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Application of Autoregressive Integrated Moving Average Modelling for the Forecasting of Solar, Wind, Spot and Options Electricity Prices: The Australian National Electricity Market

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ABSTRACT

This study aims to develop autoregressive integrated moving average (ARIMA) models to predict the solar, wind, spot and options pricing over the next 2 years, with historical data being used in a univariate manner to understand market behaviour in terms of trends. The assessment is made in the context of the Australian National Electricity Market (ANEM). The ARIMA models predict the future values of the monthly solar, wind, spot and options prices for various Australian states using time-series data from January 2006 to March 2018. The results show increases from 30.46% to 40.42% for the spot electricity prices and from 14.80% to 15.13% for the options electricity prices in the ANEM with a 2-year horizon. The results further show that wind prices are expected to increase by an average of 5.43%. However, the results also show that the average solar electricity prices will decrease by 67.7%.

Keywords: Electricity Pricing, Autoregressive Integrated Moving Average Model, Forecasting
JEL Classifications: C22, E37, Q47

1. INTRODUCTION

The majority of countries worldwide are currently experiencing energy shortages, which are severely negatively affecting both their economic growth and their level of social transformation. For example, when compared to other countries, Australia has traditionally enjoyed some of the cheapest wholesale and household energy costs. However, between 2003 and 2013, the price of household electricity in Australia increased by 72% (Australian Energy Council, 2017). In fact, the past 12-18 months have been some of the most challenging faced by Australia's energy sector since the establishment of the Australian National Electricity Market (ANEM) in 1998. The most significant impact of this challenging market situation has been felt in the country's wholesale electricity markets. Investor uncertainty with regard to the viability of investments in new means of power generation, as well as recent coal plant closures, have contributed to a power generation mix that is increasingly reliant on intermittent wind and solar energy (Coenen et al., 2018). This has, in turn, led to an increase in both electricity production and electricity pricing.

The modelling and subsequent forecasting of electricity prices are important and necessary in relation to the management of power companies, as well as for all the physical and financial participants in the electricity sector. Indeed, Akay (2015) has identified a number of reasons why modelling and forecasting are vital:

a) The bidding for generators takes place in advance. Hence, it is crucial to accurately predict prices so that optimal bidding strategies can be developed and implemented (O'Neill et al., 2017).

b) Advanced planning is required on the part of generators with respect to capacity generation (i.e., peak and off-peak generators have different input needs for production). Therefore, when the price is efficiently forecasted, more accurate planning can take place in relation to supplies (Kaytez et al., 2015).
c) The accurate prediction of the spot prices is critical for derivatives pricing, since it is important for traders to adopt positions on over-the-counter and well-developed futures trading platforms (e.g., the Australian Securities Exchange [ASX]) (Huang et al., 2015).
d) The distribution of electricity is a publicly controlled monopoly. Hence, various government reforms and regulations must be adhered to by all stakeholders (Okoro and Chikuni, 2017).

Various models and techniques have been used in relation to power systems' operation and planning, including recent developments such as independence components, principal components and neural networks (Dai and Wang, 2007; Lasheras et al., 2015), fuzzy logic (Çevik and Çunkaş, 2015; Yang et al., 2006) and the hybrid method (Zhang et al., 2010). The use of the time-series method can also be seen in many prior studies (Çevik and Çunkaş, 2015; Cho et al., 1995). However, among these different techniques, the most widely used is the time-series method, which is also capable of accommodating the absence of stationarities, seasonal patterns and signals (Bin Majid et al., 2012).

The aim of the present study is to develop autoregressive integrated moving average (ARIMA) models for predicting the solar, wind, spot and options pricing in the ANEM over the next 2 years, with historical data being used in a univariate manner to understand the electricity markets' behaviour in terms of trends. To the best of the author's knowledge, only a few prior studies have examined solar, wind, spot and options pricing either individually or in concert, while none have individually analysed the associated time-series data in order to identify trends. In the present study, this will be achieved using ARIMA models. It is important to note that the ANEM includes the electricity markets of the Australian states of New South Wales (NSW), Queensland (QLD), South Australia (SA), Victoria (VIC), and Tasmania (TAS).

The remainder of this paper is organized as follows. Section 2 presents a review of the literature concerning the use of ARIMA models in research regarding electricity. Section 3 describes the data source, while Section 4 outlines the methodology employed in the study. Section 5 presents the empirical results, while Section 6 discusses the research findings and offers a conclusion to the study.

2. LITERATURE REVIEW

According to Rafał Weron (2014), the electricity price forecasting literature can be divided into five categories: (1) Multi-agent or game theory models simulating the operation of market agents, (2) fundamental methods employing physical and economic factors, (3) reduced-form models using the statistical properties of electricity trades for risk management and derivatives evaluation, (4) statistical models comprising time series and econometric models, and (5) artificial intelligence methods. All these different statistical approaches aim to identify the optimal model for forecasting electricity prices (Cartea and Figueroa, 2005; Shahidehpour et al., 2002; Weron, 2007). Further, they involve either direct applications of statistical techniques for load forecasting or power market implementations of econometric models.

The most popular methods in this regard include the autoregressive types of multivariate regressions, stochastic time-series models and smoothing techniques (Misiorek et al., 2006). While the efficiency and usefulness of these "technical analysis" tools in terms of the financial markets are often questioned, such methods do demonstrate a higher potential in relation to the power markets, since they are able to capture the nature of the above-mentioned features. For example, the seasonality and correlation aspects that prevail within electricity pricing processes during normal, non-spiky and other static periods. Such features render electricity prices more predictable than other types of "randomly" fluctuating financial assets.

