Market by Hybrid Intellige Short Term Electricity Price Forecasting in a Competitive nt Approach

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ABSTRACT

In this paper a hybrid intelligent methodology is presented for short term electricity price forecasting in a competitive deregulated market. This approach is based on a hybrid methodology which is following several algorithm of artificial neural network. In this artificial network two most common techniques are used for forecasting the price and minimizing the error. By combining these two techniques a hybrid approach came which shows excellent results of price forecasting in electricity industry. Data for half hour demand and price is being collected for one year along with this data temperature, humidity and fuel prices is also collected. With the help of MATLAB the data is used to forecast the electricity price. This forecasting is done with several algorithms and it is also done with different techniques and comparison is made between the algorithm and between the techniques.

Keywords: Artificial Neural Network (ANN) System, Auto Regressive Integrated Moving Average (ARIMA), Electricity Price Forecasting, U.K. Electricity Market.

I.INTRODUCTION

Deregulation processes during the last two decades across many developed economies have motivated the requirement for more accurate forecasting tools of electricity markets. For the forecasting of Short-term electricity prices it is essential by producers and consumers to derive their bidding techniques to the electricity industry. Deregulation brought electricity prices uncertainty, placing higher requirements on forecasting [1]. Hence, price forecasting tools are required for every market participants for their survival under deregulated processes. Some competitive electricity markets the series of prices explains the following characteristics: high frequency, non-constant mean and variance, daily and weekly seasonality, calendar effect on weekend and public holidays, high fluctuations and high percentage of unusual price spike.

Price forecast is a primary issue in competitive electricity industry, and various techniques have been applied for this purpose. Basically, hard and soft computing methodologies are used to forecast electricity prices. In the hard computing auto regressive integrated moving average (ARIMA) method mixed-model [2] approaches. Basically, an accurate model of the system is required, and for solving these problems several algorithms that consider the physical phenomena that generated the process. Although these techniques can be very precise, they want a lot of data collection, and the computational cost is very much. In soft computing neural network and hybrid intelligent system (HIS) approaches are used.

Basically a combination of neural networks with ARIMA model has been used in this project. Historical data has been used for learning of input- output mapping, thus there is no need to model the system. Hence, these methodologies can be much more efficient computationally and as accurate as the first ones, if the correct inputs are considered. In this paper, a hybrid intelligent approach is proposed for short-term electricity prices forecasting. This approach is based on a hybrid of neural networks. This approach is examined on the electricity market of Australia, commonly used as the test case in several price forecasting papers. It has been concluded that the Australian market has a hard non-linear behavior and time variant functional relationship [3]. So, this market is a real-world case study with sufficient complexity.

In this paper a successful application has been used for forecasting the electricity price using a hybrid approach based for time-series price forecasting considering the historical prices of the U.K. electricity market, New South Wales, in year 2010 for both ARIMA and ANN models, i.e., this paper provides ARIMA and a three-layered feed forward ANN, trained by the Levenberg-Marquardt algorithm. The rest of this paper is organized as follows [4]. In Section I, review the ARIMA and ANN modeling approaches to time-series forecasting is presented. The hybrid methodology is introduced in Section II. Results are shown in III and last Section contains the concluding remarks IV.

II.TIME-SERIES FORECASTING MODELS

There are various techniques to time-series modeling. There are few statistical models including moving average (MA), exponential smoothing, and ARIMA are linear in that predictions of the future values are constrained to be linear function of previous experiments. To solve the boundations of the linear models and account for specific nonlinear problems observed in real problems, various tutorials of nonlinear models have been proposed in the literature. These include the bilinear model [5], the threshold autoregressive (TAR) model, and the autoregressive conditional heteroscedastic (ARCH) model. Although some improvement has been seen with these nonlinear models, the gain of using them for general forecasting problems is limited. More recently, ANNs have been recommended as an option to time-series forecasting. The main strength of the ANNs is their varying nonlinear modeling capability. In this section, we focus on the basic principles and modeling process of the ARIMA and ANN models [6].

