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Flexible electricity price forecasting by switching mother wavelets based on wavelet transform and Long Short-Term Memory

Koki Iwabuchi [a,*], Kenshiro Kato [a], Daichi Watari [a], Ittetsu Taniguchi [a], Francky Catthoor [b,c], Elham Shirazi [b,c,d,e,1], Takao Onoye [a]

[a] Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan
[b] imec, Kapeldeef 75, 3001 Heverlee, Belgium
[c] ESAT, KULeuven, Kasteelpark Arenberg 10, 3001 Heverlee, Belgium
[d] EnergyVille, Dennenstraat 7, B-3600 Genk, Belgium
[e] University of Twente, Enschede, 7500 AE, Netherlands

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ABSTRACT

Under dynamic pricing, stable and accurate electricity price forecasting on the demand side is essential for efficient energy management. We have developed a new electricity price forecasting model that provides consistently accurate forecasts. The base prediction model decomposes the time series using wavelet transform and then predicts it by Long Short-Term Memory. Previous studies using this model have always decomposed time series in the same way without changing the mother wavelet. However, this makes it difficult to respond to changes in time series that vary daily or seasonally. Therefore, we periodically switch the mother wavelet, i.e., flexibly change the time series decomposition method, to achieve stable and highly accurate electricity price forecasting. In an experiment, the model improved prediction accuracy by up to 42.8% compared to prediction with a fixed mother wavelet. Experimental results show that the proposed flexible forecasting method can consistently provide highly accurate forecasts.

1. Introduction

In recent years, renewable energy is widely used in many countries. Renewable energies are expected to contribute to the achievement of a low-carbon society. While renewable energy is a clean energy source, it is not possible to control the output power. In power systems, it is essential to balance supply and demand. Otherwise, the resulting voltage and frequency fluctuations would create major problems for the consumers' electrical equipment. Therefore, electric power companies constantly forecast the demand and determine the amount of power generated by each power plant so that supply and demand can be kept in balance.

Today, with the massive introduction of solar energy into power system, balancing supply and demand is becoming more challenging. Demand response is thus attracting attention as a solution to this problem [1]. This is the process of changing consumer demand patterns. One means of demand response is dynamic pricing [2], in which electricity prices are varied from time to time, and this has been introduced in many countries, such as European nations, the United States, and Australia. For example, when excessive power generation is expected, electricity demand can be boosted by lowering electricity prices. When the price of electricity changes from time to time due to dynamic pricing, it becomes increasingly important to predict the price changes for decision making of each consumer. To be more precise, electricity price forecasting is very important for a prosumer, or consumers who also produce electricity, which has been increasing with the spread of solar power generation. Energy management by prosumers based on accurate electricity price forecasts will allow them to receive incentives on their electricity bills, and would allow for optimal energy use for groups of prosumers without hampering the optimization of the national/regional grid.

Electricity price forecasting methods can be divided into three main categories: statistical methods, machine learning methods, and hybrid methods. First, among statistical methods, Auto-Regressive (AR) models such as Auto-Regressive Integrated Moving Average (ARIMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) have been widely used. Zhao et al. [3] used an ARIMA model for

* Corresponding author.
E-mail address: iwabuchi.koki@ist.osaka-u.ac.jp (K. Iwabuchi).

1 She was previously affiliated with imec, KULeuven, and EnergyVille when her primary contribution to the research was made. She is presently working at University of Twente, Netherlands.

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differential price time-series data, where the price is represented by a weighted sum of past prices and noise. They also focused on the difference in electricity consumption patterns between weekdays and holidays. They improved short-term forecasting accuracy by adding a "weekday/holiday" term to the mathematical model. Tan et al. [4] proposed a method based on wavelet transform combined with ARIMA and GARCH models, and they tested it on data from the Spanish electricity market and other sources. Mohsenian-Rad et al. [5] focused on the fact that electricity prices are highly correlated with prices one, two, and seven days before, and they calculated the price at forecast time as a weighted sum of the prices one, two, and seven days before. By changing the weights for each day of the week, forecasts with small error were achieved. However, since these statistical methods represent predictions as a linear combination of past values, the longer the past time to be considered, the more parameters are required, making it difficult to handle complex and nonlinear time series. Therefore, machine learning is attracting attention due to its outstanding performance in dealing with complex and nonlinear problems.