Arguably, the most commonly applied statistical methods are ARIMA models (Cuaresma et al., 2004; Yang et al., 2017). Such models represent the standard modelling technique applied in time-series econometrics to understand the mean, autocorrelations and trends. Theoretically speaking, ARMA models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials: (i) One for the auto-regression, and (ii) the other for the moving average. The autoregressive (AR) element of the model shows that the evolving variable of interest is regressed on its own lagged value, while the moving average (MA) element shows that the regressive error is a linear combination of the lagged error terms. Adding the integrated (I) element into an ARMA model results in an ARIMA model. ARIMA models tend to be applied to cases in which the data show evidence of non-stationarity, that is, in which an initial differencing step (corresponding to the "integrated" element of the model) can be applied one or more times to eliminate the non-stationarity in the series often noted in relation to electricity market prices (Shumway and Stoffer, 2006).

Various applications of the AR process have been discussed in the prior literature, with such applications often considering hourly (daily, weekly, monthly, quarterly or yearly) data concerning electricity price series to be a distinct commodity. A number of AR specifications were used by Cuaresma et al. (2004), who incorporated time-varying intercepts and jumps so as to predict electricity prices in the German market. Their approach considered specifications in which every hour of the day was modelled distinctly and separately (Table 1 for further details). In their study, the AR and MA orders were comprised of lags of 1, 23, 24 and 25 h. This study by Cuaresma et al. (2004) demonstrated how some AR specifications that model every hour distinctly and separately can offer better predictive abilities when compared to other AR specifications. Further, they found that the inclusion of probabilistic processes with regard

Table 1: Prior literature concerning the modelling and forecasting of spot electricity prices

Study	Methodology/Technique	Sample/Market (s)	Results	Conclusion
Garcia-Martos et al. (2017)	ARIMA model using the AIC, SBC, RMSE and MPE	Germany	Applying daily data, this study developed a model to obtain accurate 1-day-ahead electricity forecasts for electricity prices.	This study concludes that an ARIMA-type model provides the best prediction of electricity prices.
Kaur and Ahuja (2017)	ARIMA	Apollo Hospital Ludhiana, India	This study identified the best fitted model for predicting the hospital's electricity consumption over a two-year period.	Applying different criteria, this study concludes that an ARIMA model with suitable criteria can be used to predict electricity consumption.
Voronin and Partanen (2014)	This study combines wavelet transforms, ARIMA models and neural networks	Finnish energy market, which is part of the Nordic Power Pool	The proposed model provides a significant improvement in terms of the price prediction accuracy.	This study concludes that ARIMA models are extremely important in relation to electricity demand and price forecasting.
Khashei and Bijari (2011)	ARIMA based on EEMD	China	EEMD can effectively enhance forecasting accuracy. Within this framework, the proposed EEMD-ARIMA model can significantly improve the ARIMA time-series approaches.	This study concludes that the proposed EEMD-ARIMA model should enhance the annual runoff time-series forecasting.
Weron and Misiorek (2007)	AR and TAR models with and without exogenous variables	Californian and Nordic Power Pool markets	In the basic AR models, only the system load was used as an exogenous variable for the Californian market, while the hourly air temperature was used for the Nordic Power Pool market.	This study concludes that models that use the system load as the exogenous variable usually exhibit better performance when compared to solely price-based models. However, this is not always the case when the air temperature is used as the exogenous variable.
Zhou et al. (2006)	ARIMA with error correction and confidence interval estimation	Hourly MCP forecasting for the Californian power market is used as a computer example	According to the computer test results, the extended ARIMA approach suggested for spot price forecasting is quite effective and, further, demonstrates satisfactory precision.	The study concludes that seasonal ARIMA models can be used in very bad market conditions in which the price volatility is quite high.
Cuaresma et al. (2004)	AR models, ARMA models and unobserved component models	Leipzig Power Exchange	According to the results, the specifications that modelled every hour of the data separately provided consistently better forecasting properties when compared to the specifications for the entire time series.	The study concludes that when simple probabilistic processes are considered for extreme price events, enhancements can be made in terms of the predictive capacity of univariate models for electricity spot prices.
Contreras et al. (2003)	ARIMA	Spanish and Californian electricity markets	Spanish market: Generally, more volatility is observed. The ARIMA model requires data from the past 5 h. Differentiation is not used to obtain a stable mean. Californian market: Price forecasts prior to the collapse are better. This may be because there was less volatility in the Californian market at that time. The ARIMA model requires data from the past 2 h, as well as three differentiations.	The study concludes that these distinctions may show varying bidding structures and ownership.

to the arrival of jumps provided a better fit to the empirical data, thereby allowing for an enhanced level of forecasting performance.

Threshold autoregressive (TAR) models with and without exogenous variables have also been used in prior studies. For example, Weron and Misiorek (2008) performed a comparison of the electricity pricing of 12 time-series models using the markets of California and the Nordic Power Pool. Their study highlighted the better model fits and enhanced performance of the models in which the system load was included as the exogenous variable. Therefore, it can be seen that the stylized features of electricity prices can be determined when the electricity prices are modelled using different types of AR processes. These stylized features include trend analyses that lead to some rapid mean reversions to the long-term mean levels as well as to occasional and, at times, successive jumps in prices.

A significant number of the ARIMA models discussed in the prior literature have been used alongside other methods to predict electricity prices so as to gain a deeper insight into the spot pricing framework (Contreras et al., 2003; Garcia-Martos et al., 2017; Voronin and Partanen, 2014; Zhou et al., 2006). For example, Voronin and Partanen (2014) combined wavelet transforms, ARIMA models and neural networks to predict the electricity prices in the Finnish energy market, which is part of the Nordic Power Pool. Their study concluded that ARIMA models are extremely important in terms of modelling both the electricity demand and price forecasting.

Relatively recently, Garcia-Martos et al. (2017) used an ARIMA model to obtain accurate 1-day-ahead electricity forecasts for electricity prices. From their study, it is possible to observe the application of a number of criteria that are often used in modelling to understand the nature of model fits as well as the appropriateness of the forecasting performance. Indeed, their study applied criteria such as the Akaike information criterion (AIC), Schwarz Bayesian criterion, root mean square error (RMSE) and mean percentage error (MPE) during the analysis. These criteria proved to be somewhat critical in terms of choosing, for example, an appropriate forecasting period. In Garcia-Martos et al.'s (2017) study, the parameter was selected by considering the lowest values of both the RMSE and the MPE. They concluded that the ARIMA-type model provided better predictions when compared to the other available models of electricity prices.

