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Assessment of three forecasting methods for system marginal prices

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Abstract−The electricity supply industry is being restructured worldwide into a competitive market structure in which electricity is produced by generators, transmitted by transmission companies, and distributed by suppliers according to new trading agreements. In this market, system marginal price (SMP) plays a very important role. Obviously, an accurate prediction would benefit all market participants involved. The SMP profile is a typical time series and, to some extent, similar to the load profile. In this study, an SMP forecasting model is developed based on load demand and supply as well as past SMP data. The proposed forecasting model is compared with NN method and wavelet combined with NN scheme. Due to the different life style during weekdays and weekend, we distinguish comparisons between weekdays and weekends in summer, autumn and winter. For weekend forecasting, the NN method exhibits better forecasting performance than other methods. During weekdays, the proposed SMP forecasting method shows the best forecasting performance among other methods.

Key words: Neural Network (NN), Wavelet Transform, System Marginal Prices, Price Forecasting

INTRODUCTION

The electricity industry has undergone significant transformation since the advent of electricity generation in 1882 at Pearl Street Power Station, New York. The electricity industry was organized as regulated and vertically integrated, joining generation, transmission and distribution of electricity in government-owned monopolistic companies [2]. When electricity markets were regulated, predicting future prices involved matching regional electricity demand to regional electricity supply. Future regional demand was estimated by escalating historical data, and regional supply was determined by stacking up existing and announced generation units in order of their variable operating costs [3]. Hence, in the regulated framework, the electricity industry's attention mainly focused on load forecasting, with little need for tools hedging against price risk given the deterministic nature of electricity prices.

Electricity has been turned into a traded commodity nowadays, to be sold and bought at market prices. Two ways of trading are usually assumed: pool trading and bilateral contracts trading. In pool trading, producers and consumers submit bids, respectively, for selling and buying electricity on established intervals, typically on an hourly basis. Finally, a market operator clears the market by accepting the appropriate selling and buying bids, giving rise to the electricity prices. The new electricity industry deregulated framework was intended to encourage competition among companies in order to decrease the cost of electricity. However, occurrences seldom happening in the regulated framework, such as outages and blackouts, are now subjects of increasing concern. Moreover, deregulation brings electricity price uncertainty, placing higher requirements on forecasting [4]. In particular, accuracy in forecasting these electricity prices is very critical, since more accuracy in forecasting reduces the risk of under/over estimating the revenue for producers and provides better risk management [5].

Short-term electricity price forecasting has become a very helpful tool for producers and consumers. A producer needs to forecast electricity prices to derive its bidding strategy into the pool and to optimally schedule its energy resources [6]. In the regulated framework, traditional generation scheduling of energy resources was based on cost minimization. In the new deregulated framework, since generation scheduling of energy resources, such as hydro resources [7], is now based on profit maximization, electricity price forecasting has become essential for developing negotiation skills in order to achieve better profits. Consumers need short-term electricity price forecasts for the same reasons as producers.

Useful techniques for short-term forecasting include neural networks and wavelet decomposition. A certain regularity of the data is an important precondition for the successful application of neural networks [8]. When using classical statistical techniques, a stationary process is assumed for the data. But, in most cases, an assumption of stationarity has to be discarded. Besides, one has to bear in mind that different kinds of nonstationarities may exist [8]. Neural networks have already been used to solve problems such as load forecasting [9], component and system fault diagnosis, security assessment and unit commitment [10]. The wavelet transform converts a price series in a set of constitutive series. These series present a better behavior than the original prices series and therefore can be predicted more accurately [11]. The reason for the better behavior of the constitutive series is the filtering effect of the wavelet transform.

The fundamental and novel contribution of the paper is the introduction of a new forecasting model and the comparison of the forecasting performance of the proposed model with existing prediction methods including neural networks (NN) and wavelet. The wavelet transform is used as a preprocessor of forecasting data by neural

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networks. The proposed forecasting model is based on future load supply and demand, temperature and past prices. For the purpose of comparison of forecasting performance, results of forecasting by the combination of the wavelet and neural networks are compared with those from neural networks only and those from the proposed forecasting equation. It is shown that the proposed forecasting equation outperforms over other forecasting methods for one week ahead forecasting.

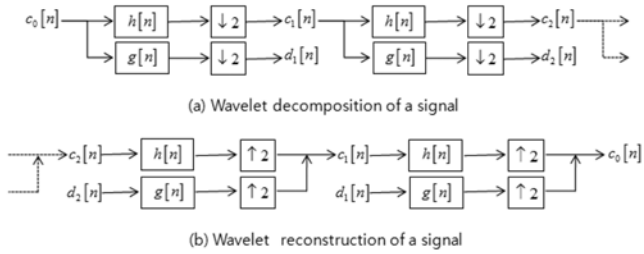

Fig. 1. The wavelet decomposition and reconstruction of a signal.

FORECASTING METHODS

1. Wavelet Transform

The basic concept in wavelet analysis is to select a proper wavelet (mother wavelet) and then perform an analysis using its translated and dilated versions. There are many kinds of wavelets that can be used as a mother wavelet, such as Harr wavelet, Meyer wavelet, Coiflet wavelet, Daubechies wavelet, Morlet wavelet, and so on. In this paper, the Daubechies wavelet is applied.

