FORECASTING SHORT-TERM LOAD AND PRICE IN RESTRUCTURED POWER SYSTEM USING HYBRID MODEL

M. Madan Gopi[1], Dr. S. Farook[2]
PG Scholar[1], Associate Professor[2]
Department of EEE.
Sree Vidyanikethan Engineering College , Tirupati, India

Abstract : Electricity load and price forecasting are two important factors required in a restructured power system. The performance of demand response is probably to be decreased in the absence of accurate load and price forecasting. In this paper, a hybrid load and price forecasting model based on hybrid time series and Adaptive Wavelet Neural Network (AWNN) models is proposed, in which Autoregressive Integrated Moving Average (ARIMA) model is used to process the non-stationary data, the Generalized Conditional Heteroscedastic (GARCH) model is used to capture the dynamics of a time series conditional variance and AWNN presents non-linear impacts. The Mean Absolute Percentage Error (MAPE) evaluates the accuracy of forecasting results. To demonstrate the effectiveness of the proposed method, day-ahead prediction of load and price in New York independent system operator (NYISO) market for north and west zone is considered.

IndexTerms – **Load and price forecasting, MAPE, ARIMA, GARCH and AWMN models.**

I. INTRODUCTION

In restructured power system, price forecasting is capture significance between various market participants in the power keeping in mind to adjust their bids in the day-ahead electricity markets and maximize their benefits. Electricity price is volatile but no random in nature making it possible the patterns based on the historical data and forecast. An accurate price forecasting technique is an important factors for the market participants as it empowers them to choose their bidding strategy to maximize benefits. In addition, an accurate short term load forecasting is the premise of the planning and the operation of power systems. With a good next-day load forecast, independent system operators (ISO) would have the capacity to effectively schedule system generation and transmission resources for the safe and economic operation of power systems [1].

Electricity price and load signals have complex characteristics such as non-linearity, non-stationary and more volatile in nature. For various applications, electricity price and load forecasting can be classified into very short-term (several minutes to a few hours), short-term (a few days), mid-term (a few months) and long-term (a few years). This paper mainly focusing on the hybrid model for day-a head price and load forecasting in electricity markets.

Many techniques and models have been developed for load and price forecasting, especially for short term price forecasting. Traditional methods, such as time-series, and intelligent methods, such as artificial neural networks, have been utilized to predict the MCP and load forecasting [2–5]. For instance, a particular general regression neural network (GRNN) is utilized to predict the next 24 hours spot price [6]. A few techniques based on neural network learning utilize the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), nonlinear system modeling and cascaded neural networks [7–10]. The EKF and some classical neural networks training methods, such as Back Propagation (BP), depend on the first-order linearization of nonlinear systems. This can present large errors in forecasting method of the disordered, non-stationary and non-linear time-series systems. The UKF, conversely accomplishes third-order accuracy by utilizing an insignificant arrangement of the price and load points [8]. Additionally, a few techniques have been applied to predict prices in electricity market using Autoregressive integrated moving average (ARIMA) time series models [11,12], hybrid wavelet transform and ARIMA and/or generalized autoregressive conditional Heteroscedastic (GARCH) models [13,14], artificial neural network (ANN) [15] and hybrid models [16,17] have been applied for day-ahead electricity price forecasting.

In this paper, hybrid time-series and adaptive wavelet neural network is developed for day-ahead price and load forecasting framework. ARIMA model is used to stimulate a non-stationary data, the GARCH model is aimed at modeling the volatility of electricity prices, and AWNN presents the non-linear and non-stationary characteristics. The proposed hybrid model provides a 24 h electricity price and load forecast of the next day based on historical data.

Several criteria such as the mean absolute percentage error (MAPE) and the variance of absolute percentage errors are used to evaluate the proposed model and calculate the forecasting accuracy. To demonstrate forecasting framework, price and load forecasts in the New York Independent System Operator (NYISO) electricity market [18] are computed and examined.

The rest of the paper is structured as follows: Section 2 outlines the proposed method. Section 3 presents historical data and results Section 4 provides some relevant conclusions.

II. PROPOSED METHOD

The proposed forecasting framework provides an in-depth analysis on the price and load signals by including short-term load and price forecasting in one framework, as shown in Fig. 1, which would determine more accurate, versatile and effective forecasting results. The proposed model provides price and load forecasts of day D separately, with historical price and load data available up to day D − 1, respectively.