Machine learning is used in a variety of research areas. For example, Wei et al. [6] used machine learning to predict stock prices. Durganjail et al. [7] used classification algorithms such as logistic regression and decision trees to predict the resale value of homes. Lu et al. [8] proposed an Artificial Neural Network (ANN) -based electricity price prediction model. Lago et al. [9] compared machine learning methods such as simple deep neural network (DNN) and LSTM with statistical methods such as ARIMA, and they showed that machine learning can provide more accurate predictions than statistical methods. In the study by Xu et al. [10], they compared simple Recurrent Neural Network (RNN), LSTM, and Gated Regression Unit (GRU) with neural networks without recursive structure. Their results showed that simple RNN, LSTM, and GRU could predict more accurately because they predict based on past information. The above study showed that RNN such as LSTM and GRU showed superior performance in electricity price prediction. However, research using hybrid models of machine learning and other methods has been the most popular approach in recent years, since they can provide more accurate electricity price prediction than prediction methods using machine learning alone.

Peng et al. [11] incorporated a differential evolution algorithm to determine the parameters of LSTM. Assuming that this would better capture the characteristics of the time series, an improvement in forecast accuracy has been shown using electricity prices in New South Wales, Australia, Germany, Austria, and other countries. Lago et al. [12] showed that a hybrid model of Lasso Estimated Auto-Regressive (LEAR) and DNN provides better prediction results than methods using LEAR and DNN individually, and they verified a significant difference in prediction accuracy by statistical tests. Since it is very effective in forecasting non-stationary time series, research combining machine learning and the wavelet transform is actively being conducted, not only for electricity price forecasting but also for other purposes. The wavelet transform is used to decompose a time series by frequency. Su et al. [13] predicted natural gas consumption with a model that integrates wavelet transform, RNN-structured deep learning, and a Genetic Algorithm. The wavelet transform reduced the complexity of the forecasting task by decomposing the original gas consumption series into several subcomponents. For the mother wavelet, which is a kind of parameter included in the wavelet transform, Daubechies 4 was used in Su's study. Barzegar et al. [14] evaluated the accuracy of four models predicting water salinity in a river in northwestern Iran; here, ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), wavelet-ANN, and wavelet-ANFIS were evaluated for accuracy. Daubechies 1 to 7, Symlet 3 to 5, and Haar were compared for the mother wavelet, with Daubechies 4 having the best accuracy. They concluded that Daubechies 4 was the best mother wavelet because its functional shape is relatively similar to that of the salt time series, which is the target time series of the wavelet transform. Liu et al. [15] proposed a short-term forecasting method for wind power based on wavelet transform and LSTM. In Liu's study, Daubechies 7 was used as the mother wavelet. In the field of electricity price prediction, Aggarwal et al. [16] proposed a wavelet transform based neural network model for predicting price profiles in electricity markets. In Aggarwal's study, Daubechies 1 through 4 were compared as mother wavelets, and finally, Daubechies 2 was adopted. The experimental results showed that using wavelet transform in the prediction model could improve prediction accuracy. Singh et al. [17] used generalized neurons, which require fewer data for training, and constructed a hybrid model with the wavelet transform. Here, Daubechies 4 was used as the mother wavelet. That study further compared various error functions and validated them with electricity prices in New South Wales, Australia.

