A SYSTEM MARGINAL PRICE FORECASING METHOD BASED ON AN ARTIFICIAL NEURAL NETWORK USING TIME AND DAY INFORMATION

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Abstract: This paper presents a forecasting technique of the short-term system marginal price (SMP) using an Artificial Neural Network (ANN). The SMP forecasting is a very important element in an electricity market for the optimal biddings of market participants as well as for market stabilization of regulatory bodies. Input data are organized in two different approaches, time-axis and day-axis approaches, and the resulting patterns are used to train the ANN. Performances of the two approaches are compared and the better estimate is selected by a composition rule to forecast the SMP. By combining the two approaches, the proposed composition technique reflects the characteristics of hourly, daily and seasonal variations, as well as the condition of sudden changes in the spot market, and thus improves the accuracy of forecasting. The proposed method is applied to the historical real-world data from the Korea Power Exchange (KPX) to verify the effectiveness of the technique.

Keywords: Electric power systems, Forecasts, Neural networks, Backpropagation.

1. INTRODUCTION

The electric power industry in many countries all over the world has been undergoing deregulation and privatisation through the introduction of competition. Korea has been keeping pace with this situation. Restructuring of electric power industry in Korea started with the establishment of the Korea Power Exchange (KPX) in April 2001, and the breakup of the generation sector from the Korea Electric Power Corporation (KEPCO) into six generation companies (GENCOs). Currently, Cost-Based Pool (CBP) electricity market is in operation. The goal of power system planning and operation for the previous vertically integrated industry was to minimize production and operation cost. However, the goal is now changed into maximizing the profit or return to the market participants since the introduction of competition in the electricity market. Indeed, it may become possible to use strategies in order to maximize the profit.

In this competitive market environment, participants bid at a specific time period to trade the electric power. In this bidding, each participant can maximize their profit though a bidding strategy that is considered under several power system conditions, such as characteristics of electric power demand at each time period. Therefore, the energy trading levels between market participants is highly dependent on the short-term price forecast (Szkuta, *et al*., 1999).

In general, hard or soft computing techniques could be used to estimate the spot prices. Hard computing techniques are built on an exact model of the system, and the solution is found using algorithms that consider the physical phenomena that govern the system. This approach can be very accurate, but it requires a great deal of information, and the computational cost can be very high. Soft computing techniques, on the hand, are very simple in structure, and it can be as accurate as the hard computing technique if the correct inputs are considered (Rodrigues, *et al*., 2004). The main stream of soft computing techniques is artificial intelligence, such as artificial neural network, fuzzy and neuro-fuzzy systems, etc.

Several techniques are proposed to forecast the electricity price accurately in response to the increasing importance of electricity price forecasting raised by market participants. Firstly, an artificial neural network (ANN) is used to forecast the SMP in Victorian Power System by Szkuta *et al.* (Szkuta, *et al.*, 1999). The SMP forecasting in the paper was implemented for a case from 14 May 1997 to 20 May 1997; however, this technique is impractical to apply in the real power market, because the forecasting error is relatively high. Rodriguez *et al.* developed the factors that impact energy price considering many power system conditions and then applied to Ontario Competitive Power System Market (Rodrigues, *et al.*, 2004). In this work, traditional neural network and neuro-fuzzy system are applied to forecast the energy price and the forecasting error was compared between these two techniques. In addition, short-term energy price forecasting method was developed using time series modeling by Nogales *et al.* (Nogales *et al.*, 2002) and price forecasting method was developed using dynamic fuzzy system by Liu *et al.*(Liu *et al.*, 2001).
The success of a forecasting technique depends on the quality of input data that could contain proper patterns representing the system dynamics. In this paper, the input data is examined from two different angles, time-axis and day-axis, in order to extract the rich characteristics of the SMP dynamics, which otherwise could be ignored.