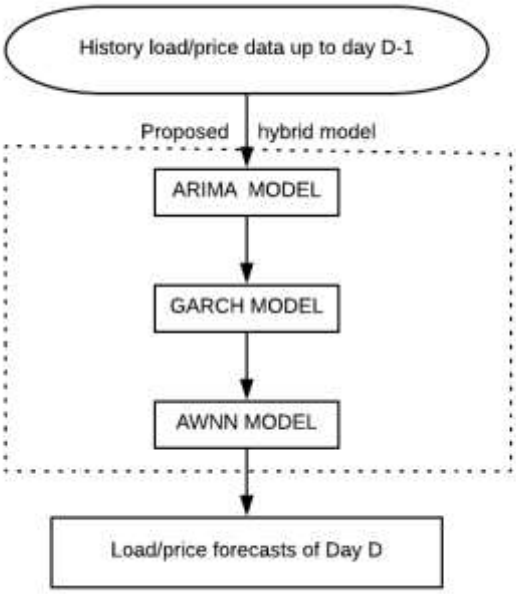

Fig. 1 Flowchart of the proposed hybrid forecasting model

Fig.1 shows the hybrid model is used for price and load forecasts, it includes ARIMA to forecast the non-stationary time series data, GARCH to simulate non-constant variances of residuals and AWNN to forecast the non-linear and non-stationary impacts of signals. It starts with the ARIMA model with input data of historical prices and load data update to D − 1 and load forecasts of day D. Forecast results from the ARIMA model is used as input to the GARCH model. The GARCH model output includes non-constant residuals. The ARIMA and GARCH results are combined and used as input to AWNN. The AWNN output is the final price and load forecast.

Electricity load and price forecasting are based on hybrid model including price and load signals as explanatory factors, whereas the load forecast in the hybrid model only uses historical load data up to day D − 1, and the price forecast in the hybrid model only uses historical price data up to day D − 1. Other explanatory factors, such as weather condition, available ancillary services, power exchanges and availabilities of generators and transmission lines are not included in the proposed forecasting framework. Such factors are less important for price and load forecasting in most situations, and addition may cause over-fitting the accuracy of the forecasting method. Feature selection techniques, such as principal component analysis, factor analysis and feature clustering, can be adopted to filter out irrelevant and redundant candidate inputs [19, 20]. In the following subsections, the individual ARIMA, GARCH and AWNN models, as well as the accuracy of forecasting results are discussed in detail.

2.1 ARIMA Model

The ARIMA model is widely used in the fields of non-stationary time series forecasting, it can be written as follows:

$$\emptyset(B)(1-B)^{d}X_t = \theta(B)\varepsilon_t \qquad (1)$$

Where X_t represents a non-stationary time series at time t, ε_t is a white noise which means zero mean and constant variance, d is the order of differencing, B is a backward shift operator described as $BX_t = X_{t-1}$, $\emptyset(B)$ is the autoregressive operator described as:$\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \ldots\ldots - \emptyset_P B^P$, and $\theta(B)$ is the moving average operator described as: $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots - \theta_q B^q$. Mostly, this method involves four phases. In the first step, a general ARIMA formulation is selected to model the electricity price and load data. If the time series contains multiple seasons, the form $(1 - B^S)$ should be added in the model, S is the order of seasonality. In the second step, by applying suitable differencing to the non-stationary time series data is converted to stationary time series data, it produce constant variance. After the underlying process is accepted as being stationary, the order of $\emptyset(B)$ and h(B) must be chosen through autocorrelation and partial autocorrelation plots The third step is parameter estimation, which includes expanding a probability work for the accessible data. The last step is diagnostic checking. If the residual term is a white noise process, at the point he model is used for forecasting purposes. Else, the process should be repeated until the point when a sufficient model is found [21].

2.2 GARCH Model

Both price and load signals present non-constant deviations over time. Under this conditions, the ARIMA model coefficients may not be asymptotically unbiased and consistent, and error terms are auto correlated. The residual analysis is an important step in the regression analysis. The GARCH model is a common tool for dealing with series conditional standard deviations [22]. A GARCH (p, q) is represented as (2) and (3), where v_t is a Gaussian N(0, 1) white noise process, $h_t = Var(\varepsilon_t/\varepsilon_{t-1})$ represents the conditional variance of time t based on time (t − 1), and c is the constant item in the GARCH model. The input series ε_t considers the residual of the ARIMA model, that is, actual price and load signals minus the forecasts offered by the ARIMA process. After combining the results of ARIMA and GARCH models, forecast results would incorporate the possibility of non-constant error variance. The application of GARCH model is an iterative procedure that is similar to the ARIMA model, which involves order determination, parameter estimation, and model diagnostic checking [23].

$$h_t = c + \sum_{i=1}^{p} \alpha_i \cdot h_{t-i} + \sum_{i=1}^{q} \beta_i \cdot (\varepsilon_{t-i})^2 \qquad (2)$$

$$\varepsilon_t^{\,2} = v_t^{\,2} \cdot h_t^{\,2} \qquad (3)$$

2.3 AWNN Model

Wavelet transforms can be classified in two types: continuous wavelet transform(CWT) and discrete wavelet transform (DWT). The continuous wavelet transform W (a, b) of function f(t) with respect to a mother wavelet as follows:

$$W(a,b)\frac{1}{\sqrt{C_\emptyset}}\int_{-\infty}^{\infty} f(t)\emptyset_{a,b}{}^{*}(t)dt \qquad (4)$$

Where

$$\emptyset_{a,b}(t) = \frac{1}{\sqrt{a}}\emptyset\left(\frac{t-b}{a}\right), t \in R, a, b \in R, a > 0 \qquad (5)$$

The dilation parameter controls the spread of the wavelet and the translation parameter determines its central position and $(*)$ represents the complex conjugate. A set of basis function $\emptyset_{a,b})(t)$ is derived from scaling and shifting the mother wavelet.