Along similar lines, a number of studies have used ARIMA models to predict electricity consumption rather than to predict pricing levels (Kaur, 2017; Khashei and Bijari, 2011). For example, Kaur and Ahuja (2017) developed an ARIMA model to predict electricity consumption within a healthcare institution, as well as to identify the most suitable forecasting period in terms of monthly, bimonthly or quarterly time series. Their prediction model was developed for the electricity series of Apollo Hospital Ludhiana, India, for the period between April 2005 and February 2016. It was noted that the ARIMA model proved to be rather efficient, in addition to being more accurate and reliable than similar methods.

Khashei and Bijari (2011) applied ensemble empirical mode decomposition (EEMD) to model and predict electricity consumption. Their study concluded that EEMD can effectively enhance the accuracy of forecasts. The proposed EEMD-ARIMA model was, in fact, able to significantly improve upon the utilized ARIMA time-series approaches. The prior studies to have used various time-series approaches for the modelling and predicting of spot electricity prices are briefly introduced and explained in Table 1.

More specifically, Table 1 demonstrates that different time-series approaches are available for the modelling and forecasting of spot electricity prices. Indeed, the list of available approaches includes ARIMA models (Garcia-Martos et al., 2017; Voronin and Partanen, 2014), ARIMA and seasonal ARIMA models (Contreras et al., 2003; Zhou et al., 2006), AR models with exogenous fundamental variables (Garcıa-Martos et al., 2017), as well as AR and threshold autoregressive models (Weron and Misiorek, 2008).

Table 1 also shows that prior studies have used various applications of the AR processes (Cuaresma et al., 2004; Weron and Misiorek, 2008). The majority of the discussed autoregressive models were intended to explain the "stylized" features of electricity pricing, as well as to identify the best fit to the empirical data (Weron and Misiorek, 2008). It has previously been shown that the incorporation of probabilistic procedures for dealing with jumps is more appropriate for empirical data, since it leads to better forecasts (Cuaresma et al., 2004).

A further review of Table 1 reveals that ARIMA-type models provide better predictions of electricity pricing in terms of the univariate analysis of autocorrelations, smoothing and trends (Contreras et al., 2003; Garcia-Martos et al., 2017; Voronin and Partanen, 2014; Zhou et al., 2006). Moreover, a number of studies have applied similar techniques to predict electricity consumption levels in different cities and countries (Kaur and Ahuja, 2017; Khashei and Bijari, 2011).

The key point stressed in all the above-mentioned studies is that an ARIMA-type model represents one of the most commonly used models for studying both trends and smoothing, as well as for predicting electricity prices, although whether or not such a model could be used in relation to renewable price modelling, such as for the solar and wind markets, is yet to be determined. In fact, it appears that no prior studies have conducted longer-term forecasts or determined the accuracy of such forecasts. The present study, therefore, seeks to address this gap in the literature by investigating the modelling and prediction that can be applied with regard to the solar, wind, spot and options data series for each state included in the ANEM.

3. METHODOLOGY

The study conducted by Box and Jenkins (1978) ushered in a new generation of forecasting tools that are collectively known as the ARIMA methodology, which emphasizes the analysis of the probabilistic (or stochastic) properties of economic time series on their own, rather than the construction of single or simultaneous equation models. ARIMA models allow each variable to be explained by its own past (or lagged) values and stochastic error terms. A number of examples of this can be found in the literature (Contreras et al., 2003; Garcia-Martos et al., 2017; Voronin and Partanen, 2014; Zhou et al., 2006). In the present study, we used the ARIMA technique to individually examine and analyse the solar, wind, spot and options prices for each state included in the ANEM.

3.1. Autoregressive Model

An autoregressive model is one in which the equation represents the linear dependence of a value from its p past values, which can be written as AR (p) and defined as follows:

$$Y_t = c + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + \ldots + \varnothing_p Y_{t-p} + \varepsilon_t \quad (1)$$

Where Y_t is the response (dependent) variable at time t; C is a constant term; Y_{t-1}, Y_{t-2},…, Y_{t-p} are the response variables at time lags Y_{t-1}, Y_{t-2},…, Y_{t-p}, respectively; $\varnothing_1$, $\varnothing_2$,…, $\varnothing_p$ are the coefficients to be estimated; and ε_t is the random shock ~$N(0,\sigma^2)$.

3.2. Moving Average Model

A moving average model is one in which the equation represents the linear dependence of a value from its q past residuals, which can be written as MA (q) and defined as follows:

$$Y_t = c + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (2)$$

where Y_t is the response (dependent) variable at time t; C is a constant term; $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients to be estimated; $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ are the errors in the previous time periods that are incorporated into the response Y_t; and ε_t is the random shock $\sim N(0,\sigma^2)$.

3.3. Autoregressive Integrated Moving Average

The general form of the ARIMA model is presented in Equation (3). The order of an ARIMA model is typically identified in the form of (p, d, q), where p indicates the order of the autoregressive part, d the amount of the difference and q the order of the moving average part (Jiang et al., 2018; Kim et al., 2017; Lasheras et al., 2015).

$$Y_t = c + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + \ldots + \varnothing_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \qquad (3)$$

Where $\varnothing$ and θ are the maximum likelihood estimates of the respective models, while ε_t is the error series.

