Randomly Modulated Periodic Signals in Australia's National Electricity Market

John Foster, Melvin J. Hinich** and Phillip Wild****

In this article, we use half hourly spot electricity prices and load data for the National Electricity Market (NEM) of Australia for the period from December 1998 to August 2007 to test for randomly modulated periodicity. In doing so, we apply signal coherence spectral analysis to the time series of half hourly spot prices and megawatt-hours (MWh) load demand from 7/12/1998 to 31/08/2007 using the FORTRAN 95 program developed by Hinich (2000). We detect relatively steady weekly and daily cycles in load demand but relatively more unstable cycles in prices.

1. INTRODUCTION

A crucial feature of price formation in electricity spot markets is the instantaneous nature of the product sold. The physical laws that determine the delivery of electricity across a transmission grid require a synchronization and balancing of the input of power at generating points and output of power at demand points together with some allowance for transmission loss associated with electrical resistance and the heating up of conductors. Across the grid, production and consumption decisions must be perfectly synchronized, without any capability for storage, otherwise the quality of supply can be severely compromised. Moreover, while electricity generation and transmission may be viewed as yielding a commodity, its ultimate consumption at the retail end is a service. Thus, the task of either the grid operator or the short-term market mechanism is to continuously monitor the demand process and allocate generating capacity, in line with fluctuations in demand (Bunn 2004, 2, Hinich, Czamanski, Dormaar, and Serletis 2007).

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* School of Economics, University of Queensland, St Lucia, QLD, 4072, Australia, Tel: +61 7 3365 6780, email: j.foster@uq.edu.au.

** Applied Research Laboratories, University of Texas at Austin, Austin, TX 78712-1087, Tel: +1 512 232 7270, email: hinich@mail.la.utexas.edu.

*** Corresponding author. School of Economics and ACCS, University of Queensland, St Lucia, QLD, 4072, Australia, Tel: +61 7 3346 9258, email: p.wild@uq.edu.au. Energy Institute 2006 Electricity Camp for helpful suggestions. All remaining errors are ours.

Recently, researchers have applied innovative methods in modelling spot wholesale electricity prices and loads. See, for example, Zhang and Dong (2001), Higgs and Worthington (2003), Deng and Jiang (2004), León and Rubia (2004), Serletis and Andreadis (2004), Higgs and Worthington (2005), Lu, Dong and Li (2005), and Worthington, Kay-Spratley, and Higgs (2005). Our contribution here is to offer forecasters a better understanding of the periodicity of prices and load in this market through the use of the Randomly Modulated Periodicity (RMP) model, recently proposed by Hinich (2000), Hinich and Wild (2001, 2005) and applied to the Alberta Electricity market in Hinich, Czamanski, Dormaar, and Serletis (2007). We use this parametric statistical model to study the Australian National Electricity Market (NEM) wholesale spot market. We examine half hourly spot electricity prices (defined in terms of megawatt-hours (MWh)) and MWh load (demand) over the period from 7/12/1998 to 31/08/2007.

Our principal objective in this article is to test for periodic structure in electricity spot prices and load data in order to establish whether the nature of the underlying periodicity permits us to competently predict the spot price and load far into the future.[1] As such, we are particularly concerned with the stability or predictability of the periodic structure of price and load time series data.

Our approach differs from the conventional conception of periodicity in the time series and signal processing literature which utilizes a deterministic periodicity (sinusoid) possibly embedded in additive noise. If the noise process is a symmetric or uniform noise process, then the periodicity will have a constant waveform, (Li and Hinich 2002, 1, Hinich and Wild 2005, 1557-1558).

Our approach also differs from the conventional approaches that have been used to model time series with changing periodic structure that can be classified as models with either 'seasonal' unit roots or 'season-dependent' parameters – see (Li and Hinich 2002, 1-2) for an overview of these two different approaches.[2]

In undertaking this, we employ a univariate approach, although, from both an economic and forecasting perspective, there is likely to be interest in broader questions concerning possible relationships between the spot price of electricity and electricity load and other covariates such as prices of primary commodities like coal and natural gas, which enter as input costs in electricity generation, economic activity and weather patterns. We see such wider investigations as complementary to the kind of statistical analysis undertaken here.

The paper is organized as follows. In Section 2 we discuss the Australian National Electricity Market (NEM). In Sections 3 and 4 we briefly outline the RMP

1. Judgement about the validity of the approach will ultimately rest upon its comparative forecast performance which will be the subject of a latter paper. This article is concerned with assessing the stability of the periodic structure of the data in question which will underpin forecasting methods employed in the latter article. The proposed forecasting methods are non-trivial and innovative, being based on 'hetrodyning' techniques.

2. Our approach is more closely related to the second approach mentioned above ('season-dependent' parameter models). The main differences are that we operate in the frequency domain and the approach to dimension reduction is different from the time domain methods identified in (Li and Hinich 2002, 2).

model proposed by Hinich (2000) and Hinich and Wild (2001, 2005). In Section 5 we briefly discuss the data used and highlight some transformations that were made to the spot price electricity data in order to implement the RMP test. In section 6, we test for randomly modulated periodicity in half hourly electricity prices and MWh load demand. In the final section, we provide concluding comments.

2. AUSTRALIAN NATIONAL ELECTRICITY MARKET (NEM)

The electricity market as a whole encompasses both supply and demand side interactions. The Australian market for electricity is structured as a gross pool arrangement. This market structure is ideal for electricity because of its peculiar properties. First, electricity cannot be stored and supply must balance demand instantaneously through time. Second, because one unit of electricity is indistinguishable from all other units, it is not possible to determine from which generator the unit of electricity was produced (NEMMCO 2005, 4).

The electricity industry involves generation, transmission, distribution and retail sale activities. More than 90% of Australia's electricity production is generated from burning coal, gas and oil. In 2003, statistics relating to generation by fuel type indicated that approximately 58.5% of generation occurred by burning black coal, 25.9% by brown coal, 7.7% by natural gas, 7.6% by Hydro and 0.3% by oil products (NEMMCO 2005, 4).

The NEM commenced operation as a de-regulated wholesale market in New South Wales, Victoria, Queensland, the Australian Capital Territory (ACT) and South Australia in December 1998. In 2005, Tasmania joined as a sixth region. Operations are essentially based on six interconnected regions that broadly follow state boundaries. The market is extensive in scope with trade in electricity accounting for around $7 billion in 2003, meeting the demand of around 8 million consumers (NEMMCO 2005, 4).

The National Electricity Market Management Company Limited (NEMMCO) was established in 1996 to administer and manage the NEM. NEMMCO is a company under the Corporations law and operates on a break-even basis by recovering the costs of operating the NEM as well as it own operational costs by levying fees against market participants (NEMMCO 2005, 5). More generally, the structure of ownership of NEM infrastructure assets is complicated, with assets being owned and operated by both state governments (i.e. public ownership) and by private businesses (i.e. private ownership). In 2003, public (government) ownership encompassed around 64% of generation assets, 57% of transmission assets, 50% of distribution assets and 55% of retail assets (NEMMCO 2005, 5).

In Australia, the wholesale spot market for electricity is a key component of the NEM. The spot market can be viewed as being derived from a continuous auction market in which asks and bids are entered by generators and users of electricity to generate five minute (market clearing) dispatch prices that are broadcast to market participants in real time. Towards the end of the five-minute interval, market clearing is achieved through an economic dispatch algorithm that selects the cheapest available resource from the offers submitted by market participants to meet incremental changes in demand experienced by the real power system. The official trade (spot) prices and positions are determined by taking half hour averages of the five-minute dispatch prices and loads. The half hourly averaged prices are those received by generators and paid by purchasers of electricity (Outhred 2000, 3-4, NEMMCO 2005, 6-7).

Currently, NEM rules set a maximum spot price of $10 000 per megawatt hour. This is the maximum price that generators can bid into the market. This maximum price is also called the Value of Lost Load (VOLL) and is automatically activated whenever NEMMCO pursues load shedding in order to ensure that supply and demand balance and that the quality of supply meets pre-determined security and reliability standards (NEMMCO 2005, 6, 9).