Adaptive Wavelet neural networks, where wavelets as activation functions are from the Continuous wavelet transforms and the unknown parameters of the networks include the weights and continuously varying wavelet coefficients (the dilations and translations) which can be learned by gradient- type algorithms as in conventional neural networks. In this paper, Morlet wavelet is considered as follows

$$\varphi(t) = e^{jw_0 t} e^{\frac{-t^2}{2}} \qquad (6)$$

Since wavelets have shown their excellent performance in non-stationary signal analysis and nonlinear function modeling, the AWNN can provide much higher convergence for the approximation. The structure of AWNN is shown in fig. 2 .

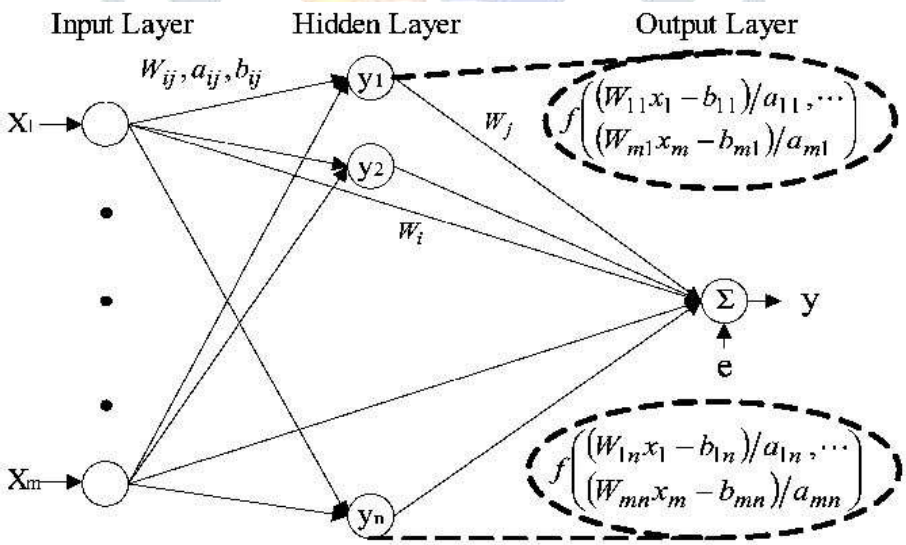

Fig. 2 Adaptive Wavelet Neural Network(AWNN) model

The output of AWNN is evaluated as (7), where the multi-dimensional wavelet function f ( ) is computed by the tensor product of one-dimensional wavelets, a_{ij} and b_{ij} are translation and dilation parameters, e is the bias of the output node in AWNN, m and n are the numbers of input layer and hidden nodes of AWNN and W_i, W_j, W_{ij} are the weights of AWNN. The Morlet wavelet shown in (11) is used as the mother wavelet, and other wavelet functions are dilations and translations derived from this prototype mother wavelet. We compared two most popular mother wavelets given in the literature with numerical tests: Morlet and Mexican Hat. We found that Morlet always gives a better forecast solution.

In the training process, the network learns and adjusts weights as well as translation and dilation parameters by using the product of gradient and learning rate. Two parameters are learning rate and momentum, are adjusted for accelerating the learning process [23]. The learning rate controls the step size for minimizing the objective function. The momentum term is computed by averaging the changes and determining the proportion of past changes that should be used for new values.

$$Y = \sum_{j=1}^{n} W_j \cdot f\left(\frac{W_{1J} \cdot x_1 - b_{1j}}{a_{1j}}, \dots\dots\dots, \frac{W_{mj} \cdot x_m - b_{mj}}{a_{mj}}\right) + \sum_{i=1}^{m} W_i \cdot x_i + e \qquad (7)$$

One of the critical issues in network training is overfitting, in which the network remembers training patterns and consequently loses certain ability to generalize. That is, it fits the training set but cannot well predict the fit for new data sets. In the training process, there is a point at which the training error continues to decrease whereas the generalization error starts to increase. The training process should stop at this point to avoid further overfitting. Correspondingly, in order to detect overfitting, the original data set is divided into three disjoint sets, that is, training set, Validation set, and generalization set. The training set is used to train the network model, the validation set is used to estimate the generalization error, and the generalization set is for forecasting.

2.3 Accuracy Of Forecasting

Several measurements are used to examine the accuracy of forecast results. The mean absolute percentage error (MAPE) index in (8) evaluates the performance of forecast results. MAPE represents the absolute average prediction error between predictions and actual targets

$$.MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{F_t - A_t}{A_t}\right| \times 100\% \qquad (8)$$

Where n= no. of observations,

A_t= actual value and

F_t= forecast value.