Chang et al. [18] proposed a hybrid model of wavelet transform and LSTM and then evaluated the model using datasets from New South Wales, Australia, and France. As in the other studies above, wavelet transform was used for time series decomposition. First, the electricity price time series was decomposed into several constituent series with minor variance. The decomposed time series were then trained and forecasted separately using LSTM, and the forecast values were summed to generate the actual forecast price. By decomposing the time series data with the wavelet transform, the data have a more stable variance, allowing LSTM to capture the electricity price fluctuations accurately. The results showed that their proposed model can significantly improve the prediction accuracy compared to Peng's model [11] and a model that combines ARIMA and ANN [19]. Chang's study predicted future electricity prices based only on past electricity prices. Therefore, we previously aimed to further improve the prediction accuracy by considering the electricity demand as well, based on their hybrid model of wavelet transform and LSTM [20]. As a result, we reduced the error by up to 53.7% in one-step-ahead prediction, which predicts the price one hour later. Both Chang's and our previous work employed Daubechies 5 as the mother wavelet.

There are various types of mother wavelets, and each one has its advantages and disadvantages in time-series decomposition performance depending on the time-series shape of the transformation target as discussed by Barzegar et al. [14]. Even though the actual electricity price time series changes its shape from period to period, in all of the above studies, the same mother wavelet was fixed and used throughout the entire experimental period, although different experiments were conducted to compare a variety of mother wavelets. In other words, even if the shape of the time series to be forecasted changes from period to period, the mother wavelet does not change during the experiment. Therefore, this study aims to develop a new model that can make predictions with more stable accuracy by periodically switching mother wavelets. To the best of the authors' knowledge, the proposed forecasting model is used for the first time not only for electricity price forecasting but also for time series forecasting, as well as other forecasting targets. The major contribution of this paper is its proposal for a partly new, partly improved electricity price forecasting method that addresses cross-daily and cross-seasonal price fluctuations.

The rest of the paper is structured as follows. In Section 2, proposed forecasting method is described. Then, in Section 3, the evaluation experiments and results of the proposed method are presented, and finally, Section 4, concludes the study.

2. Methods

The method proposed in this paper aims to achieve and accurate prediction by periodically switching the mother wavelet in the hybrid model of wavelet transform and LSTM. Fig. 1 shows an overview of the proposed method. We first decompose the electricity price time series and electricity demand time series by frequency using the wavelet transform. Then, each of the decomposed time series is learned by LSTM to predict the future electricity price. The wavelet transform has a parameter called the mother wavelet. The decomposition performance of the time series depends on which mother wavelet is used for which