There is also provision for price capping behavior associated with a Cumulative Price Threshold (CPT) that serves to cap potential financial risk in the NEM during periods of high sustained spot prices. This mechanism is triggered if the cumulative price in a single region over the preceding 336 trading intervals in a rolling seven-day period reaches some pre-specified threshold level. If this occurs, the maximum spot price is reduced from VOLL to an administered cap level and this arrangement continues until the conditions that caused the trading interval prices to increase in the sustained way have subsequently passed. The current CPT is set at $150000 and the administered Cap is set at $100/MWh in peak times and $50/MWh in off peak times (AEMC 2006, Sect. 4.3).[3] The administered price arrangements also include provisions to transfer price caps to interconnected regions (see special NEMMCO Briefing Paper cited in reference section).

Another feature of the NEM is location-dependent prices and capacity for inter-regional trade. High-voltage transmission lines, called interconnectors, transport electricity between different NEM regions. Interconnectors can be used to import electricity into a region when demand is higher than can be met by locally based generators or when prices in an adjoining region are low enough to displace the locally based sources of supply. The flow of power between regions is also limited by the physical transfer capacity of the interconnectors themselves. Currently, interconnectors link (and regional trade is possible between) Queensland and New South Wales; New South Wales, Snowy Mountains and Victoria; Victoria and South Australia; and Victoria and Tasmania (NEMMCO 2005, 17). Therefore, in summary, the wholesale market can be viewed as being divided into market regions with the possibility of price variability between regions or even between sub-regions, possibly reflecting flow and other networking constraints operating at or within regional boundaries. These effects combine to determine the relationship between spot prices at regional reference nodes (Outhred 2000, 3-4).

3. A CPT of $150000 is equivalent to an average spot price of $446.43/MWh over the previous seven days. Moreover, if the average price in a region over the previous seven days was $32/MWh, then a VOLL price for seven hours would be needed before the CPT was exceeded, thereby inducing an administered price period (NEMMCO Briefing Paper, Sect. 2).

The design of the NEM is fully symmetric so that, in principle, both demand and supply side participants have equal opportunity to set and respond to changes in market prices. However, experience indicates that few demand-side resources are formally bid in the market, weakening the price-elasticity effects of the market mechanism, increasing price volatility and possibly permitting suppliers to exercise market power and extract monopoly rents.[4] Instead, NEMMCO feeds demand forecasts directly into the economic dispatch process itself (NEMMCO 2005, 11). This operation might also serve to weaken links between commercial decision-making underpinning the demand side of the market and physical processes underpinning the supply side of the market. One implication is that this may introduce demand forecast risks that are not managed commercially, thus increasing spot price volatility (Outhred 2000, 3).

In 2003, statistics on electricity consumption by industrial sector indicated that the largest end-user group was industry, accounting for approximately 46.9% of total electricity consumption. This was followed by the residential sector, which accounted for 26.7%, and the commercial sector, that accounted for around 23.8%. Consumption of electricity by the agriculture and transport sectors was much smaller in scope, accounting for only 1.5% and 1.1% respectively. In terms of the total number of actual customers, approximately 87.7% of the customers were defined as domestic users, while 10.7% of customers were defined as businesses and finally 1.6% of total customers were defined as rural customers (NEMMCO 2005, 4).

In general, demand patterns tend to vary from region to region depending upon such factors as population, temperature and industrial and commercial needs. However, for a business day experiencing average temperatures, a typical level of demand across the NEM would be approximately 21000 megawatts (NEMMCO 2005, 11).[5] In this normal situation, there is ample supply available to service this demand.

Electricity demand also tends to be cyclical in nature, with demand being lower in the spring and autumn than in summer and winter. Australia has higher summer consumption patterns, due to higher temperatures that cause increased use of air-conditioners, particularly by the residential sector. However, severe supply pressures only emerge when there are extremely high prevailing temperatures - this is expected to occur during a few days in summer each year. Moreover, because peak demand does not arise simultaneously in all regions, total supply can typically be shared between regions using the interconnected power network.

Electricity demand in Australia also has a daily and weekly cycle. The peak hourly load in Australia has two distinct peaks that are generated by do-

4. An anonymous referee mentioned that one reason why few demand side resources are bid into the market is because of metering difficulties – for instance, it is likely that most people would not even consider monitoring energy consumption even if ‘smart meters’ become more widely available, thus producing very low short run own price elasticity of demand.

5. It should be noted that an anonymous referee pointed out that the average demand level should be approximately 29000MW’s, instead of the 21000MW’s cited in the above-mentioned NEMMCO publication.

mestic activity. Demand tends to be low in the early morning hours and begins to increase, with a first peak period occurring between 7.00 am and 9.00am. Demand then tends to drop off, flattening out between 11.30 am to 1.30pm before starting to climb once again. The second peak occurs between 4.00pm and 7.00pm. Demand also follows a weekly cycle and tends to be higher on weekdays than during the weekends.

Finally, demand for electricity is very price inelastic in Australia. Because NEMMCO feeds load estimates directly into the economic dispatch process, there is no effective price bidding by demand side participants. The demand forecast determines the quantity of electricity that has to be supplied while the supply side of the economic dispatch process determines the price and supply schedules that the generators are willing to offer in order to meet the prevailing demand. Therefore, within the context of the economic dispatch algorithm used in NEM, the supply side participants essentially determine both the five minute dispatch prices and half hour trade (spot) prices. Estimates of the own price elasticity of electricity demand generally reflect this with elasticity estimates generally accepted to be around -0.13 to -0.15, hence signifying a very inelastic demand profile (Simshauser and Docwra 2004, 289). However, some large industrial customers can agree to curtail consumption at high spot prices, introducing some price sensitivity at higher spot price levels – this practice is termed “demand side participation” (NEMMCO 2005, 16).

Volatile spot prices have encouraged trading in financial instruments (i.e. especially in the form of specialized contractual arrangements) linked to future spot prices in order to hedge positions against the risk that sharp rises in spot price of electricity might pose to the bottom lines of wholesale market participants. Hedge contracts are designed to operate independently of both the market and NEMMCO’s administration. They play no role in balancing supply and demand and are not regulated under any NEM rules or provisions (NEMMCO 2005, 24). In fact, the actual price paid for the bulk of the electricity is mainly determined by contract (rather than the spot market) prices and the net effect of participants’ contract and spot market exposures. In particular, it should be recognized that the spot market is a wholesale market and about only 30-40% of the price paid by domestic and business consumers for electricity supply is accounted for by the direct (wholesale) cost of the energy. In this context, the wholesale energy cost can be broadly interpreted as the cost of generation or the price that retailers ultimately pay for the power, including hedging, risk management and other transaction costs. Additional retail based charges include mark-ups associated with the costs of network usage, retail charges associated with providing customer services such as billing and call centre services, profit mark-up and goods and services taxes (GST) (Outhred 2000, 5-6, Energy Consumers’ Council 2003, 21-23, NEMMCO 2005, 7). However, spot price volatility and forecasts of future spot prices play a crucial role in underlying risk assessment and possible hedging strategies that are subsequently adopted by wholesale market participants.

3. CONCEPT OF RAMDOMLY MODULTATED PERIODICITY

The RMP model allows one to capture the intrinsic variability of a cycle and the signal coherence function enables one to quantify the amount of random variation in the complex amplitude of each component of the Fourier representation of the time series.

A discrete-time random process $x(t_n)$ is an RMP with period $T = N\tau$, sampling interval τ, $t_n = n\tau$ and kth Fourier frequency $f_k = k/T$, if it takes the form

$$x(t_n) = s_0 + \frac{2}{N} \sum_{k=1}^{N/2} [(s_{1k} + u_{1k}(t_n))\cos(2\pi f_k t_n) \tag{1}$$

$$+ (s_{2k} + u_{2k}(t_n))\sin(2\pi f_k t_n)]$$

where s_0, s_{1k} and s_{2k} are constants. The modulation processes $\{u_{11}(t_n),..., u_{1,N/2}(t_n), u_{21}(t_n),..., u_{2,N/2}(t_n)\}$ are unknown random processes with zero means, finite cumulants and a joint distribution that has the following finite dependence property: $\{u_{jr}(t_1),...,u_{jr}(t_m)\}$ and $\{u_{ks}(t'_1),..., u_{ks}(t'_n)\}$ are independent if $t_m + D < t'_1$ for some $D > 0$ and all $j,k = 1,2$ and all sample times (Billingsley 1979). If $D << N$ then the modulations are approximately stationary within each period.