III. Historical Data And Results

The proposed hybrid forecasting model is applied to predict electricity prices and loads for the NYISO market [10]. This model is trained using the data set from 1 January 2018 to 15 April 2018, is validated using the data set from 16 April 2018 to 30 April 2018, and tested for the week of 1-7 May 2018.

3.1 Prediction Of Load In Nyiso Market For North Zone

Separated day-ahead price and load forecasting is considered for the week of 1-7 May 2018 for north zone. Day-ahead load is forecasted using the proposed hybrid model with only historical load data up to day before day D, and day-ahead price is forecasted using the proposed hybrid model with only historical price data up to the day before day D. Figs. 3 and 4 shows the historical data of load and price in NYISO market from 1 January 2018 to 30 April 2018.

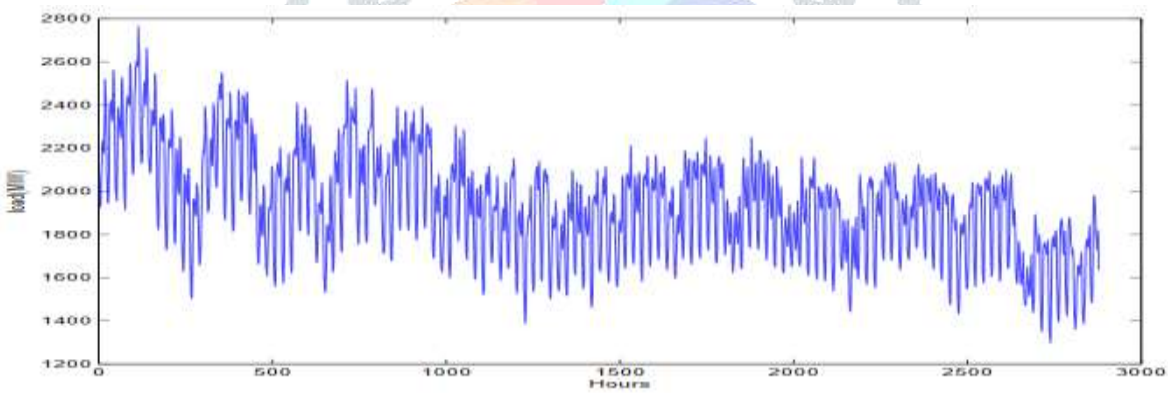

Fig.3 Historical hourly data of NYISO from 1 January 2018 to 30 April 2018

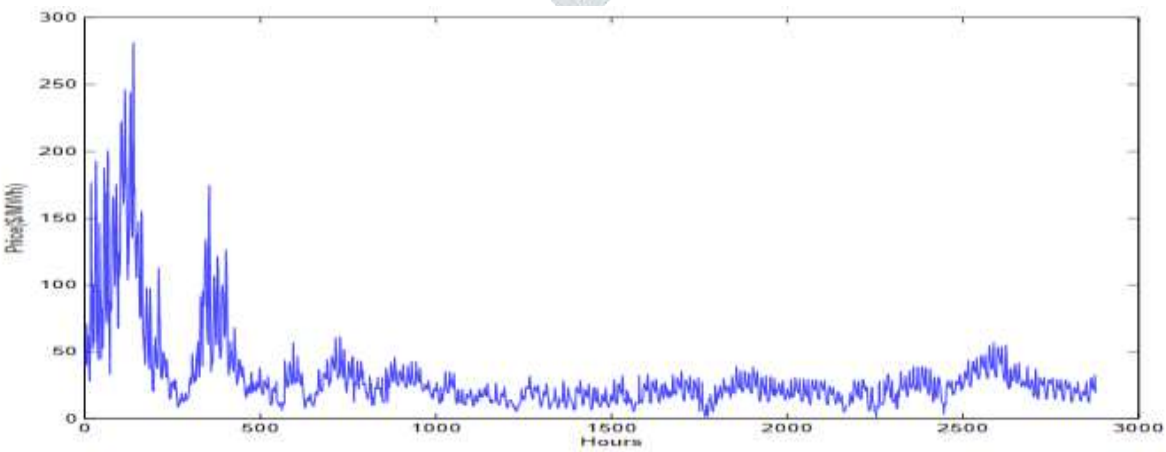

Fig.4 Historical hourly data of NYISO from 1 January 2018 to 30 April 2018

Figs. 5 and 6 show the price and load forecast results for 1–7 May 2018, which are obtained by separated price and load hybrid forecast models. It is observed that most prediction errors happen in the morning/evening peaks and earlier morning off-peaks.

