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Day-ahead electricity price forecasting by a new hybrid method

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ABSTRACT

Electricity price forecasting has become necessary for power producers and consumers in the current deregulated electricity markets. Seeking for more accurate price forecasting techniques, this paper proposes a new hybrid method based on wavelet transform (WT), autoregressive integrated moving average (ARIMA) and least squares support vector machine (LSSVM) optimized by particle swarm optimization (PSO) to predict electricity prices. The proposed method is examined by using the data from New South Wales (NSW) of Australian national electricity market. Empirical testing indicates that the proposed method can provide more accurate and effective results than the other price forecasting methods.

1. Introduction

The deregulation of electric power industry has become a crucial issue around the world. The main objective of deregulation is to increase efficiency through competition. In the new environment, there are two major ways for electricity trading: bilateral contracts and the pool market. This paper considers itself in a pool-based electric energy market, because it is the most common arrangement in practice. In such a market, the producers and consumers submit their own bids that consist of a set of quantities with their prices. Then the market operator uses a market clearing algorithm to determine the prices. In this way, the prediction of electricity price is important to producers to maximize their profits and to consumers to maximize their utilities, respectively. Therefore, this paper is focused on the day-ahead market clearing price (MCP) forecasting. However, due to the complicated factors affecting electricity prices, the price series presents a complex behavior, which makes forecasting very challenging. Thus, a good price prediction method should be able to capture the complex behavior associated with price series.

In recent years, many methods have been proposed for short-term electricity price forecasting. Among these methods, two widely used approaches are time series models and artificial neural network (ANN). Time series models such as dynamic regression (DR) and transfer function (TF) (Nogales, Contreras, Conejo, & Espinola, 2002), ARIMA (Contreras, Espinola, Nogales, & Conejo, 2003), generalized auto-regressive conditional heteroskedastic (GARCH) (Garcia, Contreras, Akkeren, & Garcia, 2005), ARIMA-EGARCH (Bowden & Payne, 2008), GIGARCH (Diongue, Guegan, & Vignal, 2009) have been proposed for this purpose. However, most of the time series models are linear predictors, which have difficulties in forecasting the hard nonlinear behavior of electricity price series (Amjady & Hemmati, 2006).

To solve this problem, ANN has been proposed for price forecasting, which is an effective way to deal with the complex nonlinear problem. Zhang, Luh, and Kasiviswanathan (2003) presented a cascaded neural-network (NN) structure for MCP prediction. Guo and Luh (2004) proposed the cascaded architecture of multiple ANN to forecast MCP. Zhang and Luh (2005) used a kind of extended Kalman filter combined with ANN to predict MCP. Very recent related papers have been considered by Vahidinasab, Jadid, and Kazemi (2008) and Areekul, Senjyu, Toyama, and Yona (2010), and so on. Although the main advantage of ANN is its nonlinear modeling capability, it has the weakness of locally optimal solution. To overcome this shortcoming, LSSVM is applied for electricity price forecasting. The reason behind the choice of LSSVM is its high accuracy and global solution. However, directly applying LSSVM model does not produce a better result. The reason is that the selection of the parameters in a LSSVM model has a heavy impact on the forecasting accuracy. Instead of using genetic algorithm (GA), PSO is used to optimize the LSSVM parameters, namely PLSSVM. Compared to PSO, GA is lack of knowledge memory, which will lead to time consuming and inefficiency in the searching suitable parameters of a LSSVM model.

Since it is difficult to completely know the features of electricity prices, hybrid method is proposed for price forecasting. The basic idea of different models combination in forecasting is to use each model's unique feature to capture different patterns in the data, which is an effective and efficient way to improve forecasts (Zhang, 2003). Combining Probability Neural Network (PNN) and Orthogonal Experimental Design (OED), an Enhanced PNN was proposed by Lin, Gow, and Tsai (2010). Tan, Zhang, Wang, and Xu (2010) proposed a novel hybrid method based on wavelet transform