2.1 ARIMA Model

For an ARIMA model, future value of a variable is assumed to be a linear function of various past observations and random errors, i.e. the underlying process that produce the time series has the form Equation (1) entails various

$$y_t = \theta_0 + \psi_1 y_{t-1} + \psi_2 y_{t-2} + \ldots + \psi_p y_{t-p} + \varepsilon_t \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \quad (1)$$

cases of the ARMA family of models. If q=0, then becomes an AR model of order. When p=0, the model reduces to a MA model of order. One extension (p, q) to the ARMA class of processes, which greatly improve their value as empirical descriptors of non stationary time series, is the class of ARIMA. Non stationary time series processes can be translated, by differencing the series once or many more, to make them stationary. The number of times d that the integrated process must be differenced to make a time series stationary is said to be the order of the integrated process. In this case, the series is called an autoregressive (AR) integrated MA process of order (p, d, q). And denoted by ARIMA (p, d, and q) based on the earlier work of Yule and Wold [7], Box and Jenkins developed a practical approach for building ARIMA models, which has the basic impact on the time-series analysis and forecasting applications. This approach consists of three iterative steps of model identification, parameter estimation, and diagnostic checking. The fundamental idea of model identification is that if a time series is generated from an ARIMA process, it have autocorrelation properties. By matching the autocorrelation patterns with the theoretical ones, it is sometimes possible to evaluate one or various potential models for the specified time series. This involves selecting the most appropriate lags for the AR and MA parts, as well as determining if variable requires first-differencing to induced stationarity. Once a tentative model is specified, estimation of the model parameters is straightforward. The parameters are estimated such that a full measure of errors is minimized. This basically involves the application of a least-squares estimation process. The final step of model building is the diagnostic checking of model adequacy. This is primarily to check if the model assumptions about the errors are satisfied. Diagnostic information may help suggest alternative model(s). This three-step model building procedure is repeated many times until a satisfied model is finally selected. Final selected model can then be applied for prediction purpose [1].

2.1.1 Time-Series Modeling with ANN Approach

The linear restriction of model form is relaxed, the possible number of nonlinear structures that can be used to define and forecast a time series is enormous. A perfect nonlinear model should be "general enough to capture several nonlinear phenomena in the data" [8]. ANNs are one of such models that are able to approximate various nonlinearities in the data. ANNs are flexible computing frameworks for modeling a wide range of nonlinear problems. One significant advantage of the ANN models over other classes of nonlinear model is that ANNs are universal approximation that approximates a large number of functions with full accuracy. Their power comes from the parallel processing of the information from the history. No prior assumption of the model form is required in the model building process. Instead, the network model is largely determined by the characteristics of the data. Network architecture of ANNs consists of the three -layer fully connected feed forward neural network, which is shown in Fig. 1 which includes input layer, hidden layer, and output layer.

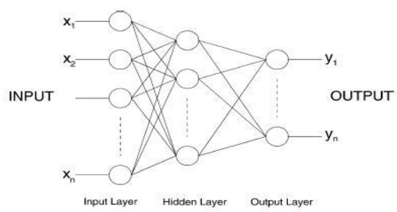

Fig. 1. Neural Network Model

III. HYBRID METHODOLOGY

Both ARIMA and ANN models had achieved goals in their respective linear or nonlinear problems. However, none of them is a universal model that is perfect for all situations. The approximation of ARIMA models to complex nonlinear problems may not be perfect. On the other part, using ANN's model linear problems have yielded combined results. For example, using simulated data, Denton showed that when some outliers or multi collinearity in the data, neural networks can significantly outperform linear regression models [10].