Table 1 reports the MAPE of price and load forecasts. The second and the third columns show the MAPE of separated price and load forecasts using the proposed hybrid model. The largest MAPE of price forecast happens on 7 May 2018, which is mainly caused by the price drop in evening peaks on that day. The peak price is 12.47 $/MWh at 20:00 on 7 May 2018 as compared to 26.06 $/MWh at 20:00 on 6 May 2012, which shows a 22.18% decrease. The largest MAPE of load forecast happens on 6 May 2018, which is mainly caused by the load drop in morning peaks of that day. The peak load is 1647.1 MW at 12:00 on 6 May 2018 as compared to 1653.5 MW at 12:00 on 5 May 2018, which shows an 6.62% decrease. It is also observed that daily load and price forecast performances are not consistent with each other when using separated price and load forecast models. That is, although in most days load forecast has a better performance than price forecast in terms of smaller MAPEs, the exception is on 6 May 2018, in which the MAPE of load forecast is 3.24%, which is higher than 5.17% of the MAPE of price forecast.

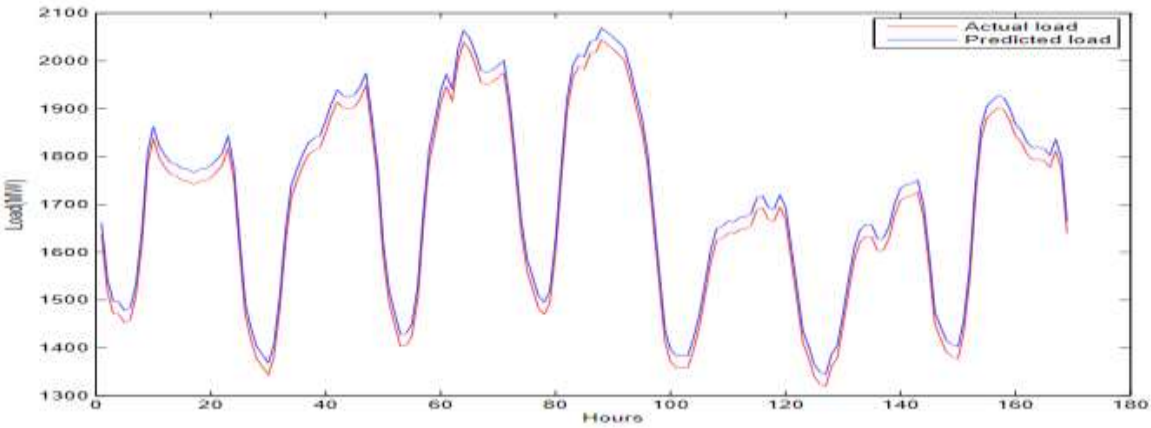

Fig.5 Actual and Forecast loads for 1-7 May 2018

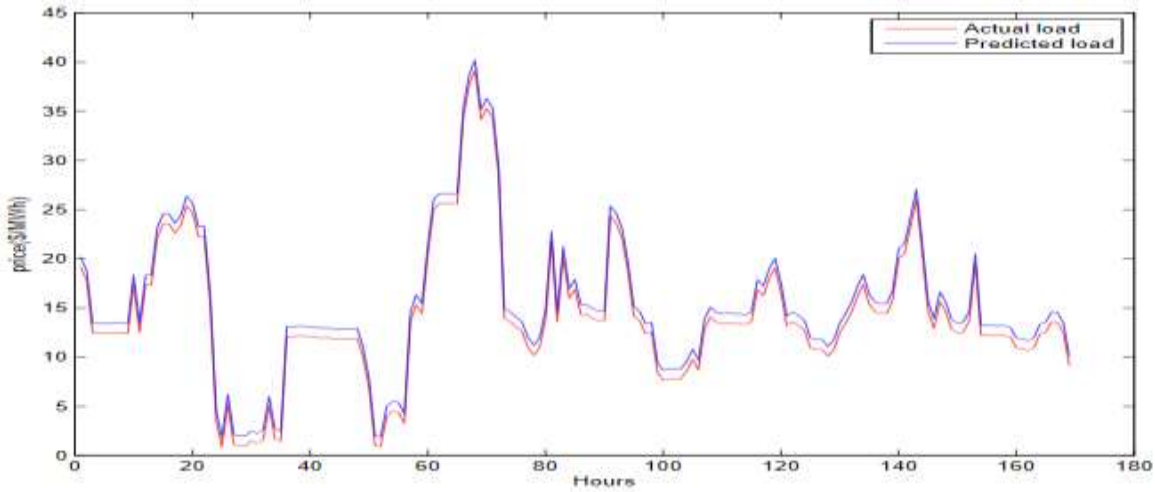

Fig.6 Actual and Forecast prices for 1-7 may 2018

3.**2 Prediction of load and price in NYISO market from west zone:**

Separated day-ahead price and load forecasting is considered for the week of 1-7 May 2018 for west zone. Day-ahead load is forecasted using the proposed hybrid model with only historical load data up to day before day D, and day-ahead price is forecasted using the proposed hybrid model with only historical price data up to the day before day D. figs. 7 and 8 shows the historical data of load and price in NYISO market from 1 January 2018 to 30 April 2018.