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combined with ARIMA and GARCH models. Unsihuay-Vila, Zambroni de Souza, Marangon-Lima, and Balestrassi (2010) presented a new hybrid approach based on nonlinear chaotic dynamics and evolutionary strategy to forecast electricity prices. Catalão, Pousinho, and Mendes (2011) proposed a hybrid approach, which was based on wavelet transform, neural networks and fuzzy logic. A new prediction strategy composed of probabilistic neural network and hybrid neuro-evolutionary system was presented by Amjady and Keynia (2011). It is reasonable to consider the electricity price series to be composed of a linear autocorrelation structure and a nonlinear component. Thus, a hybrid method that has both linear and nonlinear modeling capabilities can be a good strategy for price forecasting. Electricity price forecasting is difficult because unlike load, electricity price series present such features as non-constant mean and variance, high frequency. Thus, wavelet transform is used to convert the original price series into a set of constitutive series, which present a better behavior than the original price series. Therefore, they can be predicted more accurately. Hence, a hybrid method using WT, ARIMA and PLSSVM is proposed, where the ARIMA model captures the linear component and the PLSSVM model captures the nonlinear component. The motivation to adopt such a hybrid method is to use other method's unique feature to capture different patterns in the electricity price series. Both theoretical and empirical findings suggest that combining different methods can be an effective and efficient way to improve forecasts. The main contribution of this paper can be summarized as follows:

(1) Wavelet transform is used to convert the ill-behaved price series into a set of constitutive series. Then each subseries is separately predicted by a new hybrid model based on ARIMA and PLSSVM.
(2) A new hybrid prediction method combined with WT, ARIMA and PLSSVM is proposed in this paper for day-ahead electricity price forecasting. To the best of our knowledge, this method has never been presented in the literature.
(3) The proposed approach is compared with some other approaches to demonstrate its effectiveness regarding forecasting accuracy.

The rest of this paper is organized as follows. Section 2 provides a description of WT, ARIMA and PLSSVM models. The hybrid methodology is given in Section 3. Numerical results are presented in Section 4. Section 5 gives the conclusions of this paper.

2. Theoretical background of WT, ARIMA and PLSSVM models

2.1. Wavelet transform

A brief description of wavelet transform (DWT) is given in the following. The discrete wavelet transform is defined as:

$$W_{(m,k)} = 2^{-(m/2)}\sum_{t=0}^{T-1} f_{(t)}\phi_{(t-n\cdot 2^m/2^m)} \tag{1}$$

where T is the length of the signal $f_{(t)}$. The scaling and translation parameters are functions of the integer variables m and k ($a = 2^m$, and $b = k \cdot 2^m$). t is the discrete time index.

A fast algorithm to implement DWT has been used. This algorithm has two stages: decomposition and reconstruction. In the first stage, the original signal is decomposed into one approximation series and some detail series. The basic concept in this stage begins with the selection of mother wavelet and the number of decomposition levels. In this paper, a wavelet function of Daubechies wavelet of order 4 (DB4) is used. The reason is that this wavelet offers an appropriate trade-off between wave-length and smoothness, resulting in an appropriate behavior for price forecasts (Amjady & Keynia, 2008). Also, three decomposition levels are considered, since it describes the price series in a more thorough and meaningful way than the others (Amjady & Keynia, 2008). In the second stage, DWT components can be assembled back into the original signal. More details of this model can be found in Appendix A.

2.2. ARIMA model

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

$$\varphi(B)(1-B)^d X_t = \theta(B)\varepsilon_t \tag{2}$$

where X_t represents a non-stationary time series at time t, ε_t is a white noise, d is the order of differencing, B is a backward shift operator defined by $BX_t = X_{t-1}$, $\varphi(B)$ is the autoregressive operator defined as: $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p$, and $\theta(B)$ is the moving average operator defined as: $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$.

Generally, the standard statistical methodology to construct an ARIMA model includes four phases: data preparation, model identification, parameter estimation and diagnostic checking. First, the autocorrelation function (ACF) and partial ACF (PACF) are considered to identify the ARIMA (p, d, q) model. Then, estimation of model coefficients is achieved by means of the maximum likelihood method. Furthermore, the hypothesis of the model is validated by Akaike Information Criterion (AIC). More details of this model can be found in Appendix B.