The ARIMA model involves a series transformation to a state of stationary covariance, followed by identification, approximation, diagnosis and prediction steps (Ediger and Akar, 2007; Sen et al., 2016). The ARIMA model can be described as follows:

Step 1: Individually check the stationarity of all the influencing factors' historical data, since the ARIMA model is only applicable in the case of stationary time series. A stationary time series has a constant mean and a constant variance. If the data are not stationary, a differencing operation is performed. If the data are still not stationary, differencing is repeatedly performed until the data are finally in stationary. The augmented Dickey–Fuller (ADF) test is used in this step. If the ADF t-statistic is lower than the Mackinnon critical value under a significance level of 5%, the series is supposed to be stationary.

Step 2: Estimate the number of autoregressive orders (p), the number of differencing orders (d) and the number of moving-average orders (q) involved in the development of a univariate ARIMA model (p, d, q). This is achieved through the examination of the autocorrelation plot (ACF) and the partial autocorrelation plot (PACF) of the time series of each individual variable. These plots offer an indication of the significant orders p and q to be used in the model setup. However, it is not accurate to estimate the p and q using only the ACF and PACF graphs. There are several criteria, such as the AIC and the Schwarz criterion (SC), which can be employed in a quantitative analysis to obtain specific values.

Step 3: Validate the ARIMA model obtained in Step 2 and test it on the residuals. If the residual term shows normal distribution behaviour with constant variance and zero mean, then it resembles a white-noise error and, therefore, there is no need for further ARIMA modelling. The cumulative periodogram white-noise test and the portmanteau test for white noise are examples of the null hypothesis that the data stem from a white-noise process of uncorrelated random variables with a constant mean and a constant variance.

Step 4: Predict future data for each electricity price.

4. DATA SOURCES

In the present study, the dataset consists of monthly observations, while the sample covers the period from January 2006 to March 2018. The variables included in the estimations are the spot, options, solar and wind electricity prices (as expressed in Australian dollars per megawatt [$/MW]) from five electricity markets in Australia, namely the NSW, QLD, SA, TAS and VIC markets (save for the options electricity price in the case of TAS). The choice of study period was constrained by the availability of time-series data concerning the solar and wind electricity prices.

The time-series data for the spot electricity prices were collected on a monthly basis from the Australian Energy Market Operator (AEMO). The AEMO collates and reports the average daily, monthly and annual observations for each price for the five market regions within the ANEM. The data concerning the options prices (closing prices) were collected from among the ASX Energy daily market data and then converted into monthly terms (January 2006 to March 2018). All the utilized data include only those options contracts with a non-zero trading volume.

The MAC Global Solar Energy Index and the ISE Global Wind Energy Index were used as the solar and wind electricity price proxy variables, respectively. Time-series data concerning the two indices were collected on a monthly basis from Bloomberg.

5. RESULTS

5.1. Data Preliminaries

Table 2 presents a summary of the descriptive statistics concerning the monthly spot, options, solar and wind electricity prices for the five investigated electricity markets. The means, medians, maximums, minimums, standard deviations, skewness, kurtosis, Jarque-Bera statistics and P values are reported in the Table 2.

Between January 2006 and March 2018, the mean and median electricity spot prices were found to be broadly consistent across NSW, QLD and VIC, where the base generation technologies are similar and where relatively low-cost fuels are used. SA exhibited the highest mean and median prices per megawatt hour at $59.75 and $48.57, respectively, which indicates that SA relies more heavily on higher-cost gas-turbine generators when compared to the low-cost coal-based generators relied on in NSW, QLD and VIC. All the markets were significantly positively skewed, ranging from 1.61 (VIC) to 3.03 (TAS), which indicates the greater likelihood of large price increases than of price falls. The kurtosis, or degree of excess, ranged from 5.47 for VIC to 14.99 for NSW, thereby indicating leptokurtic or heavy-tailed distributions with many extreme observations. As the Jarque-Bera results were

Table 2: Descriptive statistics for the spot, options, solar and wind electricity prices ($/MWh) from January 2006 and March 2018

Variable	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera	Probability
Spot electricity prices									
NSW	49.53	41.43	230.66	20.61	28.93	2.82	14.99	1076.77	0.00
QLD	52.00	43.08	239.59	17.64	34.53	2.48	11.47	590.83	0.00
VIC	47.29	40.46	143.28	16.52	25.43	1.61	5.47	101.78	0.00
SA	59.75	48.57	229.39	17.59	40.55	2.06	7.80	245.40	0.00
TAS	52.63	42.54	252.37	16.70	35.02	3.03	14.98	1106.07	0.00
Options electricity prices									
NSW	9.98	10.05	22.63	1.78	4.25	0.32	3.70	5.61	0.06
QLD	9.96	9.32	17.48	1.55	3.99	-0.29	2.61	3.05	0.21
VIC	10.81	11.01	24.33	1.73	4.46	0.22	3.63	3.75	0.15
SA	11.14	9.79	28.25	1.69	5.62	0.69	3.50	13.46	0.001
Solar and wind electricity prices									
Solar	352.01	218.03	1548.20	65.73	316.32	1.527	1.813	33.37	0.00
Wind	181.72	177.23	358.69	63.82	74.12	0.74	3.13	13.62	0.00

statistically significant, the analysis rejected the null hypothesis of a normal distribution for all the spot prices, which is consistent with the findings of prior studies (Akay, 2015; Higgs, 2009; Higgs and Worthington, 2005; Thomas et al., 2011).

Of the four options markets, the highest options prices were seen in SA and VIC, which averaged $28.25 and $24.33 per megawatt hour, respectively. The lowest options price was seen in QLD, which exhibited a price of $1.55. The standard deviations for the options electricity prices ranged from $3.99 (QLD) to $5.62 (SA). Further, the distributions of the options electricity price observations were slightly negatively skewed for QLD, while they were positively skewed for NSW, VIC and SA. The options price series for NSW, QLD, SA and VIC all demonstrated positive kurtosis.

From the descriptive statistics, it can be seen that the solar electricity prices exhibited a median of $218.03, which is not closed to the mean of $352.01. All the values of the solar electricity prices fell between $65.73 and $1548.20. Further, the maximum average monthly wind electricity values reached up to $358.69, while the mean price was $181.72. However, the wind electricity prices ranged from $63.82 to $358.69.