Similar to the Fourier transform, there are different wavelet transforms, called continuous wavelet transform (CWT), also known as integral wavelet transform (IWT), discrete wavelet transform (DWT), and fast discrete wavelet transform (FWT). Fast wavelet transform is known as multi-resolution analysis (MRA) or Mallat pyramidal algorithm. For a given square-integrable (or finite-energy) function (or signal), f(t), its continuous wavelet transform is defined by

$$(\mathrm{Wf})(\mathrm{a},\mathrm{b}) = \mathrm{a}^{-\frac{1}{2}} \int_{-\infty}^{\infty} \mathrm{f}(\mathrm{t})\, \psi\left(\frac{\mathrm{t}-\mathrm{b}}{\mathrm{a}}\right) \mathrm{dt} \tag{1}$$

where $\psi(t)$ is the mother wavelet. The value of the wavelet transform (Wf)(a, b) is called wavelet coefficient, which stands for the similar degree between the signal and the wavelet at the translation b and the dilation a. The translation means the time shift and the dilation means the time scale. In other words, it means how many components of the wavelet at the dilation a are included in the original signal at the translation b. Through a simple mathematical map, formulation (1) can be rewritten as a convolution of signal f(t) and the wavelet at scale a. So the wavelet works as a band-pass filter (the band corresponds to the scale). DWT is the most commonly used for computer implementation. Similar to the fast Fourier transform (FFT), there is a fast algorithm for the DWT, known as the fast DWT or Mallat and Daubechies' pyramidal algorithm. First, an original discrete signal $c_0[n]$ is decomposed into two components, $c_1[n]$ and $d_1[n]$, by a low-pass filter, h[n], and a high-pass filter, g[n], respectively. The transform is an orthogonal decomposition of the signal. The $c_1[n]$, named the approximation of the signal, contains the low frequency components of the signal $c_0[n]$, and the $d_1[n]$, named the detail of the signal, associates with the high-frequency components of the $c_0[n]$. Then, the approximation $c_1[n]$ is again decomposed into a new approximation $c_2[n]$ and a new detail $d_2[n]$ by a bigger scale followed by third scale, fourth scale, and so on, according to your application. The original signal, $c_0[n]$, can also be reconstructed by these approximations and details. Fig. 1(a) and 1(b) illustrate the decomposing and reconstructing process, respectively [12-14].

2. Neural Networks

Neural networks (NN) are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [15]. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent. Multilayer perceptrons are the best known and most widely used kind of NN. The units are organized in a way that defines the network architecture. In feedforward networks, units are often arranged in layers: an input layer, one or more hidden layers and an output layer. To find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions. The configuration chosen consists of a one hidden layer that uses a hyperbolic tangent sigmoid transfer function and a one unit output layer with a pure linear transfer function. This configuration has been proven to be a universal mapper, provided that the hidden layer has enough units [16]. If there are too few units, the network will not be flexible enough to model the data well, but if there are too many units the network may over-fit the data. Typically, the number of units in the hidden layer is chosen by trial and error, selecting a few alternatives and then running simulations to find the one with the best results. Forecasting with NN involves two steps: training and learning. Training of feedforward networks is normally performed in a supervised manner. One assumes that a training set is available, given by the historical data, containing both inputs and the corresponding desired outputs, which is presented to the network. The adequate selection of inputs for NN training is highly influential to the success of training. In the learning process an NN constructs an input output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. The error minimization process is repeated until an acceptable criterion for convergence is reached. The most common learning algorithm is the backpropagation algorithm [17], in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer.

To predict load demand, three different input data were tried: Case 1 - data of two and one week ago (i.e., historical data of the 14 and

Table 1. Comparison of predicted demand

Period	RMSE		
	Case 1	Case 2	Case 3
2009.12.15-2009.12.18	0.037565	0.058632	0.057159

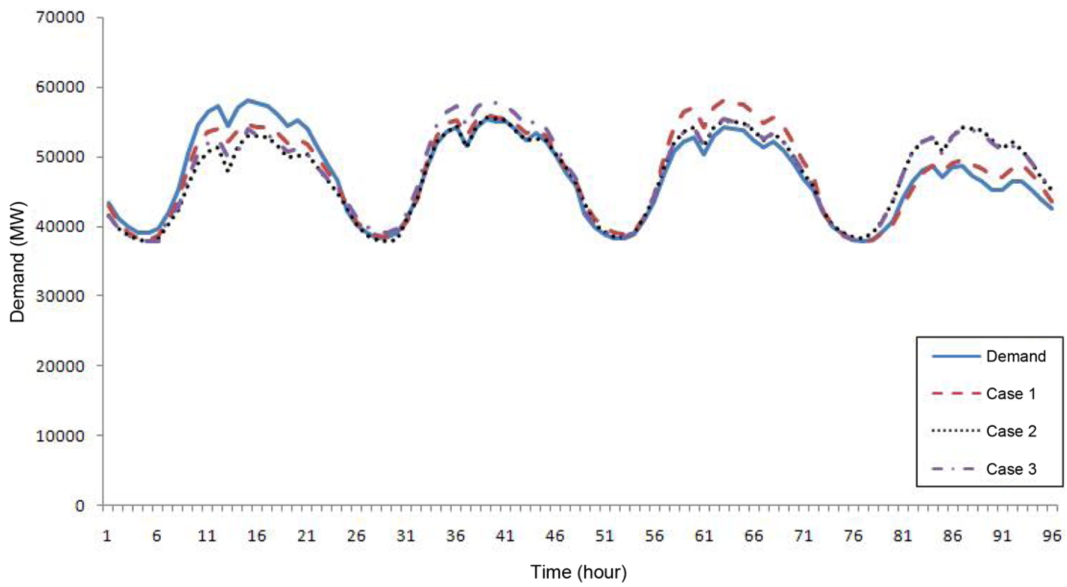

Fig. 2. Comparison of predicted demand for each case (December 15, 2009-December 18, 2009).