2.3. PLSSVM model

2.3.1. LSSVM model

LSSVM is proposed by Suykens and Vandewalle (1999). The reason behind the choice of LSSVM is that the LSSVM regression algorithm achieves the global solution by solving a set of linear equations, which allows LSSVM to be faster than SVM (Iplikci, 2006). Given a training data set of N points $\{x_i, y_i\}_{i=1}^N$ with input data $x_i \in R^n$ and output data $y_i \in R$, the decision function can be defined as:

$$y(x) = w^T\varphi(x) + b \tag{3}$$

In Eq. (3), $\varphi(x)$ denotes the nonlinear function that maps the input space to a high dimension feature space; w denotes the weight vector; b is the bias term.

For the function estimation problem, the structural risk minimization is used to formulate the following optimization problem:

$$\text{Minimize}: \quad \frac{1}{2}\|w\|^2 + \frac{1}{2}c\sum_{i=1}^{n}\varepsilon_i^2 \tag{4}$$

$$\text{Subject to}: y_i = w^T\varphi(x_i) + b + \varepsilon_i, \; i = 1, \ldots, N$$

In Eq. (4), c represents the regularization constant, and ε_i represents the training error.

To derive the solutions w and ε, the Lagrange multipliers are introduced as following:

$$L(w, b, \varepsilon, a) = \frac{1}{2}\|w\|^2 + \frac{1}{2}c\sum_{i=1}^{n}\varepsilon_i^2 - \sum_{i=1}^{n}a_i[w^T\varphi(x_i) + b + \varepsilon_i - y_i] \tag{5}$$

In Eq. (5), a_i is the introduced Lagrange multiplier.

According to the Karush–Khun–Tucker conditions, the finally result into the LSSVM model for function estimation can be described as:

$$f(x) = \sum_{i=1}^{n}a_i K(x, x_i) + b \tag{6}$$

In Eq. (6), the dot product $K(x, x_i)$ is known as the kernel function. This paper applied the radial basis function (RBF), because it is a common function that is useful in nonlinear regression problems. The RBF with a width of σ can be defined as:

$$K(x, x_i) = \exp(-0.5\|x - x_i\|^2/\sigma^2) \tag{7}$$

When using LSSVM with the RBF kernel function, the parameters σ and c should be established. This paper used PSO to obtain the optimal parameters.

2.3.2. PSO

The PSO is an evolutionary computational technique, which is based on the simulation of flocking and swarming behavior of birds and insects (Eberhart & Kennedy, 1995). Compared to other evolutionary computational methods, it can efficiently find optimal or near optimal solutions to the problem under consideration. PSO uses a set of particles, representing potential solutions to the problem. Then each particle moves towards the optimal position, which could be found out by adjusting the direction of its previously best position and its best global position.

Define each particle as a potential solution to a problem in an m-dimensional search space. $X_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ is the current position of particle i, $V_i = (v_{i1}, v_{i2}, \ldots, v_{im})$ is the current velocity, $P_i = (p_{i1}, p_{i2}, \ldots, p_{im})$ is the previous position, and $P_g = (p_{g1}, p_{g2}, \ldots, p_{gm})$ is the best position among all particles. Then the best position of particle i can be computed by the following equations:

$$v_i^{k+1} = w \cdot v_i^k + c_1 \cdot r_1 \cdot (p_i^k - x_i^k) + c_2 \cdot r_2 \cdot (p_g^k - x_i^k) \tag{8}$$

$$x_i^{k+1} = x_i^k + \alpha \cdot v_i^k \tag{9}$$

where v_i^k and x_i^k is the current velocity and position of the particle i, respectively; w is called the inertia weight; c_1 and c_2 are two positive constants called acceleration coefficients; r_1 and r_2 are two independently uniformly distributed random variables with range [0, 1].

2.3.3. PLSSVM model

Since the LSSVM parameters σ and c have a great influence on the prediction accuracy, the PSO is selected as an optimization technique to optimize the parameters. This method is very easy to implement, and there are few parameters to adjust. The process of optimizing the LSSVM parameters with PSO is described below and the flowchart is shown as Fig. 1.