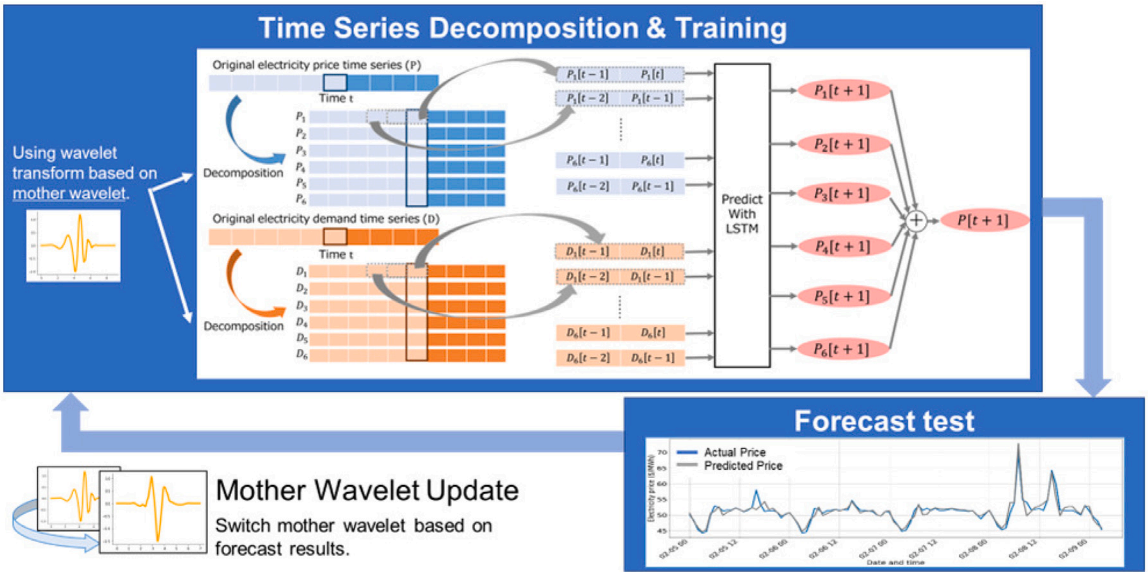

Fig. 1. Overview of proposed method; training and forecast test are repeated while switching mother wavelets based on forecast results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

shape of the time series. Therefore, in the proposed method, the mother wavelet is periodically switched to the one that matches the time series shape as a way to prevent the degradation of prediction accuracy. In this section, the hybrid model of wavelet transform and LSTM are explained in detail with reference to Fig. 1, followed by a description of the mother wavelet switching technique.

2.1. Hybrid model of wavelet transform and LSTM

Forecasting with a hybrid model of wavelet transform and LSTM involves three key steps: preprocessing, decomposition of time series data, and forecasting with LSTM. First, outlier processing by the Pauta criterion and Min–max normalization are performed for both electricity price and demand in the preprocessing stage. Next, we use the wavelet transform to decompose the data on electricity price and demand. The decomposition level was set at level 5 as in the previous study [20]. Time series decomposition by wavelet transform is shown in Figs. 2 and 3. Although the electricity price time series is used here as an example, the same procedure is done for the electricity demand time series. First, the original price time series is wavelet transformed to obtain the component series shown in Fig. 2. The approximation extracts the trend, which is the low-frequency component, and each detailed series contains the higher-frequency component, such as information on abrupt changes. Then, using the inverse wavelet transform for the approximation and each detailed series, each of these terms is transformed again into the time domain, as shown in Fig. 3.

After decomposing the time series data by wavelet transform, LSTM is used to train each constituent series. The LSTM model used for prediction consists of an input layer, an LSTM layer, and an output layer, and the activation function of the LSTM layer is a sigmoid function. Adam [21] was used as the optimization method. Hyperparameters such as the number of neurons in the LSTM layer, the number of learning epochs, the batch size, and Adam's learning rate were determined by an automated procedure to objectively analyze the accuracy of the model [9]. Specifically, parameter tuning was performed using the tree-structured Parzen estimator [22], which is one of the Bayesian optimization methods. The reason for adopting the tree-structured Parzen estimator is that it can naturally handle not only continuous variables but also discrete, categorical, and conditional variables, which are difficult to handle with standard Bayesian optimization algorithms. It is also relatively computationally inexpensive [23]. After

Fig. 2. Original electricity price time series and decomposed component series (frequency domain).