It is evident from (1) that the random variation occurs in the modulation processes u_{k1} (t) and u_{k2} (t) themselves rather than being modeled as an additive noise process. Therefore, the RMP process in (1) can be viewed as a random effects model.

The process in (1) can be expressed respectively as the sum of a deterministic (periodic) component and a stochastic process $x(t_n) = s(t_n) + u(t_n)$ where

$$s(t_n) = E[x(t_n)] = s_0 + \frac{2}{N} \sum_{k=1}^{N/2} [s_{1k} \cos(2\pi f_k t_n) + s_{2k} \sin(2\pi f_k t_n)] \tag{2}$$

and

$$u(t_n) = \frac{2}{N} \sum_{k=1}^{N/2} [u_{1k} \cos(2\pi f_k t_n) + u_{2k} \sin(2\pi f_k t_n)]. \tag{3}$$

The process $s(t_n)$, the expected value of the time series $x(t_n)$, is a periodic function. The fixed coefficients s_{1k} and s_{2k} determine the shape of $s(t_n)$. Now suppose that the observed time series is given by $y(t_n) = x(t_n) + e(t_n) = s(t_n) + u(t_n) + e(t_n)$ where $s(t_n)$ and $u(t_n)$ are defined by (2) and (3) above. Assume further that the additive noise process $e(t_n)$ is strictly stationary with finite dependence of span D and finite moments. Then the combined noise and modulation process $\kappa(t_n) = u(t_n) + e(t_n)$ satisfies finite dependence and is stationary within the observation range.

4. SIGNAL COHERENCE SPECTRAL ANALYSIS

In order to provide a measure of the modulation relative to the underlying periodicity, we employ the concept of *signal coherence spectrum* (SIGCOH) introduced in Hinich (2000) and extended in Hinich and Wild (2005) to the case of detecting an RMP in additive stationary noise. Conceptually, the signal coherence measure can be interpreted as quantifying the degree of association between the modulation and underlying periodicity for each given frequency.

A common approach to processing time series with a periodic structure is to partition the observations into M frames, each of length $T = N\tau$, where τ is the sampling interval (typically set to unity). Therefore, there is exactly one waveform in each sampling frame. The periodic component of the time series is then simply the mean component of the source time series $y(t_n)$.

It is possible to interpret the concept of signal coherence as measuring how stable the time series is at each frequency across the frames. It follows that for each Fourier frequency $f_k = k/T$ the value of the signal coherence function is given by

$$\gamma_y(k) = \sqrt{\frac{|s_k|^2}{|s_k|^2 + \sigma^2_\kappa(k)}}, \tag{4}$$

where $s_k = s_{1k} + is_{2k}$ is the amplitude of the kth sinusoid, $\sigma^2_\kappa(k) = E\,|\,\mathrm{K}(k)\,|^2$ and

$$\mathrm{K}(k) = \sum_{n=0}^{N-1} (u(t_n) + e(t_n)) \exp(-i2\pi f_k t_n), \tag{5}$$

is the discrete Fourier transform (DFT) of the combined modulation and noise process $\kappa(t_n)$. It is evident from its construction in (4) that $\gamma_y(k)$ is bounded to lie on the (0,1) interval. One polar case arises when $\gamma_y(k) = 1$. This occurs if $s_k \neq 0$ and $\sigma^2_\kappa(k) = 0$, implying that the component at frequency f_k has a constant amplitude and phase over time – there is no random variation across the frames at that frequency (perfect coherence). The other polar case arises when $\gamma_y(k) = 0$, which occurs when $s_k = 0$ and $\sigma^2_\kappa(k) \neq 0$. This implies that the mean value of the component at frequency f_k is zero so that all of the variation across the frames at that frequency is a pure noise process (no coherence).

The signal coherence function is estimated from actual data by taking the Fourier transform of the mean frame and for each of the M frames. The mean frame is given by

$$\bar{Y}(k) = \frac{1}{M} \sum_{m=1}^{M} Y_m(k), \tag{6}$$

which is the sample mean of the DFT

$$Y_m(k) = \sum_{n=0}^{N-1} y((m-1)\,T + t_n)\exp(-i2\pi f_k t_n), \quad (7)$$

where $\{y((m-1)T + t_n), n = 0,\ldots, N-1\}$ is the m^{th} data frame. We define the "residual" process $D_m(k) = Y_m(k) - \overline{Y}(k)$ as the difference between the Fourier transforms of the m^{th} frame and the mean frame for each frequency k.

The amplitude-to-modulation standard deviation (AMS) is given by $\rho_y(k) = |s_k| / \sigma_\kappa(k)$ for frequency f_k. It follows that $\rho_y^2(k) = \gamma_y^2(k) / 1 - \gamma_y^2(k)$. Therefore, SIGCOH can be viewed as measuring the amount of "wobble" in each frequency component of the source time series $y(t_n)$ about its amplitude when $s_k > 0$ in (4). An AMS of 1.0 is equal to a signal coherence value of 0.71 and an AMS of 0.5 is equal to a signal coherence value of 0.45.

The SIGCOH estimator introduced in Hinich (2000) is

$$\hat{\rho}_y^2(k) = \frac{|\overline{Y}(k)|^2}{\sigma_\kappa^2(k)}, \quad (8)$$

where $\overline{Y}(k)$ is the DFT of the mean frame and $\sigma_\kappa^2(k) = 1/M\sum_{m=1}^{M} |Y_m(k) - \overline{Y}(k)|^2$ is the sample variance of the residual DFT process $D_m(k)$. This estimator is consistent as $M \to \infty$. If $D << N$, and $N = T/\tau$, then the distribution of $M/N\,\rho_y^2(k)$ is asymptotically chi-squared with two degrees-of-freedom with non-centrality parameter $\lambda_k = M/N\,\rho_y^2(k)$ as $M \to \infty$ (Hinich and Wild 2001). These $\chi_2^2(\lambda_k)$ statistics are asymptotically independently distributed over the frequency band when $D << N$.

If the null hypothesis for frequency f_k is that $\gamma_y(k) = 0$ with associated AMS equal to zero, then the statistic $(M/N\,\hat{\rho}_y^2(k))$ with $\hat{\rho}_y^2(k)$ defined in (8) will be approximately central chi-squared. Therefore, the statistic $(M/N\,\hat{\rho}_y^2(k))$ can be used to falsify the null hypothesis mentioned above. The tests across the frequency band are approximately independently distributed tests and the statistic $\hat{\rho}_y^2(k)$ is the most straightforward way to place statistical confidence on SIGCOH point estimates.

We can also construct a joint test based on the distribution of the CUSUM statistic

$$S = \sum_{k=1}^{K}\left(\frac{M}{N}\hat{\rho}_y^2(k)\right). \quad (9)$$

The statistic S is approximately chi squared $\chi_K^2(\lambda)$ where $\lambda = \sum_{k=1}^{K}\lambda_k$ for large values of M.

5. DATA AND ASSOCIATED TRANSFORMATIONS

Recall from the discussion in Section 1 that we use half hourly spot electricity prices and load data for the period from 7/12/1998 to 31/08/2007.[6] This produced a resulting sample size of 142,873 observations. We apply the tests to time series load and price data from New South Wales (NSW), Queensland (QLD), Victoria (VIC) and South Australia (SA). It should be noted that we do not investigate the properties of the data associated with Snowy Mountains Hydro because it does not service its own distinct NEM region, but instead, exports power to New South Wales and Victoria.

In applying the RMP tests, we convert all data series to continuous compounded returns by applying the formula:

$$r(t) = \ln\left(\frac{y(t)}{y(t-1)}\right)*100 , \qquad (10)$$

where:

- $r(t)$ is the continuous compounded return for time period "t"; and
- $y(t)$ is the source price or load time series data.