7 days previous to the day whose demands are to be predicted); Case 2 - data of two and one day ago; Case 3 - data of one week and one day ago (i.e., historical data of the 7 and 1 day previous to the day whose demands are to be predicted). Results of forecasting are shown in Table 1 and Fig. 2. RMSEs (root mean square errors) are used to compare the accuracy of the prediction for three cases. As can be seen from Table 1, Case 1 (RMSE=0.037565) exhibits better forecasting performance over other two cases (Case 2: RMSE=0.058632, Case 3: RMSE=0.057159). Based on this observation, we used data of one and two weeks ago to forecast SMP.

3. The Proposed SMP Forecasting Model

In general, factors that impact the SMP include power demand, ambient temperature, operating reserves, predicted shortfalls and variations in fuel prices. The main variable that derives the SMP is the power demand. But, in addition to seasonal variations, sometimes the relationship between the SMP and the power demand displays a distorted pattern as shown in Figs. 3 and 4. To improve forecasting performance, we can employ supply and demand principles. It is well known that market prices and the amount of trading goods are determined by interactions between supply and demand in competitive markets. As shown in Fig. 5, the market balance price and the balance turnover is indicated by the point of intersection between the market supply curve and market demand curve. This intersection is called the balance point of demand and supply. If for some reason the market price becomes higher than the balance price, the market price decreases toward the balance price if demand is smaller than supply. In contrast, if the market price becomes lower than the balance price, then the market price increases toward the balance price if corresponding demand is larger than supply. If the demand curve decreases rightward and the supply curve increases rightward, movement of the market demand curve toward the right side causes an increase in both balance price and balance trade. However, movement of the market supply curve toward the right side causes a decrease in balance price. As the amount of Q increases

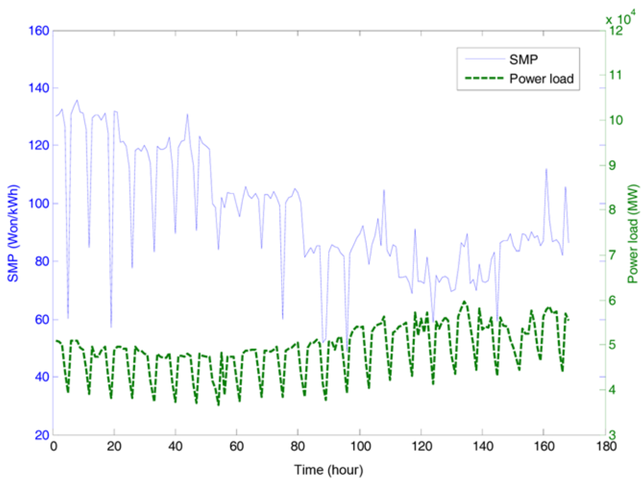

Fig. 3. Chronological SMP and load curve (August 10, 2009-August 16, 2009).

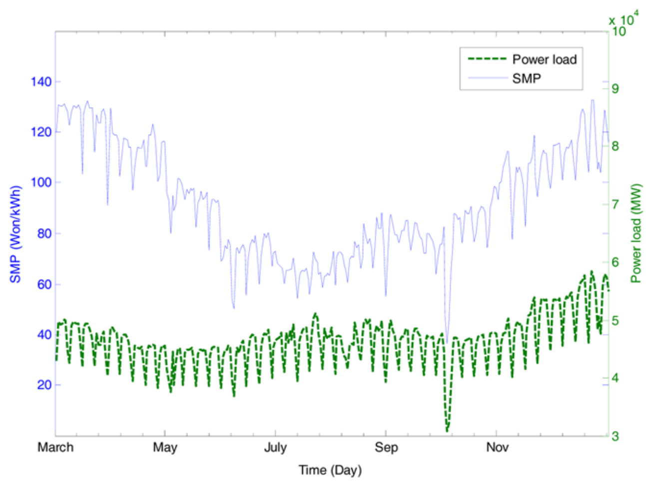

Fig. 4. Chronological SMP and load curve (March 1, 2009-December 31, 2009).

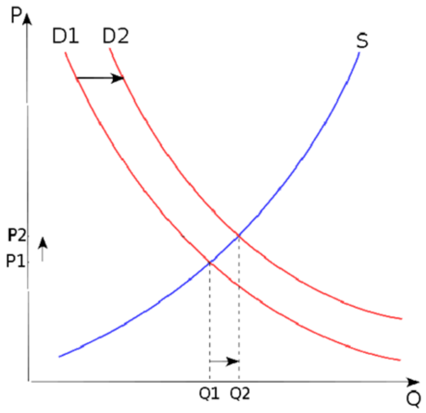

Fig. 5. The supply and demand curve.