Since it is hard to know about the full characteristics of the data in a real problem, hybrid technology that has both linear and nonlinear modeling capabilities can be a good strategy for practical use. By combining different models, different aspects of the underlying patterns may be captured. It may be reasonable to consider a time series to be composed of a linear autocorrelation structure and a nonlinear component, i.e. where denotes linear component and denotes the nonlinear component. These two components have to be estimated from the data. First, we let ARIMA to model the linear component, then the residuals from the linear model will contain only the nonlinear relationship. A linear model is not sufficient if there are still linear correlation structures left in the residuals. However, residual analysis is not able to detect any nonlinear patterns in the data [11]. In fact, there is currently no general diagnostic statistics for nonlinear autocorrelation relationships. Therefore, even if a model has passed diagnostic checking, the model may still not be adequate in that nonlinear relationships have not been appropriately model. Any significant nonlinear pattern in the residuals will indicate the limitation of the ARIMA. ARIMA model building can be summarized in four steps, which are as follows.

1. Model identification: Using graphs, statistics, ACF, PACF, transformations, etc., achieve stationary and tentatively identify patterns and model components.
2. Parameter estimation: Determine the model coefficients through the method of least squares, maximum likelihood methods and other techniques.
3. Model diagnostics: Determine if the model is valid. If valid, then use the model; otherwise, repeat identification, estimation, and diagnostic steps.

Forecast verification and reasonableness: It is necessary to revisit the question of identification to see if the selected model can be advanced. Several techniques and confidence intervals determine the validity of forecasts and track model performance to detect out of control situations[12]. In the second step, a neural network model is developed to model the residuals from the ARIMA model. Since the ARIMA model cannot capture the nonlinear structure of the data, the residuals of linear model will contain information about the nonlinearity. The results from the neural network can be used as predictions of the error terms for the ARIMA model [13]. The hybrid model exploits the unique feature and strength of ARIMA model, as well as ANN model, in determining different patterns. Thus, it could be advantageous to model linear and nonlinear patterns separately by using different models, and then combine the forecasts to improve the overall modeling and forecasting performance[14]. Therefore, we would compare its forecasts with those of alternative methods. There are different alternative method for this purpose: the Mean Absolute Percentage Error (MAPE criterion), mean absolute error (MAE criterion) and RMS Error (RMSE criterion), which are defined as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{(A_t - F_t)}{A_t}\right|100\% \quad (2)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|(A_t - F_t)| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2} \quad (4)$$

IV. EMPIRICAL RESULTS

4.1 Datasets

The proposed a hybrid ARIMA and neural network model is performed using data of U.K. Electricity market in year 2008 is considered in this real-world case study. The price curves are given in Fig. 2. Moreover, models similar to the one reported in this paper are routinely used by the power industry.

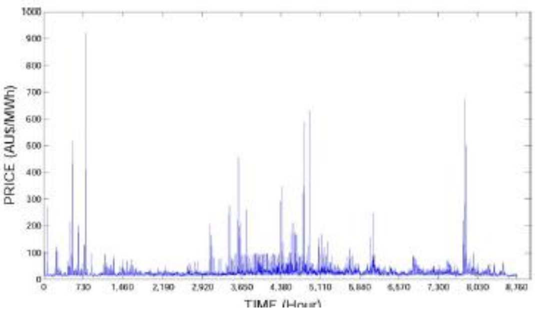

Fig. 2. Electricity prices: January to December 2008 in the U.K. Electricity Market

The data have been extensively studied with a vast variety of linear and nonlinear time-series models, including ARIMA and ANN. To assess the forecasting performance of different models, each dataset is divided into two samples of training and testing. The training dataset is used exclusively for model development, and then the test sample is used to evaluate the established model. To illustrate the behavior of the proposed technique, results comprising four weeks corresponding to the four seasons of year 2008 are presented. In this manner, representative results for the whole year are provided.

For the sake of a fair comparison, the fourth week in each of the seasons of January, May, August, and October are selected, i.e., weeks with particularly good price behavior are purposely not sought. To build the forecasting model for each one of the considered weeks, the information available includes hourly price historical data of the four weeks previous to the first day of the week, whose prices are to be predicted.