2. FORMULATION

The SMP is the market price that is determined to consider the characteristics of generators in bidding, under a given power system condition and demand. It is determined by the highest bidding price among generators that is succeeded in the bidding. In general, factors that impact the energy price are power demand, temperature, operating reserves, predicted shortfalls, etc., and the main variable that drives the price is the demand (Rodrigues, *et al.*, 2004). The SMP has a specific characteristic for each time period, such as daily cycle and seasonal variation, which is the basis for forecasting the future SMP based on the past SMPs.
If we consider all possible factors that affect the SMP, forecasting will be very accurate, which, however, is very difficult to do in the real market. Therefore, this paper considers only the past power demand and SMP to forecast the future SMP. The data can be defined on a point (w,t) in the two-dimensional space, with the week (w) and time (t) as the coordinates. In the paper, the time (t) is defined as the chronological time for one week, starting from Monday, 12:00 AM and ending at Sunday midnight. The past demand and SMP data are then defined on an input domain $\Omega = \Omega_w \times \Omega_t$, where

$\Omega_w = \left[w, w-1, w-2, \cdots, w-n\right]$ and

$\Omega_t = \left[t, t-1, t-2, \cdots, t-m\right]$.

Here n and m represent the data length in the respective coordinates.

Then, the SMP forecasting problem can be formulated as follows:

$$y(w,t) = f(Y(w,t), D(w,t)) \qquad (1)$$

where

$Y(w,t) = \{y(\overline{w},\overline{t}) :\ (\overline{w},\overline{t}) \in \Omega,\ \ (\overline{w},\overline{t}) \neq (w,t)\}$

$D(w,t) = \{d(\overline{w},\overline{t}) :\ (\overline{w},\overline{t}) \in \Omega\}$

$y(w,t)$: SMP in week w, (chronological) time t

$d(w,t)$: power demand in week w, time t

Input data is defined on a two-dimensional space. However, when we train a neural network, data need to be fed sequentially as a one-dimensional sequence. In Section IV, two different approaches of grouping the input pattern will be illustrated and a way of combining the two approaches will be presented.

3. ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN), which mimics the human brain, has drawn much attention recently, because it's massive parallel structure can be utilized in computation, which is much more efficient than in the traditional serial-type computer. ANN is applied in many field of study such as pattern recognition, noise filtering, forecasting, etc. (Szkuta, *et al.*, 1999). In power systems, ANNs have already been used to solve problems such as load forecasting (K. Y. Lee, *et al.* 1992), component and system fault diagnosis, security assessment, unit commitment, etc. (Dillon and Niebur, 1996).
In this paper, a multilayer feed-forward neural network (or back-propagation neural network) is used to forecast SMP. Fig. 1 represents a basic structure of a three-layer back-propagation neural network with one input layer, one hidden layer, and one output layer (Fausett, 1994; K. Y. Lee, *et al.* 1992). In the back-propagation neural network, each input unit receives an input signal and broadcasts this signal to each neurons in the hidden layer. Each hidden unit then computes its activation and sends its signal to neurons in the output layer. Each output unit computes its activation to form the response of the ANN for the given input pattern. This activation is compared with a target value and then weights in the network are adjusted to reduce the difference between the activation and the target value.

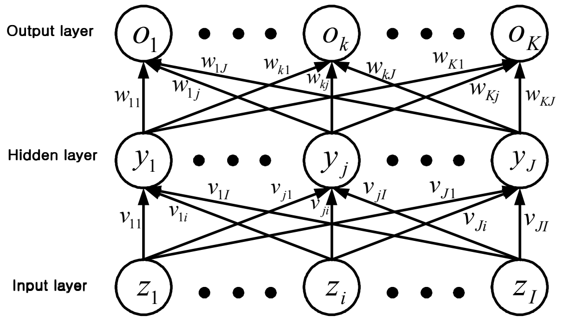

Fig. 1. Basic structure of Back-propagation NN

The objective function for the neural network training can be formulated as to minimize the error between the target and the output as follows:

$$\min \ error = \sum_{p=1}^{P} \sum_{k=1}^{K} \frac{1}{2}(d_{pk} - o_{pk})^2 \qquad (2)$$

where
P : number of patterns
K : number of output units
d_{pk} : target value of the k-th output unit for the p-th pattern
o_{pk} : calculated value of the k-th output unit for the p-th pattern.

4. FORECASTING OF SMP WITH NEURAL NETWORK

The neural network for forecasting SMP is affected by the activation function, the number of hidden layers, and the number of units in each layer. Moreover, even if the same input data and activation functions are used, it may lead to a very different result according to the manner in which the input data pattern is organized. Therefore, it is very important to find an appropriate manner of organizing the input data pattern in order to improve the efficiency of the algorithm. In this section two different methods of organizing the input data pattern are presented for the SMP forecasting. The first method is a *time-axis approach* where a data pattern is organized as a vector of weekly SMP recorded for a fixed (chronological) time. The second approach is a *day-axis approach* where a data pattern is organized as a vector of hourly SMP for a fixed week. Recall that the time is defined in this paper as the chronological time for an entire week, from Monday to Saturday.