Step 1. Initialization. The population of particles is initialized, each particle having a random position and a random velocity.
Step 2. Fitness evaluation. For each particle, evaluate its fitness. In this paper, the fitness function is defined as the following:

$$Fitness = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{10}$$

where y_i and $\hat{y}_i$ represent the actual and forecast values, respectively.

Step 3. Update the previous and global best according to the fitness evaluation results.
Step 4. Update the velocity and position value of each particle. The velocity of each particle is calculated by Eq. (8), and each particle moves to its next position using formula (9).
Step 5. Termination. The particle's velocity and position are updated until the stop conditions are satisfied.

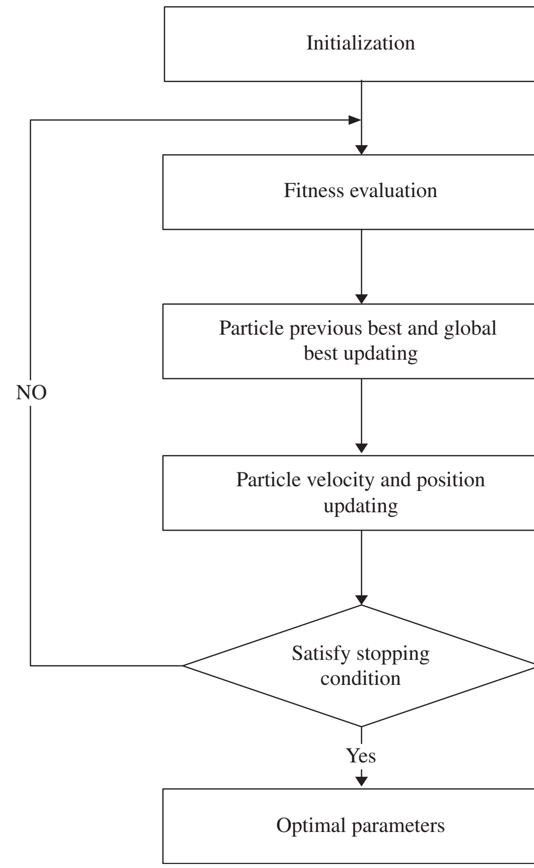

Fig. 1. The flowchart of PSO algorithm.

3. The proposed method

Electricity price forecasting is difficult because unlike load, electricity prices are impacted by many factors such as load, generator availability, and volatility in fuel price. Although these factors do help to improve predictions, in this paper, no exogenous variables are considered for the fair comparison with other methods. Because this paper focuses on the advantages of the proposed method. Moreover, some other variables such as generator availability, fuel costs are often limited by the availability of data.

The wavelet transform is used to convert the ill-behaved price series into a set of better-behaved constitutive series. Then, these subseries can be predicted more accurately. Since it is difficult to completely know the features of these subseries, hybrid approach that has both linear and nonlinear modeling capabilities can be a good choice for prediction. Both ARIMA and PLSSVM models have achieved successes in their own linear and nonlinear domains, but none of them is a universal model that is suitable for every situation. This is largely due to the fact that a real-world problem is often complex and no single model can capture different aspects of the underlying patterns well. The approximation of ARIMA model to complex nonlinear problems may not be adequate, and, using PLSSVM to model linear problems may have yielded mixed results. Hence, a hybrid method based on ARIMA and PLSSVM is proposed to forecast these subseries. By combining different models, different aspects of the underlying patterns may be capture.

It may be reasonable to consider a subseries to be composed of a linear autocorrelation structure and a nonlinear component as following:

$$Y_t = L_t + N_t \tag{11}$$

where Y_t is the subseries, L_t is the linear component and N_t is the nonlinear component. These two components have to be estimated from the data. First, we let ARIMA model to approximate the linear component. Since the ARIMA model cannot capture the nonlinear structure of the data, then the residuals from the linear model will contain only the information about the nonlinearity (Areekul, 2010).