V. RESULTS AND DISCUSSIONS

In this study, the approach for analysis and building a time-series model is a method of finding, for a model (ARIMA) that adequately represents a data generating process for a given set of data. The test time-series data was processed by taking the first-order regular difference and the first seasonal difference in order to remove

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the growth trend and the seasonality characteristics. We checked stationary of time series of each of the seasons, identified ARIMA (*p*, *d*, and *q*) model by comparing characteristic of ACF and PACF (Correlogram testing), estimated parameters by ordinary least-squares method (OLS), and checked hypothesis of the model are validated by Akaike information criterion (AIC), which was used to determine the best model and final forecasted 168 h (one week) in each of the seasons. Table I presented the values of RMSE, MAE, and MAPE from price forecasting performance of the proposed ARIMA model.

In this section, artificial neural network (ANN) model is used to model the residuals obtained from forecasting by ARIMA model in each season to estimate nonlinear composite

TABLE I
COMPARISON OF FORECASTING RESULTS WITH ARIMA MODEL

Seasonal /Period	$RMSE$	MAE	$MAPE$ (%)
Summer 22-28/01/06	21.46670	11.09193	16.06611
Fall 21-27/05/06	51.61487	7.32228	13.60895
Winter 20-26/08/06	14.80462	5.18713	14.30258
Spring 22-28/10/06	5.22527	2.80880	10.46092

TABLE II
COMPARISON OF FORECASTING RESULTS WITH ARIMA-ANN MODEL

Seasonal /Period	No. neurals	$RMSE$	MAE	$MAPE$ (%)
Summer	5	18.76591	10.93323	15.62946
22-28/01/06	10	18.75462	10.95033	15.61561
	15	18.73184	10.92935	15.57793
	20	18.67366	10.95044	15.63311
Fall	5	28.07132	7.15738	13.08895
21-27/05/06	10	28.08384	7.15268	13.08870
	15	28.02828	7.12094	13.03785
	20	28.09795	7.15938	13.09134
Winter	5	10.30130	5.05679	13.88013
20-26/08/06	10	9.98764	5.05677	13.87992
	15	10.05073	5.03424	13.84539
	20	10.18238	5.05740	13.88174
Spring	5	4.53984	2.70438	10.04090
22-28/10/06	10	4.24231	2.69892	10.02813
	15	4.22661	2.68450	9.98964
	20	4.37781	2.70510	10.04278

We propose an ANN and hybrid (ARIMA-ANN) models to price forecast and use MATLAB for training the ANN. The proposes ANN model is a three-layered feed forward neural network which has the feature of memory and learning is constructed, trained by the Levenberg-Marquardt algorithm its proposed for forecasting the next 168 hour (one week) electricity prices.

The hidden layer has 5, 10, 15, and 20 neurals for finding best suitable accuracy and output layer has one unit. The same experience was repeated about testing and finding the best number of neurals in hidden layer. Table II shows the result of forecasting 168 h (one week), presented the values of RMSE, MAE, and MAPE from price forecasting performance of the proposed hybrid (ARIMA-ANN) model in each of the seasons. From Table II, the performance of 5, 10, 15, and 20 neurals in hidden layer are similar in values, in which 15 neurals in the hidden layer have best suitable accuracy. Therefore, numerical results for actual and forecasting prices in each of the seasons with hybrid (ARIMA-ANN) proposed approach are shown in Figs.3–6 for the summer, fall, winter, and spring, respectively.

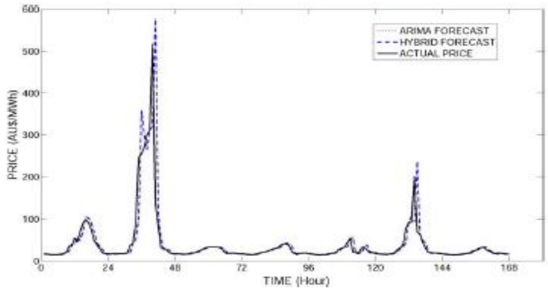

Fig. 3. Forecasting Results of January 22–28, 2008.