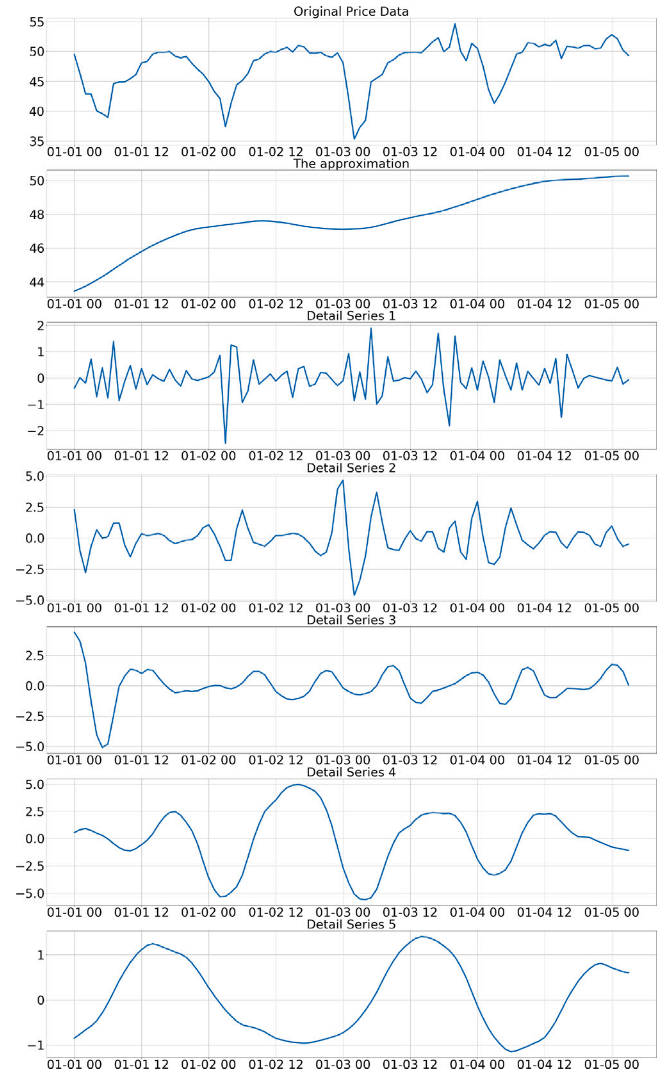

Fig. 3. Original electricity price time series and decomposed component series (time domain).

inputting each time series data into this LSTM model and generating predicted values for each component of the electricity price, the overall predicted price value was obtained by adding the predicted values together.

The input–output relationship to LSTM at time t is shown on the right side within the square of "Time Series Decomposition & Training" in Fig. 1. In Fig. 1, the electricity price component series is represented by blue and the electricity demand component series by orange. $P_n[T]$ is the value of the nth component series of the electricity price at time T, $D_n[T]$ is the value of the nth component series of the electricity demand at time T, and $P[T]$ is the electricity price at time T. The length of the time series input to LSTM is two steps between the current time t and time $t-1$, which is one step earlier. In addition, a time series lagged by one step is added to each component series, making a total of 24 time series as input to the LSTM. The output of LSTM is the value of the next step $t+1$ of each component series of electricity prices. The predicted values of all of these price component series are then added together to obtain the final predicted price at time $t+1$, $P[t+1]$.

2.2. Switching mother wavelet

The wavelet transform used for time series decomposition is the same as the Fourier transform. Just as in the Fourier transform, the original time series was represented by scaling and translating sin and cos waves, and in the wavelet transform, small waves called mother wavelets play this role. Since there are many different types of mother wavelets, the prediction error can be significant depending on the mother wavelet.

Nine mother wavelets commonly used in time series forecasting, as shown in Section 1, are illustrated in Fig. 4. Daubechies (db) and Symlet (sym) are the names of the mother wavelets, and the number after the name is called the vanishing moment. As with the degree in a polynomial, the larger the vanishing moment, the smoother the waveform of the wavelet. In general, when performing time–frequency analysis with wavelet transform, it is considered best to determine the mother wavelet based on its similarity to the shape of the time series to be analyzed [24]. As shown in Fig. 5, the actual shape of the electricity price time series to be analyzed varies from period to period. As shown in Fig. 5, the price of electricity in New South Wales, Australia, fluctuated significantly from April to August 2013, although it fluctuated less from September to December.

Therefore, we aim to maintain high prediction accuracy by periodically switching the mother wavelet to the observed fluctuations across the days and seasons. The proposed method performs time series decomposition and price forecasting with the various mother wavelets shown in Fig. 4, and it switches which mother wavelet is used as the final forecast value. In the switching process, the prediction of the mother wavelet with the highest accuracy in the past n weeks is adopted as the final prediction. Although not as large as the seasonal differences mentioned above, Fig. 5 shows that the shape of the time series changes even within a month, while a few days would not make much difference in the electricity price time series, so we chose to switch mother wavelets on a weekly basis. For n, we investigate the optimal value in the next section by validating the effectiveness of the proposed method.