in Fig. 5, the demand curve (D) and the supply curve (S) exhibit inversely proportional and directly proportional characteristics, respectively. We can apply the principle of supply and demand in the determination of the SMP. If the demand for electricity increases, the SMP also increases followed by increase of the supply of electricity until a balance is achieved between demand and supply. If the demand for electricity decreases, the SMP also decreases, followed by decrease of the supply of electricity until a balance is achieved between demand and supply. Based on these observations we can extract the following relation for the SMP:

$$\mathrm{SMP}\times\frac{\mathrm{P}_s}{\mathrm{P}_d}=\mathrm{SMP}_w\times\frac{\mathrm{P}_{sw}}{\mathrm{P}_{dw}} \tag{2}$$

where P_s and P_d are power supply and demand, respectively, and P_{sw} and P_{dw} are power supply and demand on 1 week ago, respectively. SMP_w is the SMP of 1 week ago. Eq. (2) can be rearranged as follows:

$$\mathrm{SMP}=\mathrm{SMP}_w\times\frac{\mathrm{P}_d}{\mathrm{P}_{dw}}\times\frac{\mathrm{P}_{sw}}{\mathrm{P}_s} \tag{3}$$

The pattern of SMP data may be regular or irregular. So if we use the data as it is, it is impossible to find the similar data pattern. The pattern shown by new forecasting Eq. (3), being based on data of past 7 days (one week), depends upon the pattern of the past 7 days. Forecasting may be affected significantly by the variations in seasonal fuel prices. For this reason, regular and irregular patterns have to be classified according to the season. Thus, regular and irregular patterns for summer are different from those for winter or spring. We may anticipate similar patterns during spring and fall. Data of past 7 days showing irregular pattern are replaced by data of 14 days ago. Variations in fuel prices matter usually in the first week of a month. To incorporate the effect of variations in fuel prices and to decrease forecasting error, a term denoting variations in fuel prices is added to Eq. (3) to give Eqs. (4) and (5). It should be noted that Eqs. (4) and (5) are used only in the forecasting of the first week of each month.

$$\mathrm{SMP}=\mathrm{SMP}_{w2}\times\frac{\mathrm{P}_d}{\mathrm{P}_{dw2}}\times\frac{\mathrm{P}_{sw2}}{\mathrm{P}_s} \tag{4}$$

$$\mathrm{SMP}=\mathrm{SMP}_w\times\frac{\mathrm{P}_d}{\mathrm{P}_{dw}}\times\frac{\mathrm{P}_{sw}}{\mathrm{P}_s}\times\frac{\mathrm{C}_{LNG}}{\mathrm{C}_{LNGw}} \tag{5}$$

where SMP_w and SMP_{w2} are SMPs of 1 week and 2 weeks ago, respectively, and P_{dw2} and P_{sw2} are power demand and supply on 2 weeks ago, respectively. C_{LNG} and C_{LNGw} denote cost of LNG at present and 1 week ago, respectively.

RESULTS AND DISCUSSION

The power demand is one of the most significant factors that impact the SMP. The power demand shows somewhat steady daily, seasonal and yearly patterns [18], while the patterns of SMP show significant variations because the SMP is affected by weather, power generating facilities and fuel prices in addition to the power demand. Fig. 3 and Fig. 4 depict characteristics of patterns of the SMP and the load during the same period. Fig. 3 shows the characteristics of patterns of the SMP and the load of the same week (August 10, 2009-August 16, 2009), and Fig. 4 shows those for three seasons (spring, summer and fall: March 1, 2009-December 31, 2009).

In this work, three different forecasting methods (the proposed forecasting model, neural networks and the wavelet transformation combined with neural networks) are employed to predict the SMP for summer, fall and winter in 2009. The data used in the training of neural networks were collected from Korea Electricity Trading Office (the past SMP data) and Korea Meteorological Office (data on hourly and daily temperatures). The relevant data are divided into five regions: summer, fall, winter, weekdays and weekend. Values of RSME (root mean square error) of forecasting results are compared for each forecasting method. The RSME is defined by

$$\mathrm{RMSE}=\sqrt{\frac{1}{\mathrm{N}_t}\sum_{i=1}^{N_t}\left(\frac{\mathrm{SMP}_{i,actral}-\mathrm{SMP}_{i,predicted}}{\mathrm{SMP}_{i,actral}}\right)^2} \tag{6}$$

where N_t is the number of observations in test data set and $SMP_{i,actral}$ and $SMP_{i,predicted}$ are the actual and predicted values of SMP, respectively.

1. Forecasting and Comparison of SMP in Summer

The results of SMP forecasting from July 18, 2009 to July 20, 2009 (i.e., a typical weekend in summer) are shown in Fig. 6. The predicted results are in line with the actual trend and have good stability. In particular, the proposed forecasting model offers the best predicting performance (RMSE=0.12050) compared to the other two forecasting methods. The values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed on July 18, 2009, were 25.3 °C, 76.1, 7.3 mm, 86.9% and 6.3 m/s, respectively. Among these factors, the rainfall, the average humidity and the average wind speed exhibit quite different behavior from one and two weeks ago. On July 19, 2009, the values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed were 24.4 °C, 73.8, 0.7 mm, 81.4% and 2.4 m/s, respectively. In this case, values of the rainfall and the wind speed show significant difference from those on one and two weeks ago. On the third day, July 20, 2009, the values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed were 25.5 °C, 75.4, 0.0 mm, 80.5% and 1.8 m/s, respectively. In this case, only the value of the rainfall shows a significant difference from that on one and two weeks ago. We can say that the relatively large forecasting error in summer weekends comes from variations of rainfall, humidity, wind speed and life