In order to apply (10), $y(t)$ cannot take negative or zero values. However, it became evident that for Queensland, Victoria and South Australia, there was the occasional occurrence of negative spot prices. The negative spot prices represented payments made by generator operators to NEMMCO in order to keep their generators running in circumstances when resulting power supplied would exceed the prevailing load requirements. This principally reflected the time and costs involved in shutting down and then subsequently re-starting generating plant (especially for base-load) when demand increased. These negative price episodes are outlined in Appendix A.

In the presence of negative prices, some transformations had to be made to the respective price series to remove negative prices before we were able to apply (10) to convert the data to returns. Two particular scenarios were adopted. The first scenario involved setting any values which were negative or zero to the previous non-negative value. This was implemented by the following decision rule:

$$\mathit{if}\ y(t) = \begin{cases} \leq 0, & x(t) = y(t-1) \\ \mathit{else}, & x(t) = y(t) \end{cases}, \qquad (11)$$

where $y(t)$ is the source time series data and $x(t)$ is the transformed data series.

6. The half hourly load and spot price data were sourced from files located at the following web addresses: http://www.nemmco.com.au/data/aggPD_1998to1999.htm#aggprice1998link, http://www.nemmco.com.au/data/aggPD_2000to2005.htm#aggprice2000link, and http://www.nemmco.com.au/data/aggPD_2006to2010.htm#aggprice2006link.

The second method involved applying a linear interpolation routine to the transformed series $x(t)$ obtained from the application of (11). This was implemented using the following decision rule:

$$
\text{if } y(t) = \begin{cases} \leq 0, \; z(t) = \left\{ \dfrac{[x(t-1) + x(t+1)]}{2} \right\} \\ \text{else}, \qquad z(t) = x(t) \; [= y(t)] \end{cases}, \tag{12}
$$

where $z(t)$ is the new transformed data.

Under both schemes, if $y(t) > 0$, both $x(t)$ and $z(t)$ inherit the original value corresponding to $y(t)$. However, if $y(t) \leq 0$, then $x(t)$ inherits the previous value $y(t-1)$ while $z(t)$ inherits the mid-point value between the positive (by construction) values $x(t-1)$ and $x(t+1)$. In the present situation, the $x(t-1)$ and $x(t+1)$ values correspond to the original values $y(t-1)$ and $y(t+1)$ subsequently producing a value for $z(t)$ that is the average of the two source data points $y(t-1)$ and $y(t+1)$ - that is, a linearly interpolated point between the two source series data points.

The results of applying these transformations in the case of the negative prices can be discerned from inspection of Appendix A. For example, compare the last three columns in Appendix A, which list the results from applying (11) and (12) respectively together with the original negative price values. In the results presented in the next section, we adopt the transformation associated with the linear interpolation scheme outlined in (12).

6. IS RMP PRESENT IN NEM PRICE AND LOAD DATA?

Here, we do not pre-whiten the half hourly electricity demand and spot price data, as is done in, for example, Hinich, Czamanski, Dormaar, and Serletis (2007). The pre-whitening operation is designed to make the data have a flat spectrum. Furthermore, because the AR operation is a linear transformation, it cannot create coherence. However, an improperly applied de-trending method can potentially reduce signal coherence. Thus, to avoid this possibility, we apply the RMP tests to the data produced from (12) which is analysed for the presence of a randomly modulated periodicity with a fundamental period of one week (or equivalently 336 half hours).

Recall from Section (2) that one ‘stylised fact’ is that the load curve has a weekly and daily cycle. However, our interest is in the stability of this waveform – that is, the extent to which the cycles in the demand are ‘wobbly’. In the case of the spot electricity price time series, we would not expect to see as well-defined weekly or daily cycles when compared to the load data. Instead, the time path of spot prices would be expected to exhibit many spikes, indicating higher volatility and stronger mean-reverting behaviour than commonly associated with the load data.

We applied signal coherence spectral analysis to the data, using the FORTRAN 95 Spectrum program developed by Hinich. The first key result is that, in all cases, the joint RMP test defined by (9) signified very strong rejection of the null hypothesis of no periodicity (i.e. of pure noise) at the 0.5% level of significance. In all cases, the associated p-value was 0.00000. These test results are available from the authors upon request.

The Power and SIGCOH spectrums of the load (demand) time series for NSW, QLD, VIC and SA are shown in Figures 1-4, respectively. In constructing these graphs, we adopted a floor of 0.0 for the power spectrum. As such, power spectrum values [i.e. decibels (dB)] less than zero are not plotted. This was done for convenience in order to promote clarity of view in relation to the horizontal axis. In fact, the incidence of negative power spectrum (dB) results are marginal in scope and certainly do not affect our conclusions.

In a similar way, a floor of 0.45 was adopted for the SIGCOH spectrum results. This particular decision was based on the observation made in Section 4 that a SIGCOH value of 0.45 corresponds to an AMS value of 0.5. While adopting the floor value of 0.45 for SIGCOH spectrum is subjective, we can interpret it as implying that cycles with AMS below 0.5 signify a level of random variation in waveform at a particular frequency that will render as questionable the 'predictability' of that component for forecasting purposes.

It is apparent from inspection of these figures that two broad conclusions can be made in relation to assessment of SIGCOH spectrum results. First, in all four cases, the weekly cycle has a high degree of coherence with the SIGCOH values being greater than 0.9 for NSW, VIC and QLD. In fact for these three particular states, the second harmonic (of 168 half hours) also has SIGCOH values greater than 0.9 and together represent the most coherent components for these particular data series. In the case of SA, however, the SIGCOH values for these two cycles are very significant in terms of their comparative magnitudes but are now less than 0.9 in magnitude – see Figure 4. This indicates that the weekly cycle has a marginally less well-defined periodic structure than is the case with the three other states – there is marginally more "wobble" in the weekly cycle in the case of SA when compared to NSW, QLD and VIC.

The other noticeable feature is that there appears to be mid and high frequency structure evident for all four states. There is evidence of SIGCOH values greater than 0.6 appearing at the mid and high frequency end of SIGCOH spectrum of all four states except possibly for NSW in the mid-band frequency range – see Figure 1. This type of structure was not evident, for example, in the study of the Alberta market cited in Hinich, Czamanski, Dormaar, and Serletis (2007).

To investigate this issue further, plots of conventional power spectra (log spectrum in decibels) for the load data are also documented in Figures 1-4 as well. It is apparent from inspection of the power spectrum results outlined in these figures that a well-defined harmonic structure appears in power spectra. Moreover, there is no evidence of a trend in the data – the power spectra do not exhibit the large spectral power at low frequencies commonly associated with data containing trends. The evident 'flatness' of the power spectra also indicates that pre-whitening operations were not needed in these cases. When combined with

Figure 1. Plot of Power and SIGCOH Spectra for NSW NEM Half Hourly Load Data

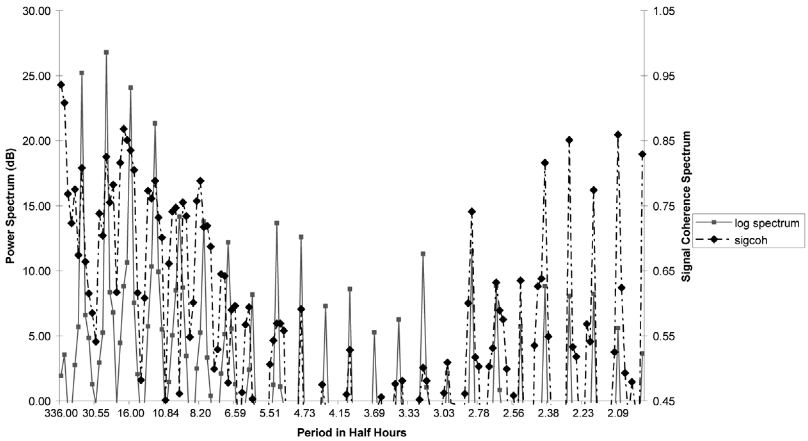
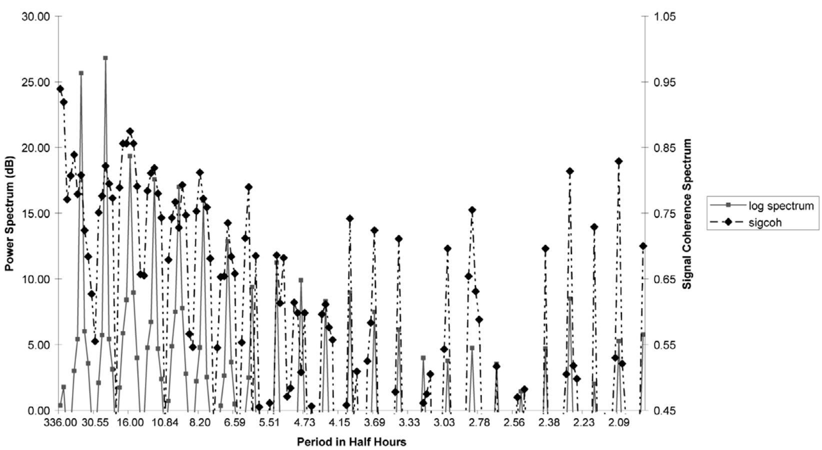


Figure 2. Plot of Power and SIGCOH Spectra for QLD NEM Half Hourly Load Data



the signal coherence results, these results give some indication that at least some of the shorter period components could be expected to meaningfully contribute to the forecasting of load demand.