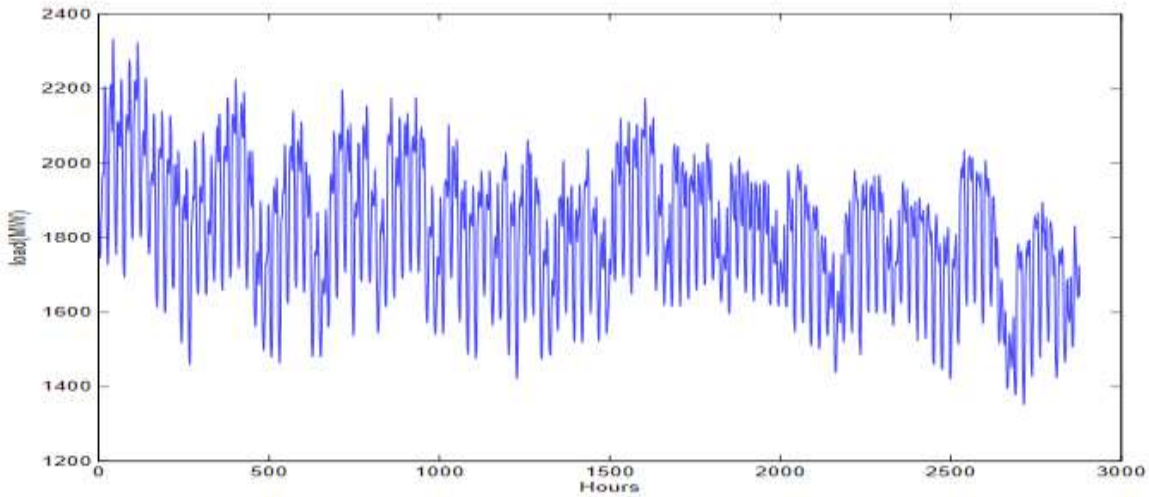

Fig.7 Historical hourly data of NYISO from 1 January 2018 to 30 April 2018

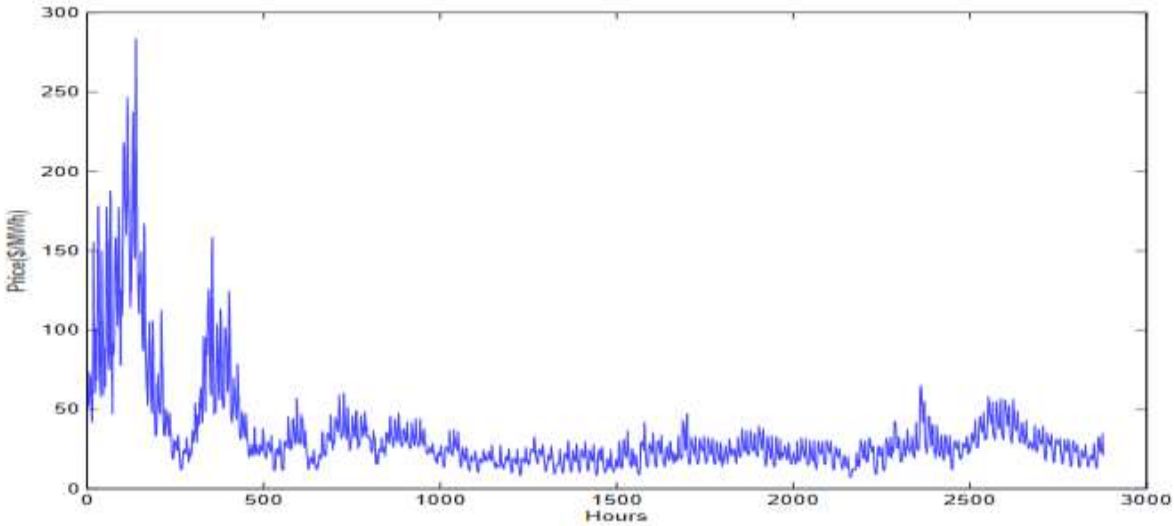

Fig.8 Historical hourly data of NYISO from 1 January 2018 to 30 April 2018

Figs. 9 and 10 show the price and load forecast results for 1–7 May 2018, which are obtained by separated price and load hybrid forecast models. It is observed that most prediction errors happen in the morning/evening peaks and earlier morning off-peaks. Table 1 reports the MAPE of price and load forecasts. The second and the third columns show the MAPE of separated price and load forecasts using the proposed hybrid model. The largest MAPE of price forecast happens on 7 May 2018, which is mainly caused by the price drop in evening peaks on that day. The peak price is 10.45 $/MWh at 20:00 on 7 May 2018 as compared to 29.06 $/MWh at 20:00 on 6 May 2012, which shows a 24.18% decrease. The largest MAPE of load forecast happens on 6 May 2018, which is mainly caused by the load drop in morning peaks of that day. The peak load is 1547.1 MW at 12:00 on 6 May 2018 as compared to 1663.5 MW at 12:00 on 5 May 2018, which shows an 6.01% decrease. It is also observed that daily load and price forecast performances are not consistent with each other when using separated price and load forecast models. That is, although in most days load forecast has a better performance than price forecast in terms of smaller MAPEs, the exception is on 6 May 2018, in which the MAPE of load forecast is 3.52%, which is higher than 4.95% of the MAPE of price forecast.