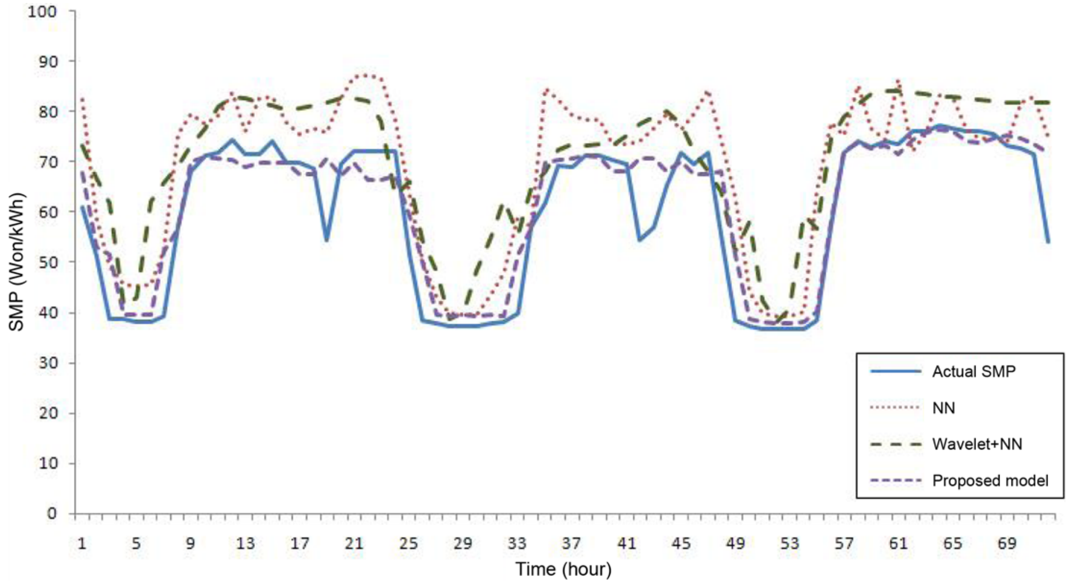

Fig. 6. Comparison of SMP forecasting performance (July 18, 2009-July 20, 2009).

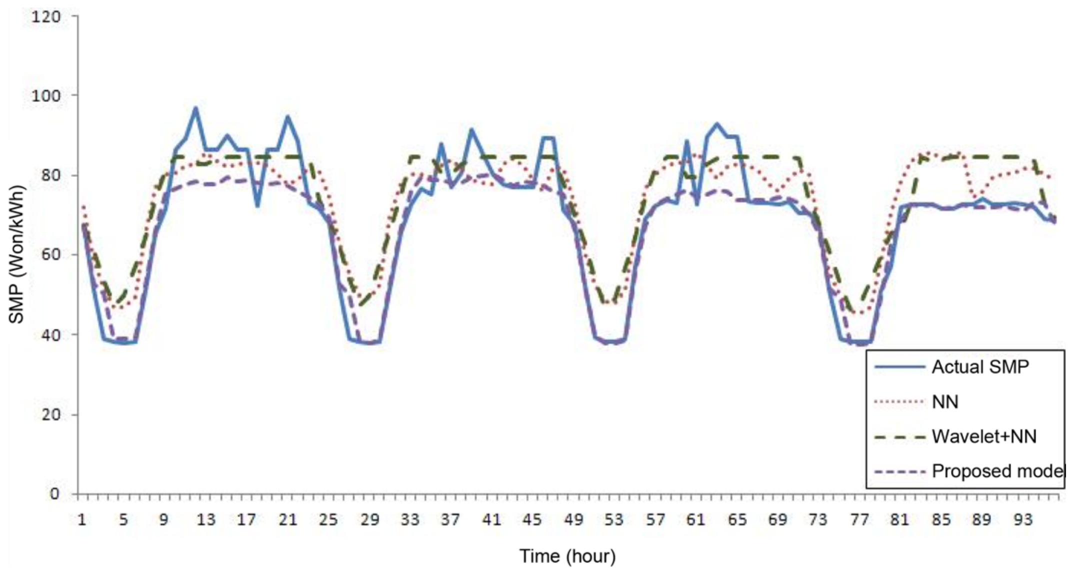

Fig. 7. Comparison of SMP forecasting performance (July 21, 2009-July 24, 2009).

style of consumers.

Fig. 7 illustrates results of SMP forecasting from July 21, 2009 to July 24, 2009 (i.e., weekdays in summer). Compared to the results for weekends (Fig. 6), the forecasting errors are reduced to give better tracking performance and stability. We can see that, even for weekdays, the proposed forecasting model offers the best predicting performance (RMSE=0.08207) compared to the other two forecasting methods. The values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed on July 21, 2009, were 25.5 °C, 75.4, 0.0 mm, 75.8% and 1.8m/s, respectively. Again, the rainfall, the average humidity and the average wind speed exhibit quite different behavior from one and two weeks ago. On July 22, 2009, the values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed were 25.2 °C, 73.4, 0.0 mm, 66.7% and 2.0 m/s, respectively. In this case, values of the rainfall, humidity and the wind speed show significant difference from those on one and two weeks ago. For July 23, 2009, the values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed were 25.3 °C, 73.8, 0.0 mm, 67.4% and 1.7 m/s, respectively. In this case, the values of the rainfall and the average humidity are significantly different from those on one and two weeks ago. Finally, for July 24, 2009, the values of the average ambient temperature, the discomfort index, the rainfall, the average humidity and the average wind speed were 25.0 °C, 73.4, 0.2 mm, 66.5% and 2.7 m/s, respectively. In this case, only the value of the rainfall has a significant difference from that on one and two weeks ago. As can be seen in Table 2, all three methods show good forecasting performance when they are applied to weekdays rather than weekends. The main fac-

Table 2. Comparison of SMP forecasting results

Period	RMSE		
	Neural network	Wavelet+ neural network	Proposed forecasting model
2009.07.18-2009.07.20	0.22139	0.27477	0.12050
2009.07.21-2009.07.24	0.16462	0.18212	0.08207
2009.10.17-2009.10.19	0.09232	0.13944	0.17306
2009.10.20-2009.10.23	0.07337	0.07844	0.06732
2009.12.12-2009.12.14	0.04599	0.06292	0.06966
2009.12.15-2009.12.18	0.09421	0.11310	0.07698

tors which generate a difference in forecasting results between weekdays and weekends are the rainfall, the average wind speed and the life style of consumers. Among these factors, the life style can hardly be taken into account in the forecasting model. It is obvious that incorporation of the rainfall and the average wind speed in the SMP forecasting model may enhance the forecasting performance.