Finally, evidence of the possible role that short period components might play in forecasting load demand can also be discerned from inspections of the periodograms of the state load time series data that are displayed in Figure 5. The periodogram of the data series can be calculated as the squared modulus (or

Figure 3. Plot of Power and SIGCOH Spectra for VIC NEM Half Hourly Load Data

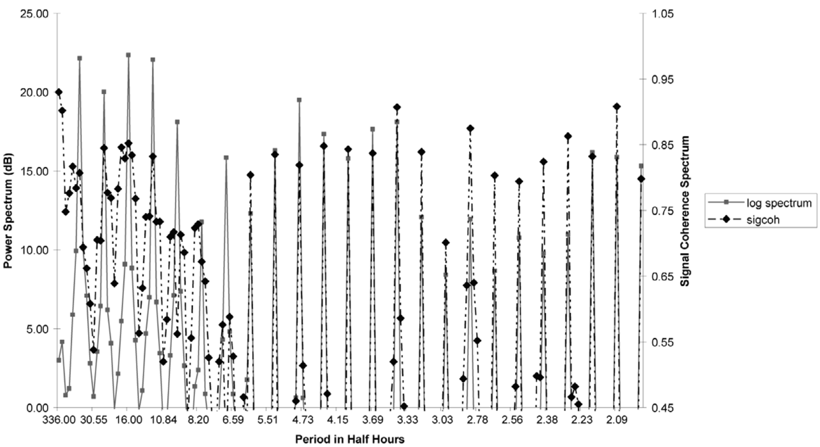
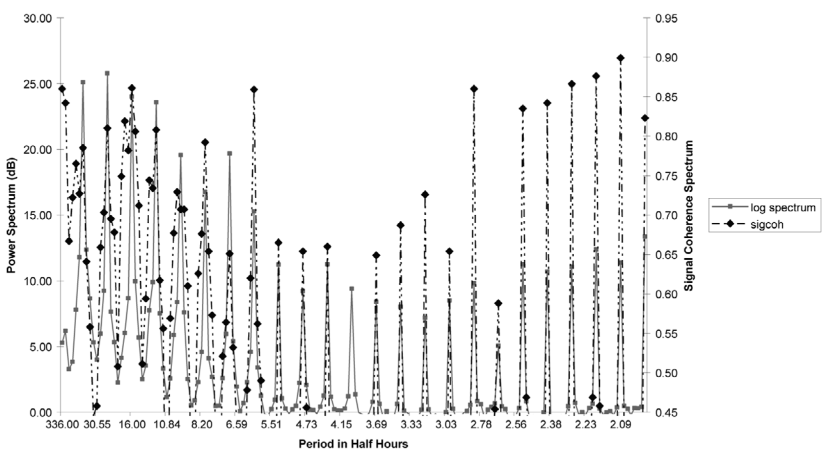


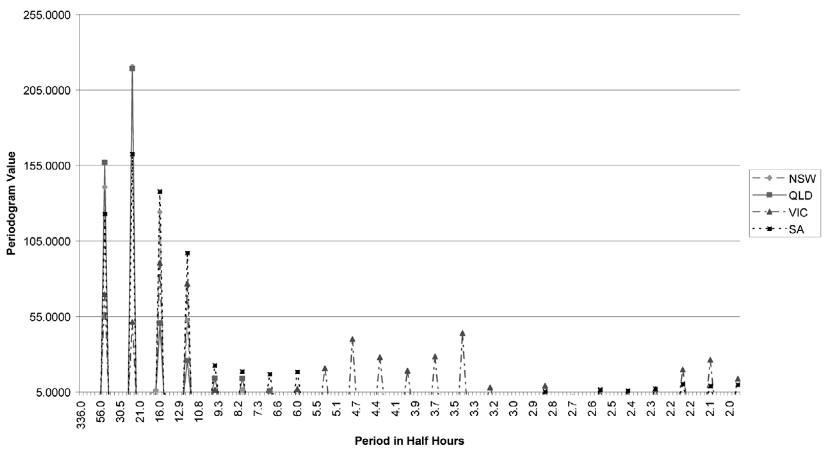
Figure 4. Plot of Power and SIGCOH Spectra for SA NEM Half Hourly Load Data



square of the absolute value) of the Discrete Fourier Transform (DFT) for each Fourier frequency of the mean frame divided by the number of sample points. In constructing Figure 5, we once again impose a floor of 5 on the periodogram values. As such, only periodogram values greater than or equal to 5 are plotted.

It is apparent from inspection of Figure 5 that, in the cases of NSW, QLD and SA, there does not appear to be much (if any) periodic structure at either mid or high frequency bands for the range established by the above-mentioned floor.

Figure 5. Plot of the Periodograms of State NEM Half Hourly Load Demand Data



This contrasts with the case of VIC where there appears to be more pronounced periodic structure associated with the mid frequency band and, to a lesser extent, the high frequency band. Thus, when compared with the SIGCOH and power spectra evidence cited above, the periodogram evidence raises some question over how much the shorter period components might be expected to contribute to the forecasting of load in at least three of the states considered – notably, NSW, QLD and SA.

The Power and SIGCOH spectrums of the spot price time series data for NSW, QLD, VIC and SA are documented in Figures 6-9, respectively. We again adopt the same "floor" values for both the power and SIGCOH spectra that were outlined above in relation to Figures 1-4.

It is apparent from inspection of these figures that a number of broad conclusions can be made in relation to SIGCOH spectrum results. First, in all four cases, the weekly cycle once again has a significant degree of coherence. However, the SIGCOH values are of a smaller order of magnitude than was the case with the load data with values being typically between 0.65 and 0.75 in magnitude. This indicates that there is more "wobble" in the spot price weekly waveform pattern than was the case for the load data. Furthermore, the low frequency band tends to have greater overall coherence than the mid and high frequency bands of the Signal Coherence spectra. Second, as was the case with the load data, there appears to be mid and high frequency structure in SIGCOH of spot price data for all four states. In particular, there is evidence of SIGCOH values greater than 0.6 appearing at the mid and high frequency end of SICGOH spectrum of all four states although the results for SA are clearly of a smaller order of magnitude and density (see Figure 9) when compared with the other states of NSW, QLD and VIC.