4.1 Time-Axis Approach

This approach is based on the observation that the weekly power demand at a given time exhibits similar pattern. For example, demand at noontime on Monday stays about the same from week to week. A similar pattern can be observed for the demand at some other time, say 11:00 AM on Monday, although its values might be differ somewhat. Another observation is that the changes from week to week can be predicted from the pattern learned for a given time of the week.
The concept of the time-axis approach is depicted in Fig. 2, where 4 patterns of weekly SMP are given for 4 consecutive time instants, and an SMP for the next time instant is forecasted. The first 4 patterns are used to train the neural network, and the SMP for the current week for the next time instant is forecasted based on the corresponding SMPs for the previous weeks.
The current SMP is affected by the past SMPs and the pattern in which the current SMP is included. In addition to the past SMPs, the SMP is also influenced by the power demand. Therefore the following nonlinear model is proposed for the SMP forecasting in the time-axis approach:

$$y(w,t) = F(W, y(w-1,t), y(w-2,t), \ldots, y(w-n,t), \\ d(w,t), d(w-1,t), d(w-2,t), \ldots, d(w-n,t)) \qquad (3)$$

where
$y(w,t)$: SMP in week *w*, at (chronological) time *t*
$d(w,t)$: power demand in week *w*, time *t*
W : weight matrix of ANN
n : index for input data length
F(.) : nonlinear function representing ANN

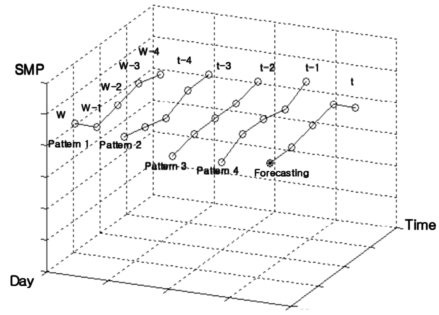

Fig. 2. Time-axis approach.

In contrast to the conventional approaches, the nonlinear function is used with the weight matrix to represent the SMP model. The weight matrix *W* can be thought of as a storage that contains a certain SMP pattern, and *F*(.) is the general nonlinear function that can comprise all the SMP patterns. The weight matrix in (3) is adjusted in the learning mode of ANN by applying a number of the SMP patterns. For example, in Fig. 2, four SMP patterns corresponding to chronological times {*t-i*: *i*=1,2,3,4} are used to train the ANN, where each pattern has the input data length of four (*n*=4). Once the weight matrix is estimated, the SMP is forecasted with the SMPs of previous weeks as well as the power demand at time *t* as follows:

$$\hat{y}(w,t) = F(\hat{W}, y(w-1,t), y(w-2,t), \ldots, y(w-n,t), \\ d(w,t), d(w-1,t), d(w-2,t), \ldots, d(w-n,t)) \qquad (4)$$

where $\hat{W}$ denotes the weight estimate and $\hat{y}(w,t)$ indicates the SMP forecast for week *w*, time *t*.

4.2 Day-Axis Approach

This approach is based on the observation that the hourly power demand in a given week exhibits similar pattern from week to week. For example, the load cycle in the second week in April, from Monday to Sunday, is repeated in the third week in April without much deviation. Another observation is that the hourly changes can be predicted from the pattern learned for a given week.
The concept of the day-axis approach is depicted in Fig. 3, where 4 patterns of hourly SMP are given for 4 consecutive weeks, and an SMP for the following

week is forecasted. The first 4 patterns are used to train the neural network, and the SMP for the current week for the next time instant is forecasted based on the SMPs in the previous time instants. This method reflects the characteristics of hourly, daily, and seasonal variation of power demand, but it cannot reflect the spot market that undergoes a sudden change.