2. Forecasting and Comparison of SMP in Autumn

Fig. 8 illustrates results of SMP forecasting from October 17, 2009 to October 19, 2009 (i.e., a typical weekend in autumn). The values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 17, 2009, were 13.8 °C, 13.0 °C, 12.3 mm and 3.4 m/s, respectively. The average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (October 10, 2009) and two weeks (October 3, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 18, 2009, were 14.1 °C, 13.9 °C, 0.6 mm and 2.3 m/s, respectively. In this case, only the wind chilled temperature exhibits quite different behavior from one week (October 11, 2009) and two weeks (October 4, 2009) ago. Finally, for October 19, 2009, the values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed were 12.2 °C, 11.0 °C, 7.9 mm and 4.0 m/s, respectively. The average ambient temperature, the wind chilled temperature and the rainfall exhibit quite different behavior from one week (October 12, 2009) and two weeks (October 5, 2009) ago. From this observation, we can see that inclusion of the wind chilled temperature and the rainfall in the forecasting model may enhance the predicting performance. For autumn weekends, we can see that the NN method (RMSE=0.09232) gives more accurate forecasting than other methods.

Fig. 9 illustrates results of SMP forecasting from October 20, 2009 to October 23, 2009 (i.e., typical weekdays in autumn). The values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 20, 2009, were 10.7 °C, 10.1 °C, 0.4 mm and 1.9 m/s, respectively. The average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (October 13, 2009) and two weeks (October 6, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 21, 2009, were 13.8 °C, 13.6 °C, 0.0 mm and 2.1 m/s, respectively. Again, the average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (October 14, 2009) and two weeks (October 7, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 22, 2009, were 12.8 °C, 12.6 °C, 0.0 mm and 1.5 m/s, respectively. Only the average ambient temperature exhibits quite different behavior from one week (October 15, 2009) and two weeks (October 8, 2009) ago. Finally, the values of the average ambient temperature, the wind chilled temperature, the rainfall and the average wind speed on October 23, 2009, were 14.9 °C, 14.6 °C, 3.6 mm and 2.1 m/s, respectively. Only the rainfall shows quite different behavior from one week (October 16, 2009) and two weeks (October 9, 2009) ago. We can see that the average ambient temperature and the rainfall mainly contribute to the forecasting error. Relatively small variations in the average ambient temperature and the rainfall compared to other seasons result in more accurate forecast-

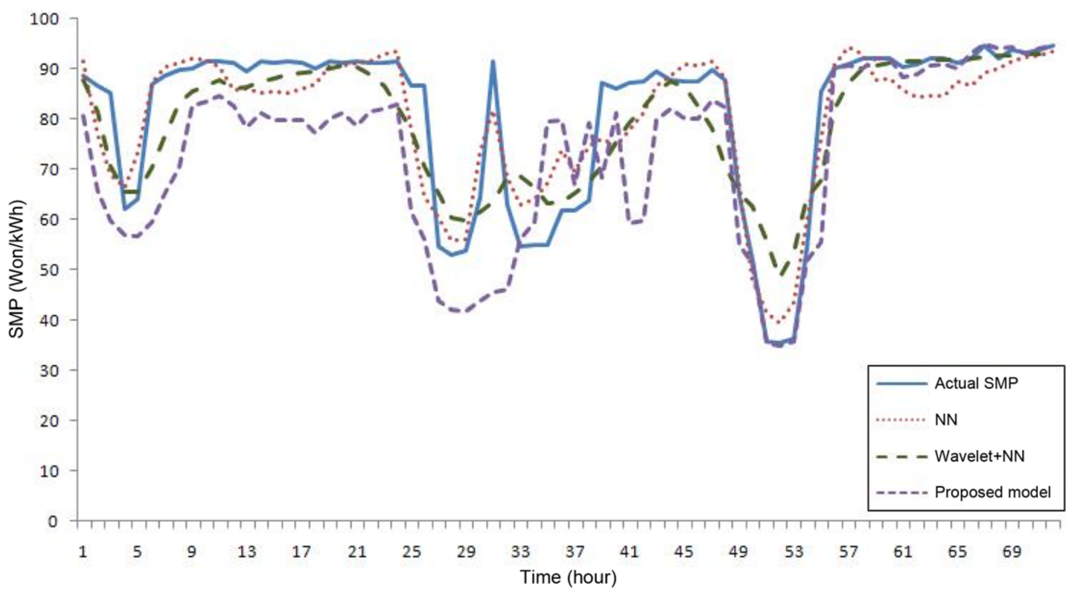

Fig. 8. Comparison of SMP forecasting performance (October 17, 2009-October 19, 2009).