Let ε_t denote the residual at time t from the linear model:

$$\varepsilon_t = Y_t - \widehat{L}_t \tag{12}$$

where $\widehat{L}_t$ is the forecasted value for time t from the linear estimated component. Any significant nonlinear pattern in the residuals will indicate the limitation of the ARIMA. In order to discover nonlinear relationships in residuals, PLSSVM is proposed in this paper. With n input nodes, the PLSSVM model for the residuals can be described as:

$$\varepsilon_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-n}) + \eta_t \tag{13}$$

where f is a nonlinear function determined by the PLSSVM and η_t is the random error. Let $\widehat{N}_t$ indicate the forecast of the residuals (13) from the PLSSVM model, the combined prediction will be:

$$\widehat{Y}_t = \widehat{L}_t + \widehat{N}_t \tag{14}$$

where $\widehat{Y}_t$ is the forecasted subseries, $\widehat{L}_t$ and $\widehat{N}_t$ are the forecasted results of L_t and ε_t. The procedure of the whole proposed method can be summarized as the following:

(1) By wavelet transform, an electricity price series P_t is decomposed into one approximation series defined as $a3_t$ and three detail series defined as $d1_t, d2_t, d3_t$, respectively.
(2) To duplicate the original series, it is important to reconstruct the approximate and detail series. By wavelet reconstruction, series of $a3_t, d1_t, d2_t, d3_t$ are denominated as $A3_t, D1_t, D2_t, D3_t$. So the original price series with less loss can be defined as $P_t = A3_t + D1_t + D2_t + D3_t$.
(3) For each subseries $(A3_t, D1_t, D2_t, D3_t)$, an ARIMA model is firstly used to forecast the linear part. Then, the PLSSVM model is developed to predict the residuals from the ARIMA model. The combined prediction results of each subseries can be defined as $\widehat{A}3_t, \widehat{D}1_t, \widehat{D}2_t, \widehat{D}3_t$.
(4) The original price prediction is obtained by composing the forecasted results of series $\widehat{A}3_t, \widehat{D}1_t, \widehat{D}2_t, \widehat{D}3_t$, which can be represented as $\widehat{P}_t = \widehat{A}3_t + \widehat{D}1_t + \widehat{D}2_t + \widehat{D}3_t$.

4. Numerical results

The proposed method is examined for MCP prediction on NSW electricity market. It should be noted that the electricity market of Australian is a duopoly with a dominant player. This result in price changes related to the strategic behavior of the dominant player, which are hard to predict (Areekul et al., 2010). To assess the prediction performance of different methods, each dataset is divided into samples of training and testing. The training data are used for building prediction model, while the testing data are used to test the proposed method. The selection of input variables is important to achieve high prediction accuracy. Thus, the correlation analysis is used for the input variables selection. The degree of correlation is tested using the sample ACF, sample PACF, and sample cross-correlation function (XCF).

4.1. Comparison with the previous studies

For the sake of a fair comparison, the fourth week of January, May, August, and October are selected for the summer, fall, winter, and spring seasons in the year 2006, respectively, which is the test period considered by Areekul et al. (2010). In this manner, representative results for the whole year 2006 are provided. Hourly price data of the 4 weeks previous to the first day of each test week is considered as the training samples. To evaluate the prediction capacity of this proposed method, three types of error measures, such as MAPE, MAE, RMSE have been used, which can be found in (Areekul et al., 2010).

The forecasted results obtained with the proposed method for the summer week is shown in Fig. 2 along with the actual prices. Other weeks are not plotted for the sake of conciseness. It can be seen that forecasted prices are quite close the actual MCP values. Table 1 presents the forecasting results of approximation series and detail series $(A3_t, D1_t, D2_t, D3_t)$. The final electricity price prediction is obtained by composing the forecasted results of each subseries. Table 2 summarizes the numerical results, where the comparison of prediction performance of the ANN, ANN-ARIMA, and the proposed method is presented.

From Table 2, it can be observed that the MAPE, MAE, and RMSE values of the proposed method in all test weeks are lower than the results in all other methods.