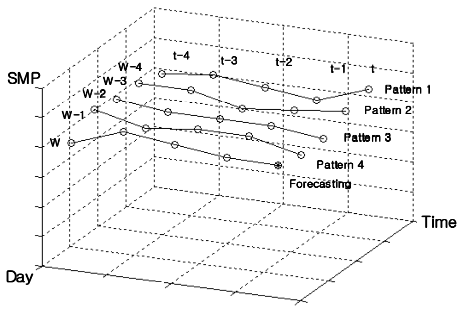

Fig. 3. Day-axis approach

In a way similar to the time-axis approach, the following nonlinear model is proposed for the SMP forecasting in the day-axis approach:

$$y(w,t) = F(W, y(w,t-1), y(w,t-2), ..., y(w,t-m), d(w,t), d(w,t-1), d(w,t-2), ..., d(w,t-m)) \quad (5)$$

where

$y(w,t)$: SMP in week *w*, at (chronological) time *t*

$d(w,t)$: power demand in week *w*, time *t*

W: weight matrix of ANN

m: index for input data length

F(.): nonlinear function representing ANN

The weight matrix in (5) is adjusted in the learning mode of ANN by applying a number of SMP patterns. For example, in Fig. 3, four SMP patterns corresponding to weeks {*w*-*i*: *i*=1,2,3,4} are used to train the ANN, where each pattern has the input data length of four (*m*=4).

Once the weight matrix at time *t* is estimated, the SMP is forecasted with the SMPs of previous hours as well as the power demand as follows:

$$\hat{y}(w,t) = F(\hat{W}, y(w,t-1), y(w,t-2), ..., y(w,t-m), d(w,t), d(w,t-1), d(w,t-2), ..., d(w,t-m)) \quad (6)$$

where $\hat{W}$ denotes the weight estimate and $\hat{y}(w,t)$ indicates the SMP forecast for week *w*, time *t*.

Although the two approaches use the same data the results of the forecast are different. This is because the two ANNs learn different patterns that are defined in different arrays of the data. Time-axis approach model can reflect the current market condition, while day-axis approach can reflect the characteristics of hourly, daily, and seasonal variations of the system marginal price. Therefore, by combining these two methods, better results can be obtained that consider both the characteristics of system marginal price and the current market condition.

5. COMPOSITION OF TIME AND DAY AXIS APPROACH

The main purpose of combining the two approaches having different characteristics is to take advantage both methods. In this paper, the performance of each method is evaluated by computing the forecasting error in the neighborhood of the forecasting point (*w*,*t*) in the week-time coordinates. When forecasting the SMP at point (*w*,*t*), the only available SMPs in its immediate neighborhood are at 4 points, {(*w*,*t*-1), (*w*-1,*t*-1), (*w*-1,*t*), (*w*-1,*t*+1)} as shown in Fig. 4. The forecasting error at each point is defined by

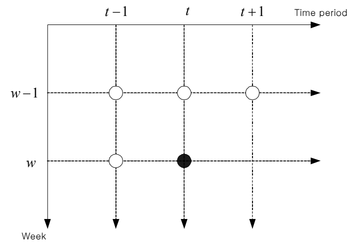

Fig. 4. Data available in the immediate neighborhood of the forecasting point in the input domain.

$$e_i = \frac{|\hat{y}_i - y_i|}{y_i} \times 100\%, \quad i = 1, 2, 3, \text{and } 4 \quad (7)$$

where y_i and $\hat{y}_i$ denote the actual SMP at point *i* and its estimate, respectively.

The performance of each method at point (*w*,*t*) is then defined by averaging the forecasting errors in an error norm defined by:

$$ErrorNorm = \sqrt{\sum_{i=1}^{4} w_i e_i} \quad (8)$$

where w_i are the relative weights corresponding to the impact each point has on the SMP forecast.

The process of combining the two approaches, time-axis and day-axis, in forecasting the SMP at a point (*w*,*t*) is then simply choosing the one that has smaller error norm. Fig. 5 illustrates the procedure of forecasting SMP by combining the two methods.

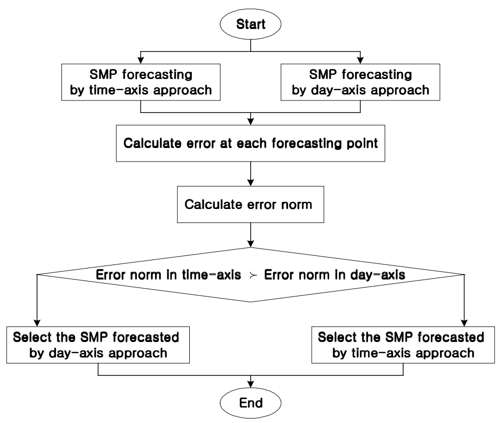

Fig. 5. Process of the SMP forecasting.