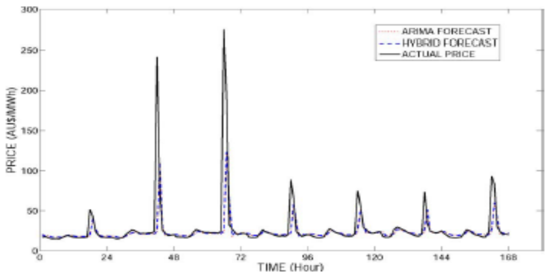

Fig. 4. Forecasting results of May 21–27, 2008.

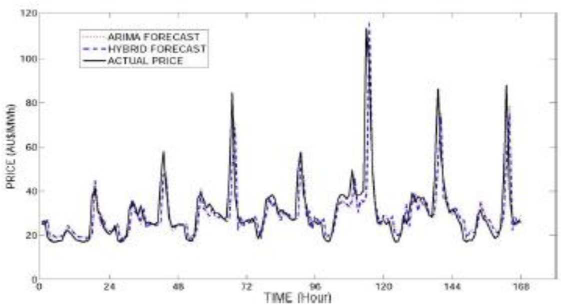

Fig. 5. Forecasting results of August 20–26, 2008

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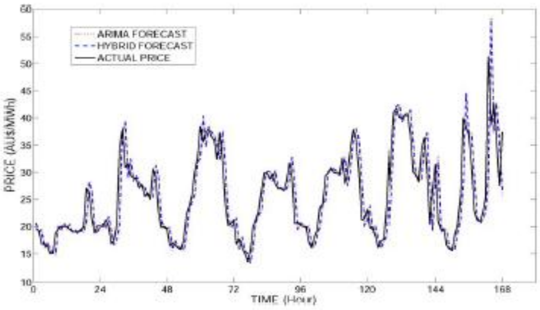

Fig.6. Forecasting results of October 22–28, 2008.

Table III summarizes the numerical results, where the comparison of forecasting performance of the proposed ARIMA, ANN, and hybrid models is presented. From Table III, it can be observed that the hourly MAPE, MAE, and RMSE of both neural network and hybrid models are better in accuracy than ARIMA model. The MAPE values obtained in every season for ARIMA model range from 10.46% to 16.06%, ANN model range from 10.03% to 15.62%, and hybrid model range from 9.98% to 15.57%. The results of the hybrid (ARIMA-ANN) model show that by combining two models together, the overall forecasting errors can be significantly reduced, which in terms of MAPE, the percentage improvements of the hybrid model over the ARIMA and ANN, are 4.5% and 0.5%, respectively. Therefore, the hybrid model gives better predictions than either ARIMA or ANN forecasts; its overall forecasting capability is improved.

TABLE III

Comparison of forecasting results with ARIMA, ANN & Hybrid Models

Seasonal /Period	Error	ARIMA Model	ANN Model	Hybrid Model
Summer 22-28/01/06	MAPE (%)	16.06611	15.62945	15.57793
	MAE	11.09193	10.94974	10.92935
	RMSE	21.46670	18.74184	18.73184
Fall 21-27/05/06	MAPE (%)	13.60895	13.09125	13.03785
	MAE	7.32228	7.181866	7.12094
	RMSE	51.61487	28.03323	28.02828
Winter 20-26/08/06	MAPE (%)	14.30258	13.85674	13.84539
	MAE	5.18713	5.048058	5.034243
	RMSE	14.80462	10.06701	10.05073
Spring 22-28/10/06	MAPE (%)	10.46092	10.03769	9.989647
	MAE	2.80880	2.693312	2.684502
	RMSE	5.22527	4.31881	4.22661