For the Summer week, the performance of the proposed method is less accurate than for the other weeks. However, it is reasonable accurate with MAPE below 2.15%. MAPE for the ANN and ANN-

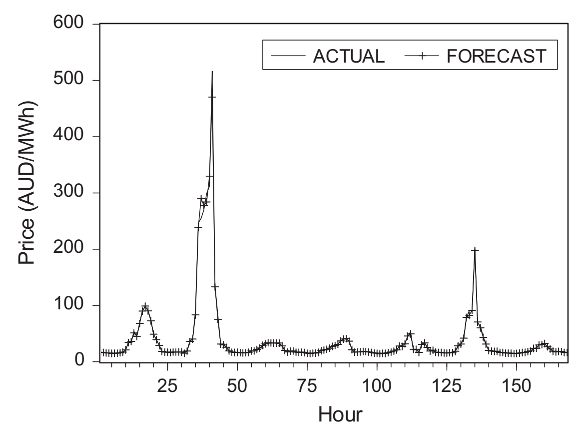

Fig. 2. Forecasted results of summer test week on NSW market for the year 2006.

Table 1
MAE for the four test weeks of each sub-series.

Test week	$A3_t$	$D1_t$	$D2_t$	$D3_t$
Summer (22–28/01/06)	0.008	0.017	0.009	0.005
Fall 21–27/05/06	0.003	0.015	0.006	0.004
Winter 20–26/08/06	0.004	0.017	0.007	0.002
Spring 22–28/10/06	0.004	0.009	0.007	0.002

Table 2
Comparison of prediction results with ANN, ANN-ARIMA, and the proposed method.

Test week	Error	ANN	ANN-ARIMA	Proposed method
Summer 22–28/01/06	MAPE (%)	15.63	15.58	2.14
	MAE	10.95	10.93	1.40
	RMSE	18.74	18.73	5.05
Fall 21–27/05/06	MAPE (%)	13.09	13.04	1.87
	MAE	7.18	7.12	0.68
	RMSE	28.03	28.03	2.31
Winter 20–26/08/06	MAPE (%)	13.86	13.85	1.98
	MAE	5.05	5.03	0.63
	RMSE	10.07	10.05	0.03
Spring 22–28/10/06	MAPE (%)	10.04	9.99	1.14
	MAE	2.69	2.68	0.28
	RMSE	4.32	4.23	0.02

ARIMA are 15.63% and 15.58%, respectively. The prediction is particular inaccurate for the morning and evening peaks. Tuesday peak is not accurately reproduced due to significant changes in prices.

As for the Fall week, the performance of the proposed technique is accurate, with MAPE below 1.88%. MAPE for the ANN and ANN-ARIMA are 13.09% and 13.04%, respectively. Only the spike of Tuesday evening is not properly reproduced, which is due to strategic behavior of the dominant player of the market.

For the Winter week, the prediction behavior of the proposed method is not as good as for the Fall and Spring weeks. Accuracy is reasonable enough with MAPE below 1.99%. MAPE for the ANN and ANN-ARIMA are 13.86% and 13.85%, respectively. This week is unstable in respect to price behavior, probably due to the strategic behavior of the dominant player of the market (Conejo, Plazas, Espinola, & Molina, 2005).

The prediction behavior of the proposed method for the Spring week is very appropriate with MAPE below 1.15%. MAPE for the ANN and ANN-ARIMA are 10.04% and 9.99%, respectively. The prediction is more accurate during weekdays than during the weekend.

In summary, the MAPE values obtained in every week for ANN range from 10.04% to 15.63%, ANN-ARIMA range from 9.99% to 15.58%, and the proposed method rang from 1.14% to 2.14%. The results indicated that by combining different models together, the overall prediction errors can be significantly reduced. This finding proved our idea about the superior capability of this proposed method for converting ill-behaved price series into a set of better behavior series. The other reason for superiority of this method may attribute to the suitable selection of input variables for each subseries using the sample ACF, sample PACF, and sample XCF. Moreover, this proposed method has its ability for capturing the features of linearity and nonlinearity associated with electricity prices. Therefore, the proposed method gives better predictions than either ANN or ANN-ARIMA forecasts.