6. CASE STUDIES

The proposed forecasting procedure was implemented using the past SMP and demand data obtained from the Korea Power Exchange (KPX) for the month of April 2002. The following two cases are studied: Case 1) Include Monday, Saturday, holiday and the day after holiday. Case 2) Exclude Monday, Saturday, holiday and the day after holiday.
Table I presents the SMP forecasting error for a month for Case 1. Although there are some exceptions, the composite method shows better results in general. The average forecasting error and standard deviation for the three approaches are also compared in Table 2. It shows that the composite method has the smallest average error and standard deviation compared to the other two approaches. Therefore, it can be concluded that the accuracy of SMP forecasting can be improved by combining the time- and day-axis approaches.
Fig. 6 shows the actual SMP and the forecasted SMP that is predicted by the composite time-and day-axis approach for one month, April 2002. In the figure, pattern of the forecasted SMP is very similar to, or coincide with the pattern of the actual SMP; but when the actual SMP rises or fall sharply, forecasted SMP cannot follow the pattern. However, we can observe that the forecasted SMP with the proposed technique is very close to the actual SMP in general. Also, judging from the results shown in Table 1, Table 2, and Fig. 6, the technique proposed in this paper can provide useful information to market participants.

Table 2 average error and standard deviation

		Time	Day	Comp
Case 1	Avg. Error	8.02	5.58	5.2
	Std Dev	5.3	5.52	3.13
Case 2	Avg. Error	5.5	4.92	4.27
	Std Dev	1.95	2.2	1.43

7. CONCLUSIONS

In this paper, the system marginal price (SMP) is forecasted using a back-propagation neural network (NN). The power demand and the past SMP data obtained from the Korea Power Exchange (KPX) are used as input data for the NN. Input data are organized in two different approaches, time-axis and day-axis approaches, and the resulting patterns are used to train the NN. Performances of the two approaches are compared and the better estimate is selected by a composition rule to forecast the SMP. Time-axis approach reflects the current market trend; on the other hand, day-axis approach reflects the characteristic of hourly, daily and seasonal variations. By combining the two approaches, the proposed composition technique reflects the characteristics of hourly, daily and seasonal variations, and the condition of sudden changes in the spot market. In addition, it improves the accuracy of forecasting. Except on holiday, the day after holiday and weekends, the forecasting error is very small. Therefore, the proposed technique can be applied to a real power market for short-term price forecasting, and provide a useful information to market participants in establishing optimal strategies.

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Table 1 SMP Forecasting error for April 2002

Day	Monday			Tuesday			Wednesday			Thursday			Friday			Saturday		
Date	1/4/2002			2/4/2002			3/4/2002			4/4/2002			5/4/2002			6/4/2002		
Axis	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp
Err(%)	16.98	6.99	13.13	5.17	5.15	4.50	5.87	5.12	4.12	5.85	7.10	7.07	6.12	9.16	6.65	12.83	10.66	9.62
Date	8/4/2002			9/4/2002			10/4/2002			11/4/2002			12/4/2002			13/4/2002		
Axis	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp
Err(%)	17.26	4.48	5.11	4.82	2.68	2.77	5.29	3.25	2.97	5.48	2.71	4.14	5.63	5.74	4.61	3.90	5.40	4.71
Date	15/4/2002			16/4/2002			17/4/2002			18/4/2002			19/4/2002			20/4/2002		
Axis	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp
Err(%)	17.07	11.79	10.65	5.20	4.29	4.02	4.83	2.45	3.47	12.97	5.90	5.52	5.64	3.38	4.36	3.69	2.35	1.46
Date	22/4/2002			23/4/2002			24/4/2002			25/4/2002			26/4/2002			27/4/2002		
Axis	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp
Err(%)	18.64	5.23	4.53	5.23	2.42	2.37	4.65	1.95	1.58	4.85	4.69	4.22	5.07	2.64	2.33	4.87	2.48	3.23
Date	29/4/2002			30/4/2002			1/5/2002			2/5/2002			3/5/2002			4/5/2002		
Axis	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp	Time	Day	comp
Err(%)	17.30	3.71	4.06	4.53	6.12	4.63	3.19	5.03	4.01	17.24	31.82	14.83	4.37	10.51	6.27	2.74	5.53	3.80