Figure 6. Plot of Power and SIGCOH Spectra for NSW NEM Half Hourly Spot Price Data

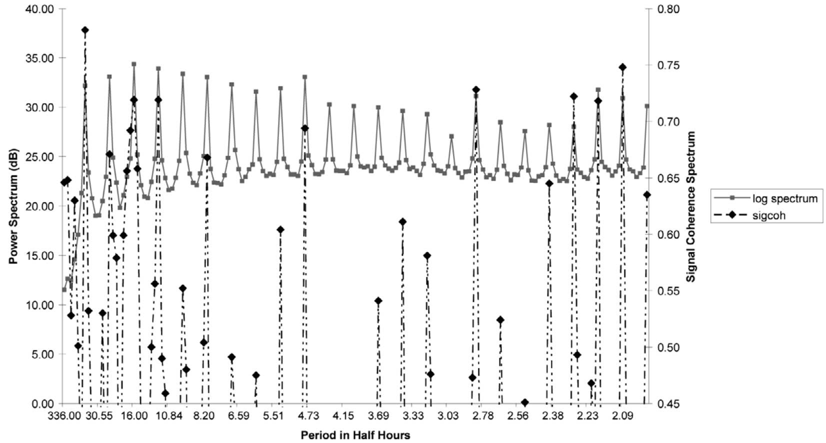
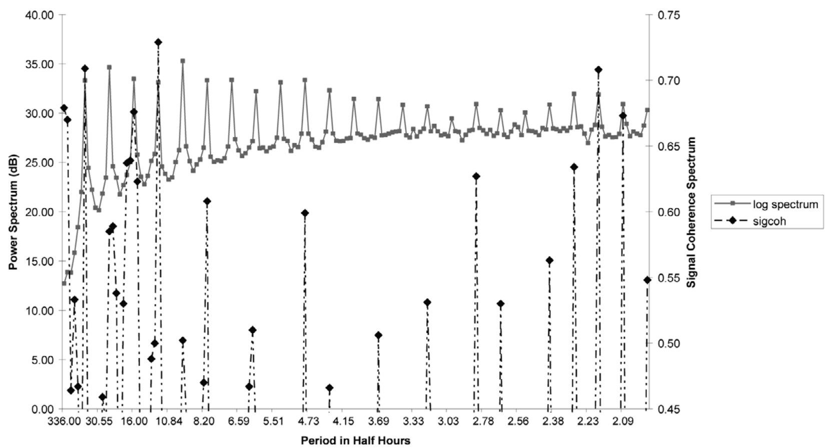


Figure 7. Plot of Power and SIGCOH Spectra for QLD NEM Half Hourly Spot Price Data



Plots of conventional power spectra (in decibels) of the spot price data are also documented in Figures 6-9. It is apparent from inspection of the power spectrum results in these figures that a well-defined harmonic structure is, once again, evident. Furthermore, the power spectra results for all four states are quite flat, indicating that no trend is present in the data and no pre-whitening operation is necessary. When these results are combined with the SIGCOH results, we have some indication that some of the shorter period components could reasonably be

Figure 8. Plot of Power and SIGCOH Spectra for VIC NEM Half Hourly Spot Price Data

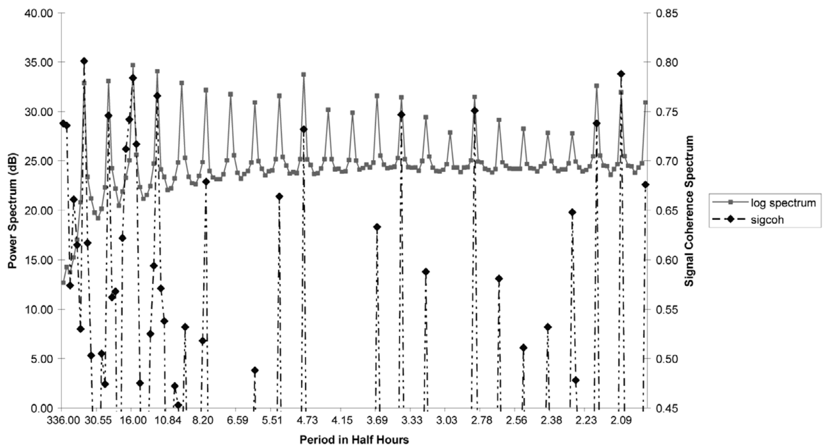
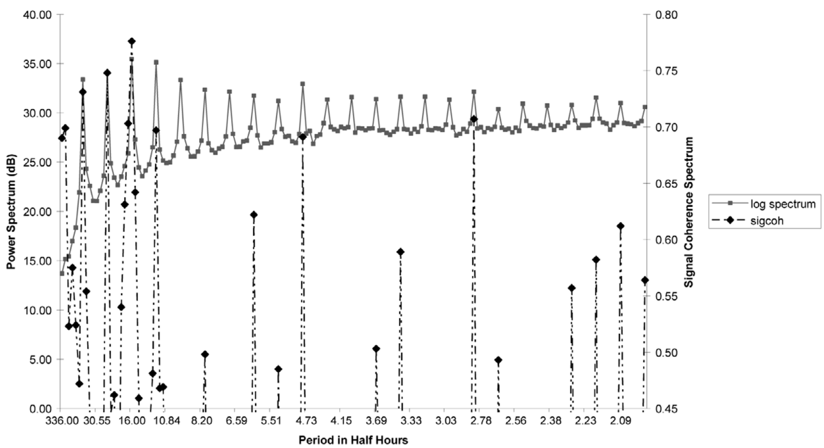


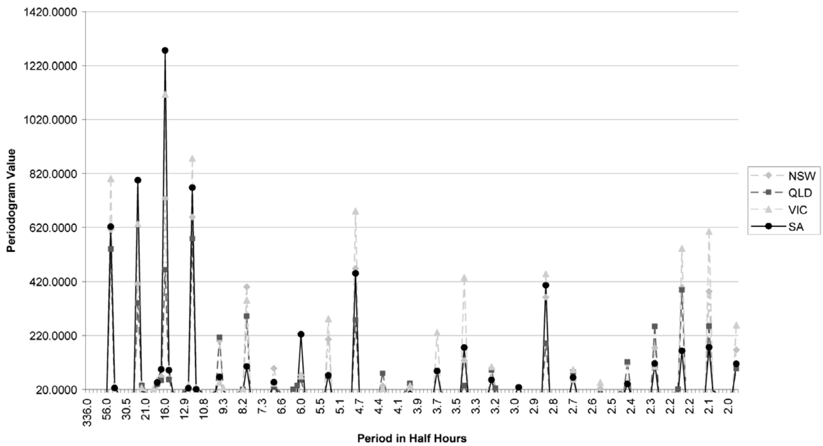
Figure 9. Plot of Power and SIGCOH Spectra for SA NEM Half Hourly Spot Price Data



expected to contribute to the forecasting of spot price movements, even though the structure is less stable than was the case for the load demand data.

Additional evidence for the possible role that short period components might play in forecasting spot prices is discernable from inspections of the periodograms of the State spot price data that are displayed in Figure 10. In constructing Figure 10, we imposed a floor of 20 on the periodograms. As such, only periodogram values greater than or equal to 20 are actually plotted. It is apparent from

Figure 10. Plot of the Periodograms of State NEM Half Hourly Spot Price Data



inspection of Figure 10 that in the cases of NSW, QLD and VIC there appears to be some periodic structure at mid and particularly high frequency bands. Assessment of results associated with SA indicates that the short period structure is of a slightly lower order of magnitude when compared with the other three states. In general, for all four states, this apparent high frequency periodicity could be interpreted as reflecting the greater degree of volatility in the spot price series when compared with the load data.

Therefore, the evidence indicates that some of the shorter period components might be expected to contribute to the forecasting of spot prices in all four states. The more marked high frequency periodicity associated with the spot price data would most likely reflect both the marked volatility and mean reversion properties of this data when compared to the load data. This is particularly apparent for the states of NSW, QLD and VIC. However, the SIGCOH values associated with the spot price data are generally of a smaller order of magnitude when compared with corresponding values from the load data. This provides support for the proposition that the weekly and daily cycles in the spot price data are not as well defined or as stable as the cyclical structure associated with the load data.

We also conducted a sensitivity analysis in order to ascertain whether the apparent upward meanshift in spot prices in all NEM markets occurring after January 2007 had any noticeable effect on the results cited above. This was accomplished by calculating the spectral results mentioned above for the sample ending at 31 January 2007 and comparing those results with the results obtained when the sample was extended until the end of August 2007. This latter sample contains the meanshift in spot prices that arose after January 2007 that was associated with capacity constraints attributable to drought induced water restrictions on hydro generation and, more importantly, base-load coal fired plant closures in Queensland.

Comparative assessment of the results for the two separate samples indicates that the qualitative conclusions cited above have not changed in any appreciable way – overlaying graphs of the spectral results for both sets of samples that support this conclusion are available from the authors upon request.