5.2. Unit Root and Stationary Tests

In the present study, unit root tests based on the ADF test were conducted prior to performing the ARIMA analysis. The ADF unit root test was used to examine the stationarity of the time series, and the results are presented in Table 3. From the table, it can be seen that all the options, solar and wind electricity prices were non-stationary in terms of their levels, although they were stationary with regard to the first differences. During this phase, the data exhibited stationarities by means of the differencing technique, which is the process whereby a new series is created. Each value in the series is replaced by the difference between that value and the proceeding value, where the first value in the series will be the second data value minus the first. In this way, the new series will have one less data item. For the spot electricity prices, no evidence was found for the presence of a unit root. The findings of this paper are consistent with those of Akay (2015), which confirms the non-presence of a unit root in Australian spot electricity prices.

Table 3: The ADF unit root test for the spot, options, solar and wind electricity prices

State	Variable	Level		First Difference	
		ADF	P value	ADF	P value
NSW	Spot	−5.177	0.0000	−12.850	0.0000
	Options	−2.398	0.1423	−7.213	0.0000
QLD	Spot	−5.319	0.0000	−12.840	0.0000
	Options	−2.491	0.1178	−6.499	0.0000
VIC	Spot	−4.024	0.0013	−12.698	0.0000
	Options	−2.535	0.1073	−7.291	0.0000
SA	Spot	−5.641	0.0000	−12.630	0.0000
	Options	−2.003	0.2851	−6.970	0.0000
TAS	Spot	−4.358	0.0004	−10.845	0.0000
	Solar	−1.642	0.4612	−8.036	0.0000
	Wind	−1.401	0.5818	−7.568	0.0000

5.3. ARIMA Model

An ARIMA model was developed for each of the spot, options, solar and wind electricity prices. This section presents the results of the analysis of the time-series data concerning the spot and options electricity prices in the ANEM so as to predict how the spot and options electricity time series may change in the future. A similar process was used to forecast the solar and wind electricity prices. The orders p and q of the ARIMA models are identified and estimated for both series using the methodology of Box and Jenkins (1978).

The results show that the autocorrelation function (ACF) and the partial autocorrelation function (PCF) both became much smoother, since the ARIMA model could successfully decompose the autoregressive process and the moving average components, thereby obtaining stationary residuals. From the ACF and PACF plots of the residuals, it can be seen that most values were within the bounds (although there was a 95% confidence interval for the Gaussian white noise). There was no discernible pattern seen in the ACF or the PACF in terms of the average monthly data. However, the ACF showed that, although the row data were largely uncorrelated, the variances exhibited some correlation. This study used the AIC and the BIC to choose the ARIMA term, which minimized the corresponding values of the criteria.

Diagnostic checking of the ARIMA model helped us to determine whether the estimated model was acceptable and statistically

Table 4: The equations used to predict the *spot*, *options*, *solar* and *wind* prices

State	Variables	Equation	ARIMA	AIC
NSW	*Spot*	$Spot_t$=0.28805+0.32581$spot_{t-1}$ − 0.92019ε_{t-1}+ε_t	(1,1,1)	1364.194
	Options	$Option_t$=0.10337−0.45549ε_{t-1}+ε_t	(0,1,1)	383.517
QLD	*Spot*	$Spot_t$=0.31164+0.36214$spot_{t-1}$ − 0.95861ε_{t-1}+ε_t	(1,1,1)	1413.217
	Options	$Option_t$=0.19389−0.35416option$_{t-1}$+ε_t	(1,1,0)	389.9463
VIC	*Spot*	$Spot_t$=0.35530+0.26438$spot_{t-1}$ − 0.80921ε_{t-1}+ε_t	(1,1,1)	1290.41
	Options	$Option_t$=0.10541−0.43884ε_{t-1}+ε_t	(0,1,1)	393.4034
SA	*Spot*	$Spot_t$=0.37805+0.23361$spot_{t-1}$ − 0.91438ε_{t-1}+ε_t	(1,1,1)	1475.164
	Options	$Option_t$=0.11702+0.26907option$_{t-1}$+ε_t	(1,1,0)	485.2769
TAS	*Spot*	$Spot_t$=0.32628+0.59721$spot_{t-1}$ − 0.95870ε_{t-1}+ε_t	(1,1,1)	1368.475
	Solar	$Solar_t$=−3.2146−0.07174$solar_{t-1}$+ε_t	(1,1,0)	1685.588
	Wind	$Wind_t$=0.41668−0.3657$wind_{t-1}$ − 0.69015ε_{t-1}+ε_t	(1,1,1)	1156.058

Table 5: White-noise tests of the *spot*, *options*, *solar* and *wind* prices

State	Variable	Bartlett's periodogram test	P value	Portmanteau test	P value
NSW	*Spot*	0.5591	0.9134	18.0691	0.9989
	Options	0.8426	0.4767	29.265	0.1717
QLD	*Spot*	0.4037	0.9968	24.6079	0.9734
	Options	1.1355	0.1517	46.6705	0.2172
VIC	*Spot*	0.6247	0.8300	33.7601	0.7460
	Options	1.1987	0.1129	17.149	0.1035
SA	*Spot*	0.5135	0.9547	42.8158	0.3513
	Options	0.6674	0.7646	24.4028	0.9753
TAS	*Spot*	0.5240	0.9465	22.1995	0.9898
	Solar	0.5505	0.9223	36.1845	0.6427
	Wind	0.7445	0.6365	39.1714	0.5074

significant, which means that the residuals were not autocorrelated and, hence, followed a normal distribution. To check the autocorrelation, we looked at the ACF and PACF of the residuals, as well as the cumulative periodogram white-noise test and the portmanteau test for white noise. Table 4 displays the results of the fitted ARIMA models, while Table 5 displays the results of white-noise tests.