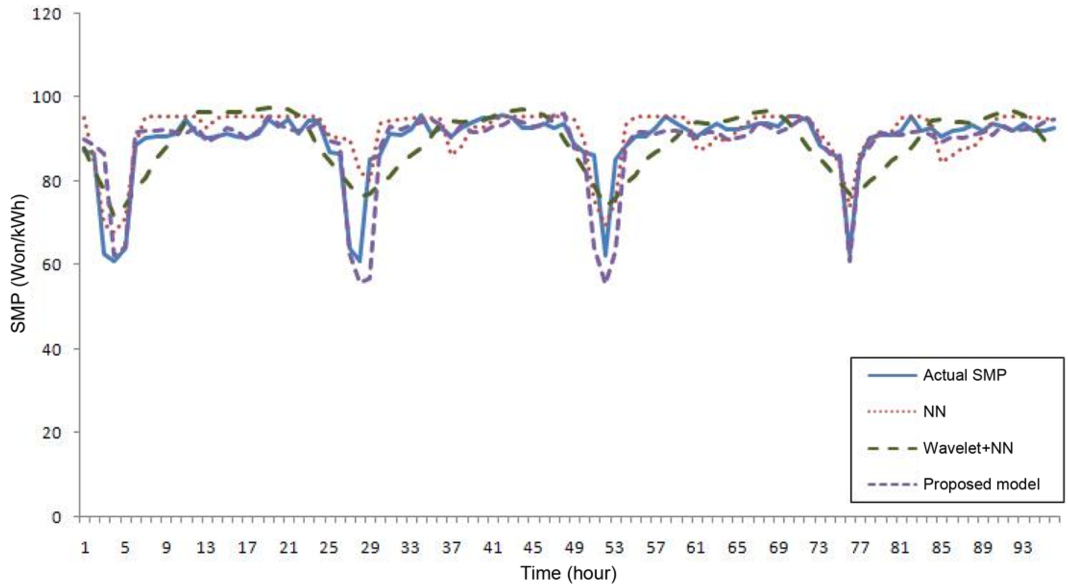

Fig. 9. Comparison of SMP forecasting performance (October 20, 2009-October 23, 2009).

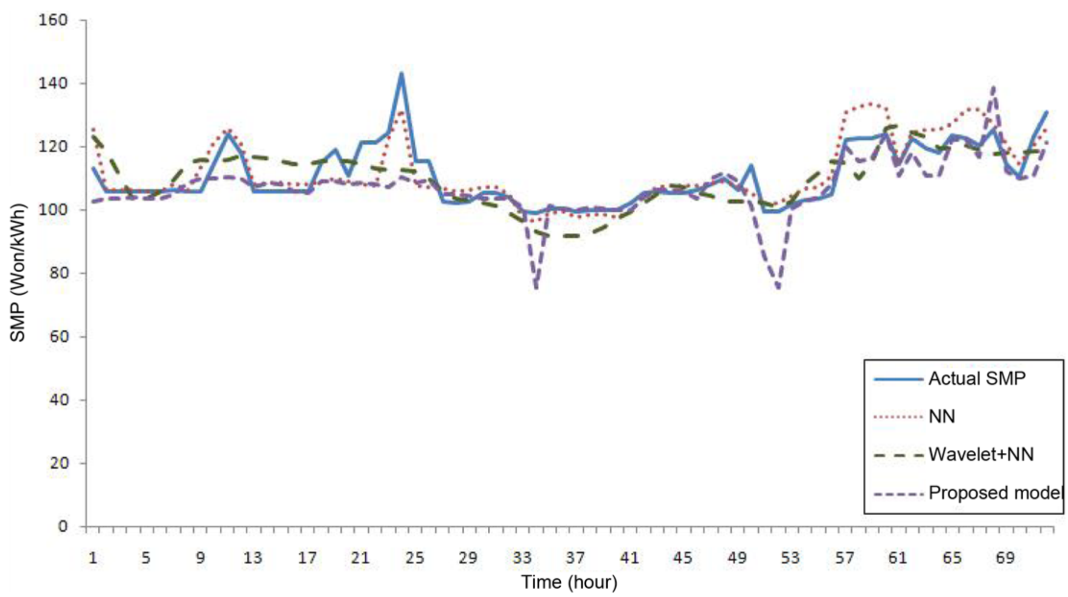

Fig. 10. Comparison of SMP forecasting performance (December 12, 2009-December 14, 2009).

ing. For typical autumn weekdays we can see that the proposed SMP forecasting model gives the best forecasting performance.

3. Forecasting and Comparison of SMP in Winter

Fig. 10 has the results of SMP forecasting from December 12, 2009 to December 14, 2009 (i.e., a typical weekend in winter). The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 12, 2009, were 5.5 °C, 3.3 °C, 0.0 mm, 0.0 cm and 2.8 m/s, respectively. The average ambient temperature, the wind chilled temperature and the rainfall exhibit quite different behavior from one week (December 5, 2009) and two weeks (November 28, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 13, 2009, were 2.3 °C, −0.1 °C, 0.0 mm, 0.0 cm and 2.6 m/s, respectively. The average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (December 6, 2009) and two weeks (November 29, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 14, 2009, were −0.2 °C, −3.6 °C, 0.0 mm, 0.0 cm and 3.0 m/s, respectively. Again, the average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (December 7, 2009) and two weeks (November 30, 2009) ago. In winter, demand on hot water increases as the ambient temperature decreases. Thus, in a typical cogeneration plant, the supply of hot water has priority over the generation of electricity in winter. As can be seen from Fig. 3, the chronological curve for electricity cost tends to increase from summer to winter. For a typical winter