A major implication arising from the above conclusions is that the mean properties of both the load and spot price data for all states considered are periodic. While this conclusion would be reasonably expected for the load data, the strength of the mean periodicity in the spot price data is particularly noticeable and will have implications for modelling spot price dynamics. Specifically, spot price dynamics are typically modelled using GARCH or jump diffusion models. However, the mean components of both GARCH and stochastic jump diffusion processes are not periodic (see Ball and Torous (1983, 1985), Higgs and Worthington 2005, Worthington, Kay-Spratley and Higgs 2005 and Lin and Lin 2007). However, the above results indicate that a (periodic) mean plus volatility model for spot prices forecasting could have advantages over existing approaches and would seem to warrant further research.

The nature of the periodicities outlined above also pose problems for estimation using conventional time series methods outlined in (Lim and Hinich 2002, 1-2), for example. The plots of periodiograms and power spectra for all data series do not contain the power (spikes) at low frequency or harmonic frequencies we would associate with 'seasonal' unit root processes.

Second, the significant but imperfect signal coherence outlined in the SIGCOH plots of the data series indicate that some wobble exists at these components which would pose problems for estimation and forecasting based upon conventional season-dependent parameter methods (Lim and Hinich 2002, 2). If the periodic components were estimated by a least squares fit of Fourier frequencies sines and cosines the modulations would be included in the residuals. The modulations are random effect in the amplitudes and thus conventional linear methods cannot capture the variation in the complex amplitude of the waveform structure of the mean periodicities. The nature of the periodicity would seem to require alternative estimation and forecasting methodologies. The authors have devised a new statistical methodology for parametric estimation and forecasting of RMP processes based on heterodyning that will allow us to model the imperfectly coherent part of the mean periodicity.

Finally, it is evident from inspection of the Figures mentioned above that some differences arise from state to state. This is particularly the case for the mid-frequency components of the load data (see Figures 3 and 5) and spot price data (to a less degree - see Figures 8 and 10) associated with Victoria when compared with the other states. The results cited above can be viewed as defining a set of empirical characteristics derived from load and spot price data published by NEMMCO for each respective state that can be exploited when constructing forecasts for each respective state. The univariate analysis employed in the article, however, does not (and cannot) convey any precise information about what factors are generating particularly the differences observed for Victoria. Given that the load profiles are linked to demand forecasts from demand side participants operating in the Victorian market, it could represent differences in forecast methodologies used in forecasting load profiles that are subsequently passed to NEMMCO. However, whatever the cause, the lack of precise knowledge about this does not preclude the use and exploitation of 'RMP' information embedded in the data in a univariate forecasting context.

7. CONCLUSIONS

We have applied signal coherence spectral analysis to the time series of half hourly spot prices and megawatt-hours (MWh) load demand for the principal states of NSW, QLD, VIC and SA, which make up the NEM in Australia.

We found that electricity load demand has a significant amount of high coherence, with both the weekly and daily cycles being stable. The mean values at each half hour of the daily demand yield reasonably good forecasts for the next week provided there is no unusual event such as extreme weather conditions.

On the other hand, electricity prices had a lower overall order of coherence in the weekly and daily cycles reflecting a less stable relationship. This means, in turn, that forecast errors will tend to have a higher error variance.

The other noticeable feature is that there was evidence of mid and high frequency (short period) structure for both the load and, more especially, the spot price data. In the latter case, this was interpreted as reflecting the greater volatility and tendency for mean-reversion associated with the spot price data when compared to the load data. This result can be contrast with the nature of the conclusions made in Hinich, Czamanski, Dormaar, and Serletis (2007) in relation to the Alberta electricity market.

A major implication arising from the results is that the mean properties of the spot price data were determined to be periodic. Typically, spot price dynamics are modelled using GARCH or stochastic jump diffusion models. However, the mean components of both GARCH and stochastic jump diffusion processes are not periodic. This would suggests that a (periodic) mean plus volatility model for spot prices forecasting could have advantages over existing approaches and warrant further research.

Furthermore, the nature of the waveform structure associated with RMP periodicities pose particular problems for forecasting and new estimation and forecasting methodologies would seem to be required. This is also an area warranting further research although methods based on 'heterodyning' seem promising.

In this article, we have adopted a univariate time series approach when analysing NEM electricity spot prices and load data. However, from both an economic and statistical forecasting perspective, particular interest is in developing multivariate models capable of explaining and linking spot prices movements and load demand to other covariates such as primary inputs, industrial and other economic activity and weather patterns. Therefore, there is much to be gained in generalizing and developing the statistical technology for forecasting electricity demand, as advocated in Hinich, Czamanski, Dormaar, and Serletis (2007). Within the context of generalizing the RMP approach used in this article, the theory and methods outlined in Li and Hinich (2002), in particular, warrants further research.

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APPENDIX A. INCIDENCE OF NEGATIVE SPOT ELECTRICITY PRICES

QUEENSLAND

T			(A)	(B)	(C)
26546	13/06/2000	5:00	18.5400009	18.5400009	18.5400009
26547	13/06/2000	5:30	18.5400009	18.2700005	-2.91000009
26548	13/06/2000	6:00	18.0000000	18.0000000	18.0000000
27507	3/07/2000	5:30	17.7099991	17.7099991	17.7099991
27508	3/07/2000	6:00	17.7099991	17.8449993	-4.28000021
27509	3/07/2000	6:30	17.9799995	17.9799995	17.9799995
33114	28/10/2000	2:30	16.3600006	16.3600006	16.3600006
33115	28/10/2000	3:00	16.3600006	16.3349991	-84.3899994
33116	28/10/2000	3:30	16.3099995	16.3099995	16.3099995
37136	20/01/2001	1:00	13.6400003	13.6400003	13.6400003
37137	20/01/2001	1:30	13.6400003	16.0799999	-20.8099995
37138	20/01/2001	2:00	18.5200005	18.5200005	18.5200005
75253	25/03/2003	5:30	15.2299995	15.2299995	15.2299995
75254	25/03/2003	6:00	15.2299995	13.7700005	-156.139999
75255	25/03/2003	6:30	12.3100004	12.3100004	12.3100004
97203	24/06/2004	12:30	19.7000008	19.7000008	19.7000008
97204	24/06/2004	13:00	19.7000008	19.7000008	-150.460007
97205	24/06/2004	13:30	19.7000008	19.7000008	19.7000008
113717	3/06/2005	13:30	16.0100002	16.0100002	16.0100002
113718	3/06/2005	14:00	16.0100002	15.7550001	-153.100006
113719	3/06/2005	14:30	15.5000000	15.5000000	15.5000000
116456	30/07/2005	15:00	13.5400000	13.5400000	13.5400000
116457	30/07/2005	15:30	13.5400000	12.8000002	-3.47000003
116458	30/07/2005	16:00	12.0600004	12.0600004	12.0600004

121399	10/11/2005	14:30	32.6300011	32.6300011	32.6300011
121400	10/11/2005	15:00	32.6300011	25.6450005	-145.279999
121401	10/11/2005	15:30	18.6599998	18.6599998	18.6599998
127724	22/03/2006	9:00	21.4899998	21.4899998	21.4899998
127725	22/03/2006	9:30	21.4899998	17.1199989	-326.700012
127726	22/03/2006	10:00	12.7500000	12.7500000	12.7500000
128476	7/04/2006	1:00	14.1899996	14.1899996	14.1899996
128477	7/04/2006	1:30	14.1899996	13.4849997	-155.850006
128478	7/04/2006	2:00	12.7799997	12.7799997	12.7799997
128524	8/04/2006	1:00	12.7799997	12.7799997	12.7799997
128525	8/04/2006	1:30	12.7799997	11.4099998	-155.919998
128526	8/04/2006	2:00	10.0400000	10.0400000	10.0400000
131848	16/06/2006	7:00	18.7600002	18.7600002	18.7600002
131849	16/06/2006	7:30	18.7600002	18.7150002	-148.649994
131850	16/06/2006	8:00	18.6700001	18.6700001	18.6700001
143397	11/02/2007	21:30	15.7700005	15.7700005	15.7700005
143398	11/02/2007	22:00	15.7700005	16.1100006	-156.929993
143399	11/02/2007	22:30	16.4500008	16.4500008	16.4500008
147598	10/05/2007	10:00	67.0599976	67.0599976	67.0599976
147599	10/05/2007	10:30	67.0599976	66.5449982	-286.779999
147600	10/05/2007	11:00	66.0299988	66.0299988	66.0299988