In the case of NSW, Tables 4 shows that the ARIMA (1, 1, 1) model was a good model for the spot electricity prices. Further, the cumulative periodogram white-noise test gave a Bartlett's (B) statistic and a corresponding p-value of 0.5591 and 0.9134, respectively, which were considered appropriate. Similarly, the portmanteau test for white noise concerning the spot electricity price residuals showed a portmanteau (Q) statistic of 18.0691 and a probability value of 0.9989. These results proved that the residuals were white noise, which means that there was no serial correlation or heteroscedasticity. We used the ARIMA (1, 1, 1) model to forecast how the spot electricity prices were impacted by their own lags in order to explain the spot electricity prices in NSW. In Figure 1a, we determined the forecasts of the ARIMA (1, 1, 1) model for a period spanning 2 years. The forecast results for the spot electricity prices in NSW showed favourable growth rates of around 30.46%.

Table 4 also presents the ARIMA results obtained from the analyses of the options electricity pricing data from NSW for the period January 2006 to March 2018, which involved 147 observations. The results showed that the ARIMA (0, 1, 1) model was the most appropriate univariate model of the options prices. In Figure 1b, the options electricity price time-series forecasts for the next 2 years (April 2018 to March 2020) are presented. The forecast results for the options electricity prices in NSW showed positive growth rates of around 14.94%.

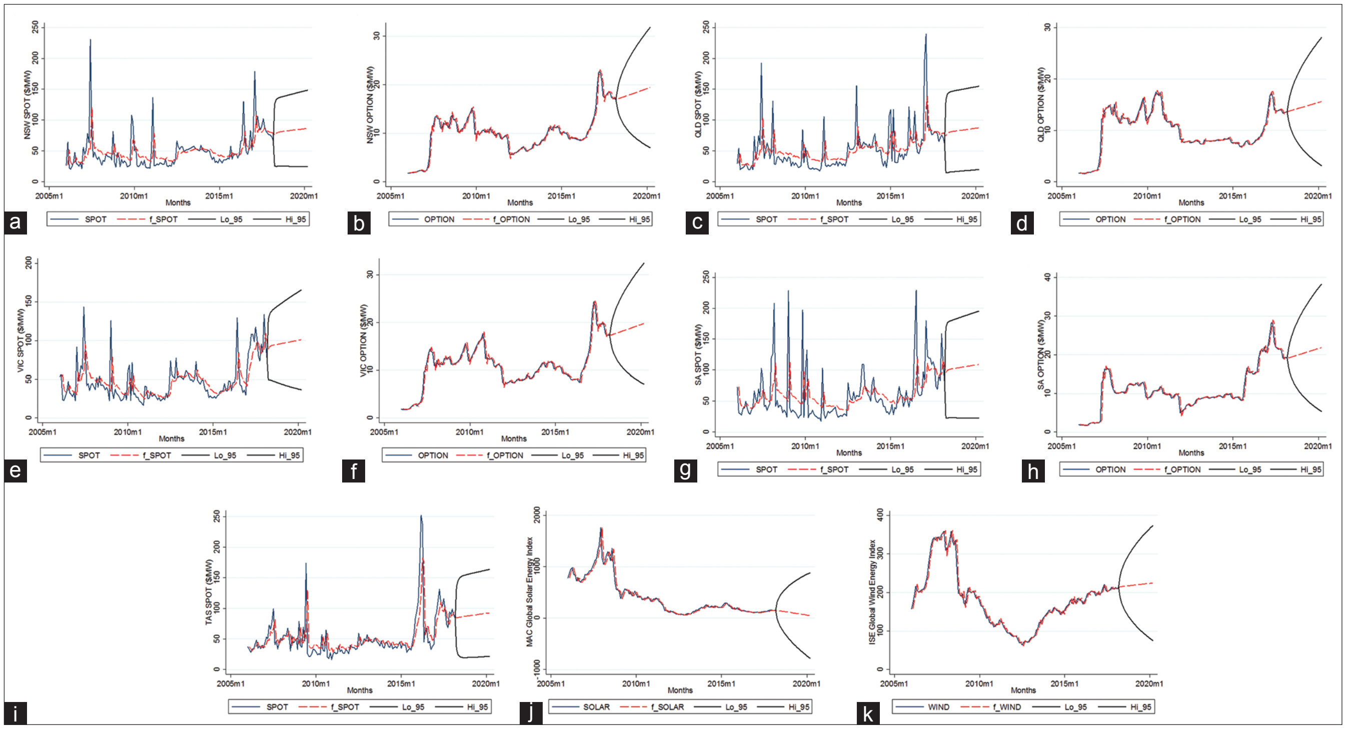
Table 6: ARIMA forecast

State	Variable	Change from April 2018 to March 2020
NSW	*Spot*	30.46% increase
	Options	14.94% increase
QLD	*Spot*	40.42% increase
	Options	14.95% increase
VIC	*Spot*	33.29% increase
	Options	15.13% increase
SA	*Spot*	35.57% increase
	Options	14.80% increase
TAS	*Spot*	11.38% increase
	Solar	67.7% decrease
	Wind	5.43% increase

In the case of QLD, the ARIMA model proved to be suitable, and it was used to forecast the spot and options electricity prices for the next 2 years. The results showed that the ARIMA (1, 1, 1) and ARIMA (1, 1, 0) models were appropriate. Figure 1c depicts a predicted increase in the spot electricity prices in QLD of around 40.42% between April 2018 and March 2020. Moreover, Figure 1d shows that QLD will experience rising options electricity prices that will lead to increased monthly average options prices ranging from \$13.64 in March 2018 to \$15.68 in March 2020.

