Sample: 2001Q1 2011Q4
Included observations: 44

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(Y(-1))-0.471754248516397*LOG(I(-1))+0.218824112106252*LOG(P(-1))-3.74247775239477	-0.478347	0.143476	-3.333996	0.0026
D(LOG(Y(-1)))	-0.227861	0.130208	-1.749976	0.0919
D(LOG(Y(-2)))	-0.044519	0.123146	-0.361513	0.7206
D(LOG(Y(-3)))	-0.223948	0.111741	-2.004162	0.0556
D(LOG(I))	0.858592	0.215495	3.984271	0.0005
D(LOG(I(-1)))	-0.313469	0.182874	-1.714126	0.0984
D(LOG(I(-2)))	-0.098873	0.179775	-0.549980	0.5870
D(LOG(I(-3)))	0.193370	0.182554	1.059251	0.2992
D(LOG(P))	-0.223753	0.070330	-3.181490	0.0038
D(LOG(P(-1)))	0.113996	0.072643	1.569265	0.1287
D(LOG(P(-2)))	-8.37E-05	0.083524	-0.001002	0.9992
D(LOG(P(-3)))	-0.283875	0.077142	-3.679892	0.0011
C	-0.136158	0.013134	-10.36707	0.0000
HDD	0.000323	6.96E-05	4.634692	0.0001
CDD*(1+AC)	0.000180	3.21E-05	5.603280	0.0000
S1	0.016011	0.023278	0.687830	0.4977
S2	0.103896	0.021831	4.759106	0.0001
S3	0.083423	0.024594	3.391999	0.0022

R-squared	0.988273	Mean dependent var	-0.000571
Adjusted R-squared	0.980605	S.D. dependent var	0.067920
S.E. of regression	0.009459	Akaike info criterion	-6.191638
Sum squared resid	0.002326	Schwarz criterion	-5.461742
Log likelihood	154.2160	Hannan-Quinn criter.	-5.920957
F-statistic	128.8892	Durbin-Watson stat	1.405343
Prob(F-statistic)	0.000000		

Table A-6 lists the dynamic estimation of long-run coefficients using DOLS.

Table A-6 — Dynamic estimation of long-run coefficients using DOLS

Dependent Variable: LOG(Y)
Method: Least Squares
Date: 20/06/12 Time: 14:42
Sample: 2001Q1 2011Q4
Included observations: 44
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.812899	1.000582	2.811263	0.0093
LOG(I)	0.563376	0.111666	5.045189	0.0000
LOG(P)	-0.240764	0.029189	-8.248597	0.0000
HDD	0.000298	7.79E-05	3.819426	0.0007
CDD*(1+AC)	0.000186	3.19E-05	5.834230	0.0000
S1	-0.016930	0.011951	-1.416630	0.1685
S2	0.064364	0.015223	4.228016	0.0003
S3	0.091415	0.022782	4.012527	0.0005
DLOG(I)	0.200189	0.220408	0.908261	0.3721
DLOG(I(1))	0.104997	0.332807	0.315489	0.7549
DLOG(I(2))	-0.032448	0.443050	-0.073238	0.9422
DLOG(I(-1))	-0.307588	0.228026	-1.348920	0.1890
DLOG(I(-2))	-0.395397	0.191756	-2.061977	0.0493
DLOG(P)	-0.016760	0.088944	-0.188431	0.8520
DLOG(P(1))	-0.189794	0.097775	-1.941139	0.0632
DLOG(P(2))	-0.045586	0.073258	-0.622257	0.5392
DLOG(P(-1))	0.091629	0.114584	0.799669	0.4311
DLOG(P(-2))	0.120689	0.066254	1.821608	0.0800

R-squared	0.968723	Mean dependent var	7.635542
Adjusted R-squared	0.948273	S.D. dependent var	0.049851
S.E. of regression	0.011338	Akaike info criterion	-5.829232
Sum squared resid	0.003342	Schwarz criterion	-5.099336
Log likelihood	146.2431	Hannan-Quinn criter.	-5.558551
F-statistic	47.36959	Durbin-Watson stat	1.064394
Prob(F-statistic)	0.000000		

Table A-7 lists the estimated DOLS error-correction model.