VI.CONCLUSIONS

This paper presents an approach for short-term price forecast problem based on hybrid correction method, which is a combination of ARIMA and ANN. The choice of forecasting model becomes the important influence factors on how to improve price forecasting accuracy. The linear ARIMA model and the nonlinear ANN model are used jointly, aiming to capture different forms of relationship in the time-series data. Hence, we present the price correction method for the generation of new method in which the new price data that are suitable to train the neural network are generated by correcting the historical day's data with the help of price correction rates. For learning the neural network, back propagation algorithm along with online learning is adopted that consist of correction and forecast errors. This paper also presents the forecasting method which could provide a considerable improvement of the price forecasting accuracy, especially the hybrid model which gives better predictions than either ARIMA or ANN forecasts, therefore its overall forecasting capability is improved. Hence hybrid methodology is best approach for forecasting of electricity price.

REFERENCES

[1] Nitin Singh, S.R. Mohanty (Sept 2015), "A Review of Price Forecasting Problem and Techniques in Deregulate Electricity Markets" Journal of Power and Energy Engineering 2015, pp. 1-19.

[2] Xian Zhang, and Xifan Wang, "Overview on Short-term Electricity Price Forecasting," Automation of Electric Power Systems, Vo1.30, No.3. Feb 10, 2006.

[3] O. B. Fosso, A. Gjelsvik, A. Haugstad, M. Birger, and I. Wangensteen, "Generation scheduling in a deregulated system. The norwegian case," IEEE Trans. Power Syst., vol. 14, no. 1, Feb. 1999, pp. 75–81.

[4] A. D. Papalexopoulos and T. C. Hesterberg, "A regression-based approach to short-term load forecasting," IEEE Trans. Power Syst., vol. 5, no. 4, Nov. 1990 pp. 1535–1550.

[5] Niimura, T. (2006), Forecasting Techniques for Deregulated Electricity Market Prices—Extended Survey. 2006 IEEE PES Power Systems Conference and Exposition, Atlanta, 29 October-1 November 2006, pp. 51-56.

[6] Hu, L., Taylor, G., Wan, H.-B. And Irving, M. (2009), A Review of Short-Term Electricity Price Forecasting Techniques in Deregulated Electricity Markets. Universities Power Engineering Conference (UPEC), 2009 Proceedings of the 44th International, Glasgow, 1-4 September 2009, pp. 1-5.

[7] S. Rahman and O. Hazim, "A generalized knowledge-based short term load-forecasting technique," IEEE Trans. Power Syst., vol. 8, no. 2, pp. 508–511, May 1993.

[8] S. J. Huang and K. R. Shih, "Short-term load forecasting via ARMA model identification including non-Gaussian process considerations," IEEE Trans. Power Syst., vol. 18, no. 2, May 2003, pp. 673–679.

[9] Jang, J.-S.R. (1993) ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man, and Cybernetics, 23, pp. 665-685.

[10] Phatchakorn Areekul, Student Member, Tomonobu Senjyu, Senior Member , Hirofumi Toyama, and Atsushi Yona, Member, "A Hybrid ARIMA and Neural Network Model for Short-Term Price Forecasting in Deregulated Market" IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 25, NO. 1, February 2010.

[11] T. Niimura, "Forecasting Techniques for Deregulated Electricity Market Prices," IEEE Power Engineering Society General Meeting, 2006.

[12] M. Ranjbar, S. Soleymani, N. Sadati, and A. M. Ranjbar, "Electricity Price Forecasting Using Artificial Neural Network," International Conference on Power Electronics, Drives and Energy Systems, 2006.

[13] H. S. Hippert, C. E. Pedreira, and R. C. Souza, "Neural networks for short-term load forecasting: A review and evaluation," IEEE Trans. Power Syst., vol. 16, no. 1, Feb. 2001, pp. 44–55.

[14] Bunn DW, Forecasting loads and prices in competitive power markets. Proc. IEEE 2000; 88(2):163–9.