4.2. Comparison with some other methods

Since electricity price forecasting accuracy varies across different test periods, the proposed technique is applied for the 12 months of 2007. The data set consists of hourly electricity prices from December 2006 to December 2007. The last day of every month is studied to validate the performance of the proposed method, whereas the historical data is 30 days prior to the beginning of the test day.

To better illustrate the efficiency of the proposed hybrid method, its accuracy in different cases has been tested and shown in Table 3. In each case, some constituting parts of the hybrid method were removed and then the remaining parts were examined on the same test sample. Thus, the proposed method is compared with some other methods such as ARIMA, LSSVM, PSO + LSSVM, ARIMA + LSSVM, ARIMA + PSO + LSSVM.

In the first examination, WT, LSSVM and PSO of the hybrid method are removed, then the ARIMA model is presented. The obtained MAPE values of ARIMA are shown in the second column of Table 3. It is clear that ARIMA model predictions are less accurate than the proposed method with the average MAPE increasing from 2.14% to 13.63%. This result indicates that the approximation of ARIMA to model electricity prices is not always satisfactory. In the second examination, WT, ARIMA and PSO of the hybrid method are not used, then the LSSVM model is presented. The obtained MAPE values of LSSVM are shown in the third column of Table 3. It is clear that LSSVM model predictions are less accurate than the proposed method with the average MAPE increasing from 2.14% to 19.79%. This result indicates that the approximation of LSSVM model to complex electricity prices is not adequate. In the third examination, WT and ARIMA are not employed. The obtained MAPE values of this case are shown in the four column of Table 3. The results obtained from PLSSVM are worse as compared to the proposed method, but show better results than LSSVM model. This explains why the LSSVM parameters optimized by PSO can have a better rate of accuracy. In the fourth examination, WT and PSO are not included. The obtained MAPE values of this examination are shown in the fifth column of Table 3. Also, the results obtained from ARIMA + LSSVM are worse as compared to the proposed method, but show better results than ARIMA and LSSVM models, which explains that hybrid method has both linear and nonlinear modeling capabilities can be a good strategy for electricity price forecasting. In the last examination, shown in the sixth column of Table 3, only the WT is removed. It is clear that the proposed method compared with ARIMA + PSO + LSSVM shows better results, which indicates that the wavelet transform produces constitutive series that can be predicted more accurately than the original price series.

It can be seen that when some part of the proposed hybrid method are removed, its accuracy degrades. Besides, effect of different parts on the accuracy of the approach is not the same, the increase in the average MAPE varies from 11.25% to 19.79%. These examinations indicate that the high accuracy of the proposed method due to its hybrid structure.

To better illustrate the statistical efficiency of the proposed method, its accuracy of the daily forecast prices for the 12 months of 2008 is also measured. The last day of every month is studied to validate the performance of the proposed method, whereas the historical data is 30 days prior to the beginning of the test day. Its accuracy in different cases has been tested and shown in Table 4.

Table 3
MAPE (%) for the 12 testing days of NSW electricity market in year 2007.

Test day	ARIMA	LSSVM	PLSSVM	ARIMA + LSSVM	ARIMA + PLSSVM	Proposed method
January	22.06	23.12	19.96	20.13	18.34	2.21
February	13.09	16.89	14.70	12.23	11.23	2.01
March	13.06	19.34	17.04	12.14	10.23	2.06
April	14.76	19.98	17.25	13.02	11.59	1.86
May	13.82	21.23	19.15	12.94	10.49	2.54
June	25.56	33.56	29.12	23.06	21.34	4.39
July	12.93	17.56	15.70	11.87	10.56	1.39
August	5.76	13.45	10.63	6.40	5.21	3.10
September	11.23	22.74	19.42	12.31	10.45	1.42
October	8.05	16.57	13.24	9.23	7.34	1.72
November	8.65	14.26	11.94	8.34	6.78	0.88
December	14.55	18.78	15.80	13.68	11.38	2.07
Average	13.63	19.79	17.00	12.95	11.25	2.14

Table 4
MAPE (%) for the 12 testing days of NSW electricity market in year 2008.