Table A-7 — DOLS(4) error-correction model

Dependent Variable: DLOG(Y)
Method: Least Squares
Date: 20/06/12 Time: 15:32
Sample (adjusted): 2001Q2 2011Q4
Included observations: 43 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(Y(-1))-2.81289891646884-0.563375862630925*LOG(I(-1))+0.240764251645576*LOG(P(-1))-0.000297596096994404*HDD(-1)-0.000186361716348683*CDD(-1)*(1+AC(-1))+0.0169300508828203*S1(-1)-0.0643639379360083*S2(-1)-0.0914149290664382*S3(-1)	-0.493421	0.178715	-2.760937	0.0114
DLOG(Y(-1))	0.064900	0.123189	0.526830	0.6036
DLOG(Y(-2))	0.193469	0.110291	1.754164	0.0933
DLOG(Y(-3))	-0.149774	0.116437	-1.286306	0.2117
DLOG(Y(-4))	0.171350	0.119605	1.432629	0.1660
DLOG(I)	0.848012	0.210852	4.021839	0.0006
DLOG(I(-1))	-0.396563	0.248161	-1.598004	0.1243
DLOG(I(-2))	-0.046840	0.190142	-0.246342	0.8077
DLOG(I(-3))	0.149499	0.178636	0.836890	0.4117
DLOG(I(-4))	-0.315134	0.184044	-1.712275	0.1009
DLOG(P)	-0.261711	0.077283	-3.386381	0.0027
DLOG(P(-1))	0.217810	0.070849	3.074293	0.0055
DLOG(P(-2))	-0.014496	0.072754	-0.199240	0.8439
DLOG(P(-3))	-0.242097	0.073789	-3.280954	0.0034
DLOG(P(-4))	0.133712	0.079383	1.684375	0.1062
C	-0.074114	0.017674	-4.193322	0.0004
D(HDD)	0.000308	4.95E-05	6.223774	0.0000
D(CDD*(1+AC))	0.000155	2.38E-05	6.509108	0.0000
S1	0.063569	0.022093	2.877287	0.0087
S2	0.159339	0.032282	4.935784	0.0001
S3	0.067352	0.027112	2.484240	0.0211

R-squared	0.991775	Mean dependent var	-0.001123
Adjusted R-squared	0.984299	S.D. dependent var	0.068624
S.E. of regression	0.008599	Akaike info criterion	-6.367762
Sum squared resid	0.001627	Schwarz criterion	-5.507641
Log likelihood	157.9069	Hannan-Quinn criter.	-6.050576
F-statistic	132.6464	Durbin-Watson stat	1.963394
Prob(F-statistic)	0.000000		

APPENDIX B - REFERENCES

AEMO (2012) Electricity Forecasting Framework Paper (draft).

Beggs, J.J. (1988) “Diagnostic Checking in Applied Econometrics”, Economic Record 64, 81-101.

Bentzen, J. and T. Engsted, (1993) “Short- and Long-Run Elasticities in Energy Demand: a Cointegration Approach”, Energy Economics, 15, 9-16.

Bentzen, J. and T. Engsted (2001) “A Revival of the Autoregressive Distributed Lag Model in Estimating Energy demand Relationships”, Energy, 26, 45-55.

Centre of Policy Studies (COPS) (2012) The Monash Model, http://www.monash.edu.au/policy/monmod.htm, accessed 7 February 2012.

Contreras, Z. (2011) “Forecasting Peak Demand for Power System Reliability Planning in the Medium-Term”, Chapter 3 in: Challenges in the Electricity Sector: Integrating Decentralised Supply, Forecasting Peak Demand and Reducing Air Pollution, PhD Thesis, University of New South Wales.