3. Experimental evaluation

3.1. Experimental setup

An experiment was conducted to evaluate the flexible forecasting method proposed in this paper. The experimental setup was the same as that used in our previous study [20]. We used the electricity price and demand data of New South Wales, Australia, from 2013. This dataset is published by the Australian Energy Market Operator (AEMO) [26], and while the original data were for every 30 min, the hourly data were used here. As a prediction method, we performed one-step-ahead prediction, which predicts the electricity price for the next hour every hour. Fig. 6 shows the one-step-ahead prediction method when the current time is t. In both the upper and lower figures, the horizontal axis represents time and the vertical axis represents electricity prices, with solid lines representing prices that are already known and dotted lines representing future prices that are yet to be known. Only electricity prices are plotted in Fig. 6, but the same procedure applies for electricity demand. First, at the current time t, we predict the price at time $t+1$ based on the price and demand at time $t-2 \sim t$. Then, at time $t+1$, one hour later, the price and demand at time $t-1 \sim t+1$ are used to predict the price at time $t+2$, another hour later. The above procedure is repeated every hour.

This experiment was performed with each of the following 19 mother wavelets: 9 ways to fix the mother wavelet with Daubechies (db) 1 to 6 and Symlet (sym) 3 to 5 and 10 ways when n, the number of weeks to be considered in switching the mother wavelet, is changed from 1 to 10 in the proposed method.

For the duration of the experiment, predictions were made by repeating the time series decomposition and learning every week, as shown in Fig. 7. Specifically, we first train a forecasting model using price and demand data for the four weeks from January 1 to 28, 2013. Next, we use the data from January 29 to February 4 as validation

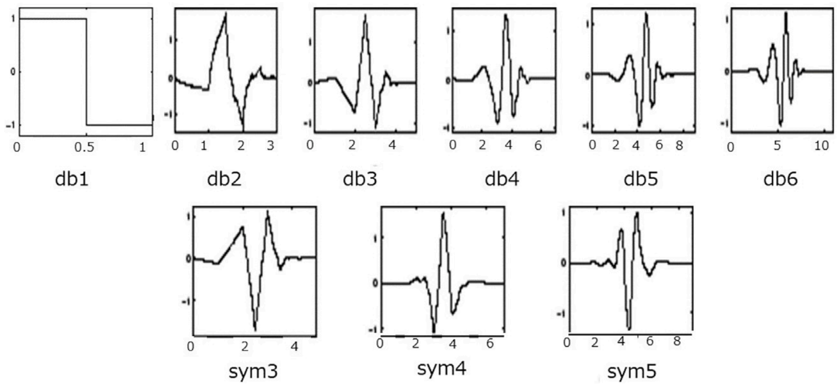

Fig. 4. Mother wavelet function often used in time series forecasting [25].

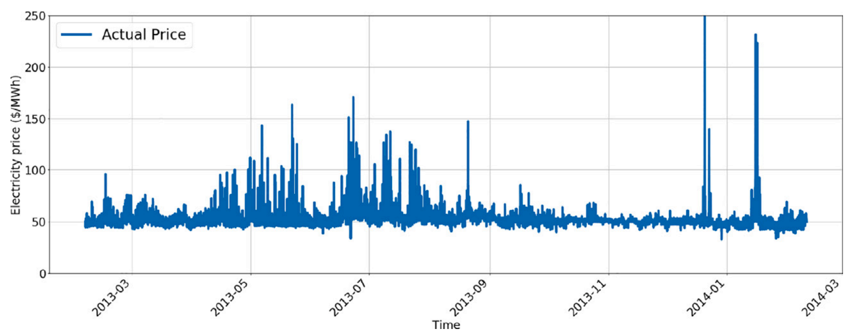

Fig. 5. Electricity prices in New South Wales, Australia in 2013 [26].