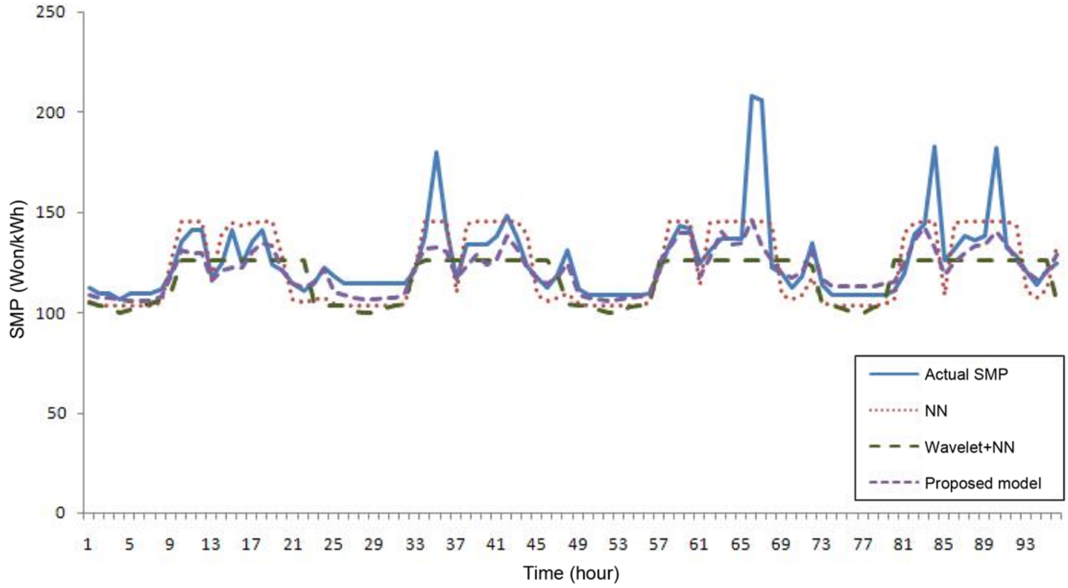

Fig. 11. Comparison of SMP forecasting performance (December 15, 2009-December 18, 2009).

weekend we can see that the NN method (RSME=0.04599) gives the best forecasting performance among other forecasting methods. To process various power consumption patterns, training based on past data is more effective than systematic techniques, which may be one of the reasons the NN method has advantages over other methods.

Fig. 11 shows the results of SMP forecasting from December 15, 2009 to December 18, 2009 (i.e., typical weekdays in winter). The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 15, 2009, were −3.8 °C, −8.2 °C, 0.0 mm, 0.0 cm and 3.3 m/s, respectively. The average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (December 8, 2009) and two weeks (December 1, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 16, 2009, were −6.3 °C, −10.6 °C, 0.0 mm, 0.0 cm and 2.8 m/s, respectively. Again, the average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (December 9, 2009) and two weeks (December 2, 2009) ago. The values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 17, 2009, were −7.1 °C, −12.2 °C, 0.0 mm, 0.0 cm and 3.4 m/s, respectively. As before, the average ambient temperature and the wind chilled temperature exhibit quite different behavior from one week (December 10, 2009) and two weeks (December 3, 2009) ago. Finally, the values of the average ambient temperature, the wind chilled temperature, the rainfall, the snowfall and the average wind speed on December 18, 2009, were −9.4 °C, −15.0 °C, 0.0 mm, 0.0 cm and 3.3 m/s, respectively. Values of the average ambient temperature and the wind chilled temperature differ from those on one week ago (December 11, 2009) and two weeks ago (December 4, 2009) by 15 °C and 12 °C, respectively. The many peaks in Fig. 11 indicate the contribution of increased power consumption before and after working hours to the prices. We can identify severe peaks as the ambient temperature and the wind chilled temperature decrease. For typical winter weekdays the proposed SMP forecasting model (RMSE=0.07698) gives the best forecasting performance. Table 2 summarizes RMSEs for weekdays and weekends in summer, autumn and winter.

CONCLUSIONS

The SMP profile is a typical time series and, to some extent, similar to the load profile. Thus, many forecasting methods can be used to predict the short-term SMP. In this work, an SMP forecasting model is developed based on load demand and supply as well as past SMP data. The proposed forecasting model is compared with the NN method and wavelet combined with the NN scheme. Due to the different life style during weekdays and weekends, we distinguish comparisons between weekdays and weekends in summer, autumn and winter. For weekend forecasting, the NN method has better forecasting performance than other methods. During weekdays, the proposed SMP forecasting method shows the best forecasting performance among other methods. Incorporation of power consumption into the proposed SMP forecasting model is yet to be investigated.

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NOMENCLATURE

a : power demand [-]
b : power demand 1 day before [-]

$c_0[n]$: power demand 1 week before [-]
$c_1[n]$: power demand 2 weeks before [-]
$c_2[n]$: max power supply during whole day [-]
C_{LNG} : max power supply 1 day before [Won/kWh]
C_{LNGw} : power supply 1 day before [Won/kWh]
$d_1[n]$: power supply 1 week before [-]
$d_2[n]$: power supply 2 weeks before [-]
$g[n]$: actual values of SMP [-]
$h[n]$: predicted values of SMP [-]
P_d : SMP 1 week before [MW]
P_{dd} : SMP 2 weeks before [MW]
P_{dw} : mother wavelet [-]
P_{dw2} : wavelet coefficient [-]

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