CSIRO, Department of Climate Change and Energy Efficiency and Bureau of Meteorology (2009) Climate Change in Australia, go to: http://www.climatechangeinaustralia.gov.au/futureclimate.php and select State, (accessed 31/05/2012), Australian Government.

Dickey, D.A. and W.A. Fuller (1979) **“**Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” Journal of the American Statistical Association, 74, p. 427–431.

Donnelly, W.A. and H.D.W. Saddler (1984) “The Retail Demand for Electricity in Tasmania”, Australian Economic Papers, 23, 52-60.

Engle, R. F. and C. W. J. Granger (1987) “Co-Integration and Error Correction: Representation, Estimation and Testing”, Econometrica, 55, 251-76.

Engle, R. F., C. W. J. Granger and J.J. Hallman (1989) “Merging Short- and Long-Run Forecasts: An Application of Seasonal Cointegration to Monthly Electricity Sales Forecasting”, Journal of Econometrics, 40, 45-62.

Fiebig, D. (1997) Load Forecasting, Report presented to TransGrid, Sydney.

Flaig, G. (1990) “Household Production and Short-Run and Long-Run Demand for Electricity”, Energy Economics, 12, 116-121.

Gangopadhyay, G. (1988) “An Overview of the Load Forecasting Process in the Electricity Commission of New South Wales”, in McColl, G. (ed.) Electricity Generation Planning in an Uncertain Environment, Centre for Applied Economic Research, UNSW.

Hickling, R. (2006) Electricity Consumption in New South Wales: An Application of Cointegration Techniques to Energy Modelling and Forecasting, TransGrid: Economics Information Paper, Sydney.

Hyndman, R. J. and S. Fan (2008a) Forecasting Long-Term Peak Half-Hourly Electricity Demand for Victoria, Monash University Business and Economic Forecasting Unit.

Hyndman, R. J. and S. Fan (2008b) Variations on Seasonal Bootstrapping for Temperature Simulation, Monash University Business and Economic Forecasting Unit.

R. J. Hyndman and S. Fan (2010) “Density Forecasting for Long-term Peak Electricity Demand”, IEEE Trans. Power Systems, Vol. 25, No.2, pp. 1142–1153,

Johansen, S. (1988) “Statistical Analysis of Cointegration Vectors”, Journal of Economic Dynamics and Control, 12, 231-54.

King, R.G., C.I. Plosser, J.H. Stock and M.W. Watson (1991) “Stochastic Trends and Economic Fluctuations”, American Economic Review 81, 819-840.

MacKinnon, J. G. (1996) “Numerical Distribution Functions for Unit Root and Cointegration Tests”, Journal of Applied Econometrics, vo l. 11, 601-618.

Narayan, P. K. and R. Smyth (2005) “The Residential Demand for Electricity in Australia: an Application of the Bounds Testing Approach to Cointegration”, Energy Policy, 33, 467-474.

NIEIR (2012) Draft Economic and Energy Price Forecasts for AEMO.

Oliver, J. (2011) Electricity Forecasting Framework Paper, Australian Energy Market Operator (AEMO), December, Melbourne.

Pesaran, M. H., Y Shin and R. J. Smith (2001) “Bounds Testing Approaches to the Analysis of Levels Relationships”, Journal of Applied Econometrics, 16, 289-326.

Saikkonen, P. (1991) “Asymptotically efficient estimation of cointegrating regressions”, Econometric Theory 7, 1-21.

Shin, Y. (1994) “A residual based test of the null of cointegration against the alternative of no-cointegration”, Econometric Theory 10, 91-115.

Silk, J.I. and F.L. Joutz (1997) “Short and Long-run Elasticities in US Residential Electricity Demand: a Cointegration Approach”, Energy Economics, 19, 493-513.

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