VICTORIA

T			(A)	(B)	(C)
23722	15/04/2000	8:00	15.6300001	15.6300001	15.6300001
23723	15/04/2000	8:30	15.6300001	13.1399994	-161.669998
23724	15/04/2000	9:00	10.6499996	10.6499996	10.6499996
32832	22/10/2000	5:30	5.82999992	5.82999992	5.82999992
32833	22/10/2000	6:00	5.82999992	6.60500002	-305.779999
32834	22/10/2000	6:30	7.38000011	7.38000011	7.38000011
53842	3/01/2002	4:00	11.4099998	11.4099998	11.4099998
53843	3/01/2002	4:30	11.4099998	11.4150000	-155.940002
53844	3/01/2002	5:00	11.4200001	11.4200001	11.4200001
68435	3/11/2002	4:30	7.07999992	7.07999992	7.07999992
68436	3/11/2002	5:00	7.07999992	4.05499983	-228.009995
68437	3/11/2002	5:30	1.02999997	1.02999997	1.02999997
68782	10/11/2002	10:00	10.3800001	10.3800001	10.3800001
68783	10/11/2002	10:30	10.3800001	13.3549995	-5.09999990
68784	10/11/2002	11:00	16.3299999	16.3299999	16.3299999
97334	27/06/2004	6:00	10.9399996	10.9399996	10.9399996
97335	27/06/2004	6:30	10.9399996	7.63499975	-163.020004
97336	27/06/2004	7:00	4.32999992	4.32999992	4.32999992
97861	8/07/2004	5:30	16.5100002	16.5100002	16.5100002
97862	8/07/2004	6:00	16.5100002	20.3950005	-329.910004
97863	8/07/2004	6:30	24.2800007	24.2800007	24.2800007

103353	30/10/2004	15:30	16.7999992	16.7999992	16.7999992
103354	30/10/2004	16:00	16.7999992	15.9449997	-153.610001
103355	30/10/2004	16:30	15.0900002	15.0900002	15.0900002
103395	31/10/2004	12:30	16.9300003	16.9300003	16.9300003
103396	31/10/2004	13:00	16.9300003	17.9599991	-153.000000
103397	31/10/2004	13:30	18.9899998	18.9899998	18.9899998
117405	19/08/2005	9:30	34.9399986	34.9399986	34.9399986
117406	19/08/2005	10:00	34.9399986	31.4599991	-142.020004
117407	19/08/2005	10:30	27.9799995	27.9799995	27.9799995
142812	30/01/2007	17:00	66.4400024	66.4400024	66.4400024
142813	30/01/2007	17:30	66.4400024	52.2550011	-104.300003
142814	30/01/2007	18:00	38.0699997	38.0699997	38.0699997
142997	3/02/2007	13:30	60.1599998	60.1599998	60.1599998
142998	3/02/2007	14:00	60.1599998	61.3250008	-0.85000002
142999	3/02/2007	14:30	62.4900017	62.4900017	62.4900017
143669	17/02/2007	13:30	72.5699997	72.5699997	72.5699997
143670	17/02/2007	14:00	72.5699997	90.8349991	-83.5299988
143671	17/02/2007	14:30	109.099998	109.099998	109.099998
144191	28/02/2007	10:30	60.4700012	60.4700012	60.4700012
144192	28/02/2007	11:00	60.4700012	62.4550018	-6.34999990
144193	28/02/2007	11:30	64.4400024	64.4400024	64.4400024
149963	28/06/2007	16:30	174.240005	174.240005	174.240005
149964	28/06/2007	17:00	174.240005	249.470001	-36.2599983
149965	28/06/2007	17:30	324.700012	324.700012	324.700012
149968	28/06/2007	19:00	1561.13000	1561.13000	1561.13000
149969	28/06/2007	19:30	1561.13000	912.505005	-12.7500000
149970	28/06/2007	20:00	263.880005	263.880005	263.880005

SOUTH AUSTRALIA

T			(A)	(B)	(C)
68435	3/11/2002	4:30	7.71999979	7.71999979	7.71999979
68436	3/11/2002	5:00	7.71999979	4.42000008	-246.570007
68437	3/11/2002	5:30	1.12000000	1.12000000	1.12000000
70229	10/12/2002	13:30	21.6800003	21.6800003	21.6800003
70230	10/12/2002	14:00	21.6800003	20.5650005	-6.03000021
70231	10/12/2002	14:30	19.4500008	19.4500008	19.4500008
70331	12/12/2002	16:30	15.4300003	15.4300003	15.4300003
70332	12/12/2002	17:00	15.4300003	18.1149998	-9.98999977
70333	12/12/2002	17:30	20.7999992	20.7999992	20.7999992
71767	11/01/2003	14:30	27.2999992	27.2999992	27.2999992
71768	11/01/2003	15:00	27.2999992	29.1399994	-61.9500008
71769	11/01/2003	15:30	30.9799995	30.9799995	30.9799995
92017	8/03/2004	11:30	26.1800003	26.1800003	26.1800003
92018	8/03/2004	12:00	26.1800003	4096.42480	-822.450012
92019	8/03/2004	12:30	8166.66992	8166.66992	8166.66992

136414	19/09/2006	10:00	32.6899986	32.6899986	32.6899986
136415	19/09/2006	10:30	32.6899986	35.0900002	-160.369995
136416	19/09/2006	11:00	37.4900017	37.4900017	37.4900017
142501	24/01/2007	5:30	35.2299995	35.2299995	35.2299995
142502	24/01/2007	6:00	35.2299995	33.9899979	-476.859985
142503	24/01/2007	6:30	32.7500000	32.7500000	32.7500000
144191	28/02/2007	10:30	62.8800011	62.8800011	62.8800011
144192	28/02/2007	11:00	62.8800011	64.9499969	-133.110001
144193	28/02/2007	11:30	67.0199966	67.0199966	67.0199966
147486	8/05/2007	2:00	24.2600002	24.2600002	24.2600002
147487	8/05/2007	2:30	24.2600002	17.1499996	-4.00000000
147488	8/05/2007	3:00	10.0400000	10.0400000	10.0400000
149221	13/06/2007	5:30	35.2700005	35.2700005	35.2700005
149222	13/06/2007	6:00	35.2700005	21.3800011	-32.8400002
149223	13/06/2007	6:30	7.48999977	7.48999977	7.48999977
149656	22/06/2007	7:00	112.750000	112.750000	112.750000
149657	22/06/2007	7:30	112.750000	197.369995	-35.2299995
149658	22/06/2007	8:00	281.989990	281.989990	281.989990
149917	27/06/2007	17:30	104.120003	104.120003	104.120003
149918	27/06/2007	18:00	104.120003	349.799988	-119.040001
149919	27/06/2007	18:30	595.479980	595.479980	595.479980
149963	28/06/2007	16:30	96.6299973	96.6299973	96.6299973
149964	28/06/2007	17:00	96.6299973	84.0350037	-93.3199997
149965	28/06/2007	17:30	71.4400024	71.4400024	71.4400024
149968	28/06/2007	19:00	328.890015	328.890015	328.890015
149969	28/06/2007	19:30	328.890015	275.345001	-6.48000002
149970	28/06/2007	20:00	221.800003	221.800003	221.800003
151957	9/08/2007	5:30	8.26000023	8.26000023	8.26000023
151958	9/08/2007	6:00	8.26000023	8.26000023	-3.23000002
151959	9/08/2007	6:30	8.26000023	19.0400009	-888.780029
151960	9/08/2007	7:00	29.8199997	29.8199997	29.8199997

Legend:
(A) Set to previous positive value: Equation (11)
(B) Interpolated Scenario: Equation (12)
(C) Actual (Source) Data
T – Time index – i.e. 26546 observation or data point.

Notes: (1) The last entry for Victoria and the fifth entry for South Australia produces significant differences between the two methods adopted to remedy negative prices incidence.