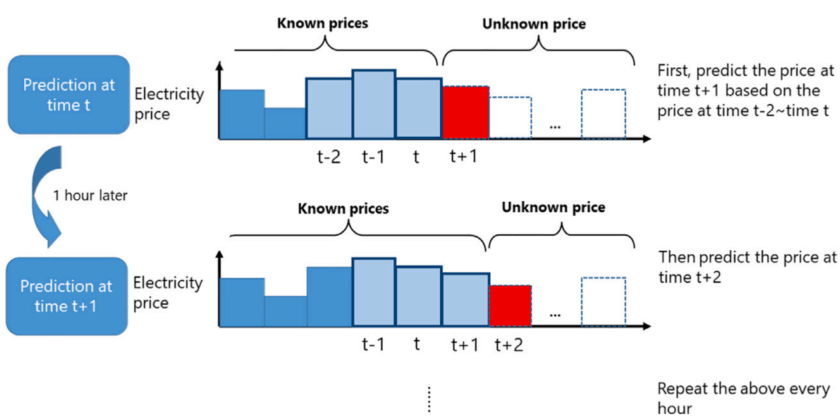

Fig. 6. Overview of one-step-ahead prediction.

data to check the learning status of the model. We then test the model's predictive performance using data from February 5 to 11. Then, all data are shifted by one week, followed by additional time series decomposition, training, validation, and testing. This is repeated and tested for 53 weeks, roughly one year. The loss function used in the evaluation was Mean Absolute Percentage Error (MAPE), which is expressed by the following equation.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|, \tag{1}$$

where n is the number of data, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

3.2. Results

Table 1 shows MAPE over the entire experimental period for each mother wavelet. The second line, "switching to the best MW", indicates the case where the proposed method constantly switches to the mother wavelet with the best prediction accuracy at that time. In other words, it represents the theoretical optimal value of the proposed method. From Table 1, we can see that the prediction accuracy varies depending on which mother wavelet is used to decompose the time series. Moreover, there are mother wavelets, including the proposed method, that are more accurate than db5, which was used in our previous work [20]. Among them, the lowest MAPE of 2.148% was obtained in one of the proposed methods that determines the mother wavelet based on the forecast results of the past three weeks. However, even with "switching MW (n = 3)", there was a difference of about 0.07% ppt compared to "switching to the best MW", which is the theoretical optimum value. The reasons for this are discussed below.

Fig. 8(a) shows, for the period of July 22 to 23, the actual electricity price, the predicted price when the mother wavelet is fixed to db4, that when fixed to sym5, and the proposed method of switching the mother wavelet. The vertical axis is the price of electricity, and the horizontal

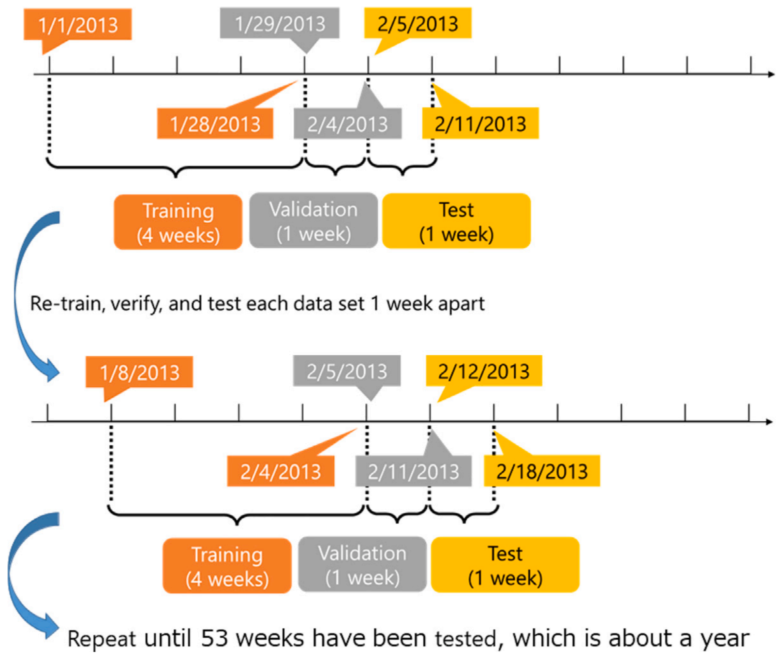

Fig. 7. Details of experimental period.