Test day	ARIMA	LSSVM	PLSSVM	ARIMA + LSSVM	ARIMA + PLSSVM	Proposed method
January	8.40	11.18	10.24	7.56	6.55	1.03
February	5.04	9.46	8.25	4.83	4.23	4.33
March	6.99	14.08	13.48	6.01	5.17	1.24
April	10.14	25.59	22.34	9.07	8.34	1.61
May	10.98	18.42	15.42	9.98	8.95	1.57
June	12.91	13.12	10.48	11.24	10.75	1.53
July	11.08	30.25	27.84	10.27	9.64	1.57
August	8.54	22.11	20.79	7.89	6.37	1.45
September	10.23	20.76	18.71	9.97	9.08	1.63
October	79.74	43.18	40.19	60.25	58.27	14.39
November	10.68	16.68	15.14	9.22	7.66	1.63
December	6.06	13.38	10.81	5.67	4.89	1.10
Average	15.06	19.85	17.80	12.66	11.65	2.75

It is also observed from Table 4 that MAPE of this proposed method is significantly lower than that of all other methods. All these comparisons reveal the forecast capability of the proposed technique.

5. Conclusions

In this paper, a new hybrid method has been presented for day-ahead price forecasting of electricity market, which is a combination of WT, ARIMA and PLSSVM. The proposed method has been examined on the NSW of Australian national electricity market and compared with some of the recently published prediction techniques. The experimental results indicate that the proposed method can provide a more accurate and effective forecasting. The superior performance of the proposed method can be attributed to three causes. First, the WT can convert ill-behaved price series into a set of better behavior series. Second, the ARIMA model can capture the linear component associated with electricity prices, and, the LSSVM model has nonlinear mapping capabilities, which can more easily capture nonlinear component of electricity prices than the ANN and time series models. Third, PSO can determine suitable parameters of the LSSVM model, where improper determining of these parameters will cause either over-fitting or under-fitting. In the future, some other advanced searching techniques for suitable parameters selection can be combined with LSSVM to predict electricity prices. Besides, some influencing factors will be added in the hybrid method. Moreover, improvements can be achieved by involving more significantly correlated information in the inputs.

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Appendix A

The basic concept in wavelet transform is to select a proper wavelet, then perform an analysis using its translated and dilated versions. Here, Daubechies wavelet is applied. This wavelet can be defined as a function $\psi(t)$ with a zero average.

A signal can be decomposed into many series of wavelets with different scales a and translation b:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{15}$$

Thus, the wavelet transform of a signal $f(t)$ at translation b and scale a is defined by:

$$wf(b,a) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt \tag{16}$$

The original signal $f(t)$ can be reconstructed by inverse wavelet transform:

$$f(t) = \int_0^{\infty}\int_{-\infty}^{+\infty}\frac{1}{a^2}wf(b,a)\psi_{b,a}(t)db\,da \tag{17}$$

Appendix B

The standard statistical method to build an ARIMA model includes the following (Conejo, 2005):

(1) A class of models is formulated assuming certain hypotheses.
(2) A model is identified.
(3) The parameters of the model are estimated.
(4) If the hypotheses of the model are validated, then go to the next step; otherwise, the procedure continues in step 2 to refine the model.
(5) The model is used to predict.

These steps are explained below.

In step 1, the hypotheses on the error terms are need to ensure the effectiveness of the forecasting. In step 2, the initial selection is based on the autocorrelation function (ACF) and partial ACF (PACF). Further refinement of the selection is based on physical knowledge and on engineering judgment. In step 3, the estimation of the parameters are based on the available historical data. Good estimators are usually found assuming that the data constitute observations of a stationary time series and maximizing the likelihood function. In step 4, a diagnosis check is used to validate the assumptions. If the estimated model is appropriate, then the residuals should behave in a manner consistent with the model. Residuals must satisfy the requirements of a white noise process, zero mean, constant variance and normal distribution. If the hypotheses of the model are validated, then the model can be used to predict prices. Otherwise, the residuals should be analyzed to refine the model. To refine the model a careful inspection of ACF and PACF is advisable. In step 5, the final model from step 3 is used to forecast future values of electricity prices.

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