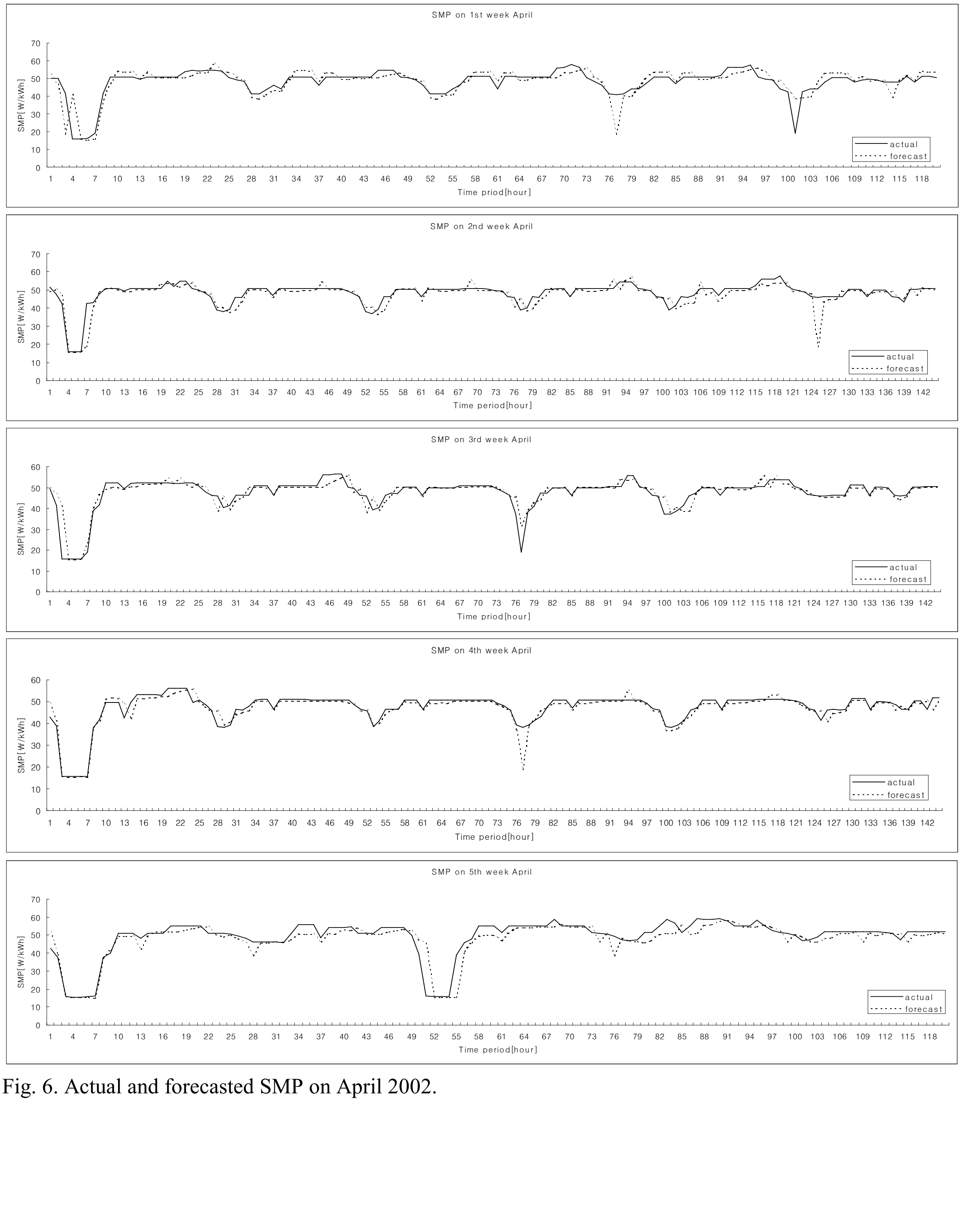

Fig. 6. Actual and forecasted SMP on April 2002.