With regard to the situation in VIC, the analyses suggested that the ARIMA (1, 1, 1) and ARIMA (0, 1, 1) were the best fitted models for the spot and options electricity prices, respectively. Figure 1e shows that the electricity spot prices are expected to increase by an average of 33.29% over the next 2 years. Further, Figure 1f shows a predicted increase in the options

Figure 1: Time-series forecasts. (a) NSW spot time-series forecasts, (b) NSW options time-series forecasts, (c) QLD spot time-series forecasts, (d) QLD options time-series forecasts, (e) VIC spot time-series forecasts, (f) VIC options time-series forecasts, (g) SA spot time-series forecasts, (h) SA options time-series forecasts, (i) TAS spot time-series forecasts, (j) MAC Global Solar Energy Index forecasts, (k) ISE Global Wind Energy Index forecasts



electricity prices in VIC of around 15.13% between April 2018 and March 2020.

In the case of SA, Table 4 presents the outputs obtained from the ARIMA testing of the spot and options pricing data. The results indicated that the ARIMA (1, 1, 1) model was appropriate for the spot prices, while the ARIMA (1, 1, 0) model was appropriate for the options prices. Figure 1g shows that the spot electricity prices are predicted to increase by 35.57% in March 2020 when compared to the prices in March 2018. Additionally, Figure 1h shows that the options electricity prices are predicted to increase by 14.80% in March 2020 when compared to the prices in March 2018.

In relation to TAS, a univariate analysis of the spot prices was used to model the time-series data, with the aim of forecasting the monthly trends of the spot prices between April 2018 and March 2020. Table 6 shows that the ARIMA (1, 1, 1) model was the most appropriate model for the spot electricity prices. Further, Figure 1i shows that the spot electricity prices in TAS are predicted to increase by around 11.38% in March 2020.

The univariate analyses of the MAC Global Solar Energy Index and the ISE Global Wind Energy Index were mainly used to study the models in terms of the trends, with the aim being to use the model to forecast the series from April 2018 to March 2020. The analyses suggested that the ARIMA (1, 1, 0) and ARIMA (1, 1, 1) models were the best fitted models for the solar and wind electricity prices, respectively. The forecast results concerning the solar electricity prices showed a negative percentage growth rate of around 67.7% (Figure 1j). Further, the average monthly wind prices are predicted to increase from \$213.17 in March 2018 to \$224.76 in March 2020 (Figure 1k).

6. DISCUSSION AND CONCLUSION

The present study examined whether the historical values of each investigated time-series variable (spot, options, solar and wind electricity prices) for each selected state (QLD, NSW, VIC, SA and TAS) could explain the changes that may occur to that variable in the future. The ARIMA method was used to determine both the best fit of the models and their appropriateness. The best fitting ARIMA (*p, d, q*) models were obtained to predict the values of the spot, options, solar and wind electricity prices for a 3-year period (April 2018 to March 2020). Identifying the variabilities and the directions in time-series data allows for the forecasting of potential changes in those variables in the future. Thus, these ARIMA models could be used for policy purposes as well as for forecasting the spot, options, solar and wind electricity prices in Australia.

The analysis of the descriptive statistics showed that the distribution of the spot prices was significantly non-Gaussian for all the regions of the ANEM, which is consistent with previous findings (Akay, 2015; Higgs, 2009; Higgs and Worthington, 2005; Thomas et al., 2011). Moreover, the unit root test results confirmed the non-Gaussian and stationary nature of the spot price series.

The results showed increases ranging from 30.46% to 40.42% for the spot electricity prices in each state, with the highest growth being seen in the case of QLD. The forecasted increase is due to the increasing cost of gas-fired generation and the closure of the Hazelwood Power Station, which was decommissioned in March 2017. The price increase seen in the case of VIC has impacted on neighbouring states, including TAS, SA and NSW. Further, the rising cost of gas has increased the cost of power produced by gas-fired power plants.

The results also showed increases in the options electricity prices of 14.94% in NSW, 14.95% in QLD, 15.13% in VIC and 14.80% in SA. The forecasted increases in the options electricity prices are due to the increasing spot prices.

The average monthly solar prices are estimated to decrease by around 67.7% between April 2018 and March 2020. Government policies that stimulate market growth have played a key role in enabling a reduction in the cost of solar power through privately funded research and development (R&D) and scale economies. The results showed that wind prices are expected to increase by an average of 5.43% over the next 2 years. Wind power is expensive because it is intermittent, while the management of electricity systems becomes increasingly difficult if the share of wind power in the total system capacity approaches or exceeds the minimum level of demand during the year.

Ultimately, the most appropriate decision-making process is the one that proves the most effective. Predicting future events based on an appropriate time-series model will help policy makers and strategists alike to make decisions and devise suitable strategic plans regarding the electricity markets. To extend this work, future studies should examine and compare the use of complex univariate models, such as the autoregressive conditional heteroscedasticity model (ARCH), the generalized ARCH model (GARCH) and the ARIMA/GARCH model.

REFERENCES

Akay, T. (2015), Forecasting Stylised Features of Electricity Prices in the Australian National Electricity Market (Unpublished Doctoral Dissertation). RMIT University, Melbourne, Australia.

Australian Energy Council. (2017), Solar Report. Available from: https://www.energycouncil.com.au/media/7687/australian-energy-council-solar-report_march-2017.pdf.

Bin Majid, S., Aras, M.S.B., Ahmad, A.B. (2012), Electricity load forecasting using data mining technique. In: Karahoca, A., editor. Advances in Data Mining Knowledge Discovery and Applications. San Diego, CA: InTechOpen. p235-254.

Box, G., Jenkins, G. (1978), Time Series Analysis: Forecasting and Control. San Francisco CA: Holden Ray.

Cartea, A., Figueroa, M.G. (2005), Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. Applied Mathematical Finance, 12, 313-335.

Çevik, H.H., Çunkaş, M. (2015), Short-term load forecasting using fuzzy logic and ANFIS. Neural Computing and Applications, 26, 1355-1367.

Cho, M., Hwang, J., Chen, C. (1995), Customer short term load forecasting by using ARIMA transfer function model. Energy Management and Power Delivery, 1, 317-322.