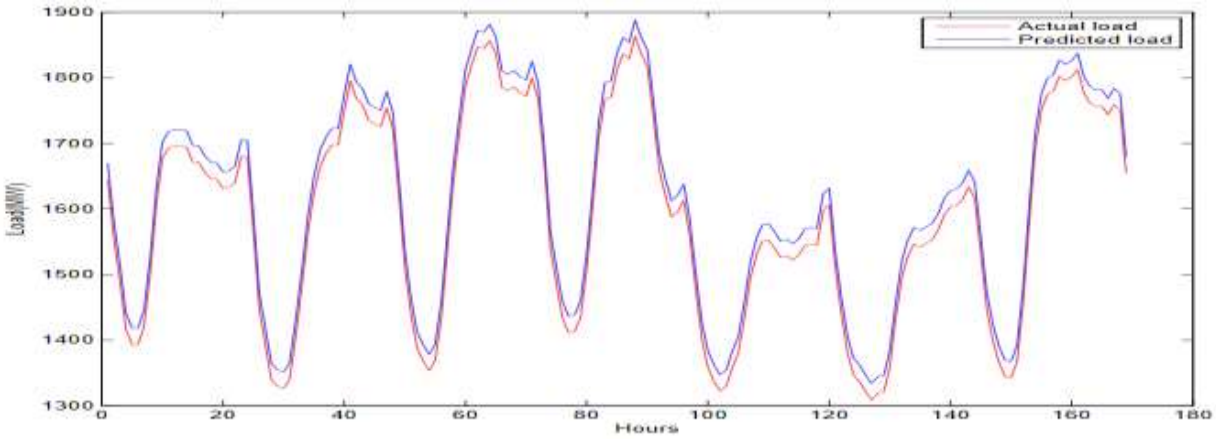

Fig.9 Actual and Forecast loads for 1-7 may 2018

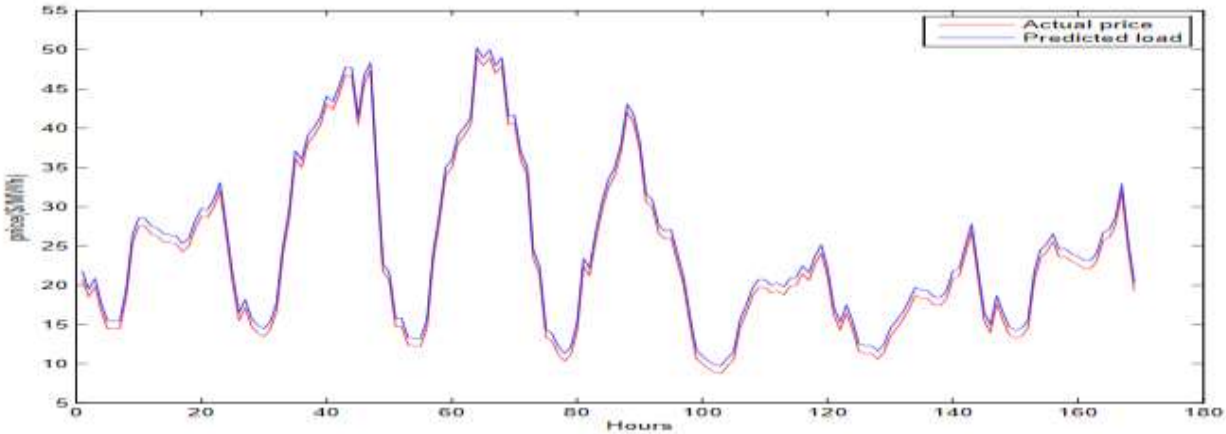

Fig.10 Actual and Forecast prices for 1-7 may 2018

Table 1 Weekly average Mean absolute percentage error of 1-7 May 2018

	ARIMA model		AWNN model		ARIMA+AWNN model		Proposed hybid model	
	Case-1	**Case-II**	**Case-1**	**Case-II**	**Case-1**	**Case-II**	**Case-I**	**Case-II**
Load forecast MAPE	3.21%	3.14%	3.03%	3.55%	2.55%	2.76%	2.30%	2.42%
Price forecast MAPE	5.07%	4.89%	4.67%	4.78%	4.08%	4.65%	3.15%	3.21%

Table 1 also compares the daily MAPE of separated price and load forecasts using the proposed method while excluding a subset of components. Three alternatives are studies. The first one uses ARIMA only, and both GARCH and AWNN are bypassed. The second one uses AWNN only, and both ARIMA and GARCH are bypassed. The third one uses both ARIMA and AWNN, and GARCH is bypassed. Better results are obtained with the proposed hybrid model as compared to the other three alternatives, in terms of smaller daily AMAPE of both price and load forecasts for all seven days. Thus, the behavior of the proposed hybrid technique is superior to the other threes. In addition, although in most days the AWNN model performs better than the ARIMA model for both price and load forecasts, ARIMA derives slightly better load forecast results than AWNN on 2 and 3 November The reason is that these two days have very similar load profiles as compared to the same days in previous weeks. Under this situation, ARIMA may better catch the relationship, whereas AWNN may induce additional errors because of overfitting and/or generalization. Furthermore, the third model which combines ARIMA and AWNN always performs better than their individual models.