Coenen, L., Campbell, S., Wiseman, J. (2018), Regional innovation systems and transformative dynamics: Transitions in coal regions in Australia and Germany. In: Isaksen, A., Martin, R., Trippl, M., editors. New Avenues for Regional Innovation Systems-Theoretical Advances, Empirical Cases and Policy Lessons. New York: Springer. p199-217.

Contreras, J., Espinola, R., Nogales, F.J., Conejo, A.J. (2003), ARIMA models to predict next-day electricity prices. IEEE Transactions on Power Systems, 18, 1014-1020.

Cuaresma, J.C., Hlouskova, J., Kossmeier, S., Obersteiner, M. (2004), Forecasting electricity spot-prices using linear univariate time-series models. Applied Energy, 77, 87-106.

Dai, W., Wang, P. (2007), Application of pattern recognition and artificial neural network to load forecasting in electric power system. Natural Computation, 1, 381-385.

Ediger, V.Ş., Akar, S. (2007), ARIMA forecasting of primary energy demand by fuel in Turkey. Energy Policy, 35, 1701-1708.

Garcia-Martos, C., Rodrıguez, J., Sanchez, M.J. (2017), Short-term forecasting of electricity prices using mixed models. In: El-Hawary, M.E., editor. Advances in Electric Power and Energy Systems: Load and Price Forecasting. Hoboken New Jersey: Wiley-Blackwell. p153-214.

Higgs, H. (2009), Modelling price and volatility inter-relationships in the Australian wholesale spot electricity markets. Energy Economics, 31, 748-756.

Higgs, H., Worthington, A.C. (2005), Systematic features of high-frequency volatility in Australian electricity markets: Intraday patterns, information arrival and calendar effects. The Energy Journal, 26, 23-41.

Huang, S., Wu, Q., Oren, S.S., Li, R., Liu, Z. (2015), Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks. IEEE Transactions on Power Systems, 30, 2170-2178.

Jiang, S., Yang, C., Guo, J., Ding, Z. (2018), ARIMA forecasting of China's coal consumption, price and investment by 2030. Energy Sources, Part B: Economics, Planning, and Policy, 13, 1-6.

Kaur, H., Ahuja, S. (2017), Time Series Analysis and Prediction of Electricity Consumption of Health Care Institution using ARIMA Model. Proceedings of Sixth International Conference on Soft Computing for Problem Solving, March 13-15, 2013. Available from: http://www.iaeng.org/publication/IMECS2013/IMECS2013_pp295-300.pdf.

Kaytez, F., Taplamacioglu, M.C., Cam, E., Hardalac, F. (2015), Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines. International Journal of Electrical Power and Energy Systems, 67, 431-438.

Khashei, M., Bijari, M. (2011), A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Applied Soft Computing, 11, 2664-2675.

Kim, S., Ko, W., Nam, H., Kim, C., Chung, Y., Bang, S. (2017), Statistical model for forecasting uranium prices to estimate the nuclear fuel cycle cost. Nuclear Engineering and Technology, 49, 1063-1070.

Lasheras, F.S., de Cos Juez, F.J., Sánchez, A.S., Krzemień, A., Fernández, P.R. (2015), Forecasting the COMEX copper spot price by means of neural networks and ARIMA models. Resources Policy, 45, 37-43.

Misiorek, A., Trueck, S., Weron, R. (2006), Point and interval forecasting of spot electricity prices: Linear vs. non-linear time series models. Studies in Nonlinear Dynamics and Econometrics, 10(3), 1-24.

O'Neill, R.P., Castillo, A., Eldridge, B., Hytowitz, R.B. (2017), Dual pricing algorithm in ISO markets. IEEE Transactions on Power Systems, 32, 3308-3310.

Okoro, O., Chikuni, E. (2017), Power sector reforms in Nigeria: Opportunities and challenges. Journal of Energy in Southern Africa, 18, 52-57.

Sen, P., Roy, M., Pal, P. (2016), Application of ARIMA for forecasting energy consumption and GHG emission: A case study of an Indian pig iron manufacturing organization. Energy, 116, 1031-1038.

Shahidehpour, M., Yamin, H., Li, Z. (2002), Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management. New York: Wiley-IEEE Press.

Shumway, R.H., Stoffer, D.S. (2006), Time Series Analysis and its Applications: With R Examples. 3rd ed. New York: Springer.

Thomas, S., Ramiah, V., Mitchell, H., Heaney, R. (2011), Seasonal factors and outlier effects in rate of return on electricity spot prices in Australia's national electricity market. Applied Economics, 43, 355-369.

Voronin, S., Partanen, J. (2014), Forecasting electricity price and demand using a hybrid approach based on wavelet transform, ARIMA and neural networks. International Journal of Energy Research, 38, 626-637.

Weron, R. (2007), Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach. Chichester UK: John Wiley and Sons.

Weron, R. (2014), Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting, 30, 1030-1081.

Weron, R., Misiorek, A. (2008), Forecasting spot electricity prices: A comparison of parametric and semiparametric time series models. International Journal of Forecasting, 24, 744-763.

Yang, H.Y., Ye, H., Wang, G., Khan, J., Hu, T. (2006), Fuzzy neural very-short-term load forecasting based on chaotic dynamics reconstruction. Chaos, Solitons and Fractals, 29, 462-469.

Yang, Z., Ce, L., Lian, L. (2017), Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. Applied Energy, 190, 291-305.

Zhang, J., Tang, Y., Lee, K., Ouyang, M. (2010), Nonepitaxial growth of hybrid core-shell nanostructures with large lattice mismatches. Science, 327, 1634-1638.

Zhou, M., Yan, Z., Ni, Y., Li, G., Nie, Y. (2006), Electricity price forecasting with confidence-interval estimation through an extended ARIMA approach. IEE Proceedings Generation, Transmission and Distribution, 153(2), 187-195.