IV. Conclusions

A new load and price method based on ARIMA combined with GARCH and AWNN models is proposed in this paper. The hybrid model is investigated for load and price prediction in the NYISO market for north and west zone and compared with other techniques. The results from the comparisons clearly show that the proposed method is more accurate than the other forecast methods.

References

[1] Shahidehpour, M., Yamin, H., Li, Z.: 'Market operations in electric power systems' (John Wiley and Sons, Inc., 2002)

[2] Nogales FJ, Contreras J, Conejo AJ, Espinola R. Forecasting next-day electricityprices by time series models. IEEE Trans Power Syst 2002;17(2):342–8.

[3] Szkuta BR, Sanabria LA, Dillon TS. Electricity price short-term forecasting using artificial neural networks. IEEE Trans Power Syst 1999;14(3):851–7.

[4] Peng TM, Hubele NF, Karady GG. Advancement in the application of neuralnetworks for short-term load forecasting. IEEE Trans Power Syst 1992;7(3):250–7.

[5] Sestito S, Leung S, Dillon TS. Short term load forecasting using an adaptive neural network. J Electr Power Energy Syst 1991;13(4):186–92.

[6] Vanaja L, Fung C, Gedeon T. A fuzzy-neural approach to electricity load and spotprice forecasting in a deregulated electricity market. In: Conference on convergent technologies; 2007. p. 1479–82.
[7] Zhang L, Luh P. Energy clearing price prediction and confidence interval estimation with cascaded neural networks. IEEE Trans Power Syst2003;18(1):99–105.
[8] Karsaz A, Khaloozadeh H. Day-ahead MCP and load forecasting with an improved dual unscented Kalman filter. In: Proceedings of 6th international conference on control and automation; 2007. p. 508–13.
[9] Zhang L, Luh P. Neural network-based market clearing price prediction and confidence interval estimation with an improved extended Kalman filter method. IEEE Trans Power Syst 2004;19(1):366–74.
[10] Bompard E, Ciwei G, Napoli R, Torelli F. Dynamic price forecast in a competitive electricity market. IET Gener Trans Distrib 2007;1(5):776–83.
[11] Contreras J, Espínola R, Nogales FJ, Conejo AJ. ARIMA models to predict nextday electricity prices. IEEE Trans Power Syst 2003;18(3):1014–20.
[12] Haiteng Xu, Niimura T. Short-term electricity price modeling and forecasting using wavelets and multivariate time series. In: Proceedings of IEEE power system and exposition, vol. 46; 2003. p. 208–12.
[13] Conejo, A.J., Plazas, M.A., Espínola, R., Molina, A.B.: 'Day-ahead electricity price forecasting using the wavelet transform and ARIMA models', IEEE Trans. Power Syst., 2005, 20, pp. 1035–1042
[14] Tan, Z., Zhang, J., Wang, J., Xu, J.: 'Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models', Appl. Energy, 2010, 87, (11), pp. 3606–3610
[15] Mandal, P., Senjyu, T., Urasaki, N., Fundabashi, T., Srivastava, A.K.: 'A novel approach to forecast electricity price for PJM using neural network and similar days method', IEEE Trans. Power Syst., 2007, 22, pp. 2058–2065
[16] Amjady, N., Daraeepour, A., Keynia, F.: 'Day-ahead electricity price forecasting by modified relief algorithm and hybrid neural network', IET Gener. Transm. Distrib., 2010, 4, (3), pp. 432–444
[17] Amjady, N., Keynia, F.: 'Day-ahead price forecasting of electricity markets by mutual information technique and cascaded neuro-evolutionary algorithm', IEEE Trans. Power Syst., 2009, 24,(1), pp. 306–318
[18] NYISO: 'NYISO Electricity Market Data', http://www.nyiso.com/, accessed May 2018
[19] Jain, A., Zongker, D.: 'Feature selection: evaluation, application, and small sample performance', IEEE Trans. Pattern Anal. Mach. Intell., 1997, 19, pp. 153–158
[20] BGuyon, I., Elisseeff, A.: 'An introduction to variable and feature selection', J. Mach. Learn. Res., 2003, 3, pp. 1157–1182
[21] Contreras J, Espinola R, Nogales F, Conejo A. ARIMA models to predict next-day electricity prices. IEEE Trans Power Syst 2003;18(3):1014–20.
[22] Bollerslev, T.: 'Generalized autoregressive conditional heteroskedasticity', J. Econ., 1986, 31, pp. 307–327
[23] Engelbrecht, A.P.: 'Computational intelligence: an Introduction' (John Wiley and Sons, 2002)