Table 1
MAPE of each mother wavelet (MW) over entire experimental period.

Mother wavelet	MAPE (%)	Description
Switching to best MW	2.074660	Ideal case of proposed method.
Switching MW (n = 3)	**2.148150**	Proposed method.
Switching MW (n = 8)	2.152941	
Switching MW (n = 6)	2.158812	
Switching MW (n = 9)	2.163366	
Switching MW (n = 5)	2.164564	
Switching MW (n = 7)	2.172413	
Switching MW (n = 10)	2.174297	
Switching MW (n = 4)	2.178161	
Switching MW (n = 2)	2.182103	
Symlet 5	2.196947	
Switching MW (n = 1)	2.206786	Proposed method.
Daubechies 4	2.212410	
Daubechies 6	2.295169	
Daubechies 5	2.307206	Used in our previous studies [20].
Symlet 4	2.399550	
Daubechies 3	2.445557	
Symlet 3	2.545998	
Daubechies 2	2.703441	
Daubechies 1	2.858116	

axis is time, expressed in the form of "month-day hour". In Fig. 8(a), for the proposed method, July 23 is the time of the weekly changeover of the mother wavelet. In other words, the proposed method uses db4 as the mother wavelet until July 22, and from July 23, it switches to sym5, which had the best accuracy over the past three weeks. From Fig. 8(a), we can see that by switching the mother wavelet to sym5 from the week of the 23rd, the predicted values are closer to the actual values than if we had used db5 as is. Fig. 8(b) shows the absolute error of the predictions made by each mother wavelet at the time corresponding to Fig. 8(a). Looking at Fig. 8(b), we can see that the error of the proposed method is large at 7:00 on the 23rd but otherwise actually smaller than the error of db5 at many other times. This means that switching mother wavelets based on last week's forecast results has effectively prevented the accuracy from deteriorating.

Fig. 9(a) shows the MAPE of each mother wavelet for each week, and Fig. 9(b) shows the ranking of each mother wavelet in order of predictive accuracy, also for each week. For the sake of clarity, some of the periods are excerpted, and the case of $n = 3$ with the best results in Table 1 is shown as representative of the proposed method. In addition, the mother wavelets, which are more accurate than db5 as used in our previous work, are shown as a solid line. First, in Fig. 9(a), the horizontal axis represents the week, and the vertical axis represents the MAPE; here, the lower the value, the higher the accuracy. This graph shows that the proposed method (solid red line) can suppress the average error for many weeks. In particular, for the week of April 30 to May 6, the MAPE is 6.91% when the mother wavelet is fixed at db1, while it is 3.95% with the proposed method. In other words, the proposed method improves accuracy by about 42.8%. In Fig. 9(b), the horizontal axis shows the same week as in the top graph. The vertical axis shows the ranking of each mother wavelet in the order of decreasing error; the higher the ranking, the higher the accuracy. Here, while the other mother wavelets are ranked 15th or lower in some weeks, the proposed method shown by the solid red line is consistently ranked 4th or higher. Furthermore, in the periods of April 2 to 8 and May 7 to 13, db5 suddenly became the most accurate. This is the reason why, in Table 1, even the best accuracy of the proposed method was slightly different from the theoretical optimum. In the proposed method, the mother wavelet is determined based on the accuracy of the past weeks, so if the accuracy of one mother wavelet suddenly becomes better, it cannot be adopted for use.

Fig. 10 shows the average rank in accuracy of the mother wavelet shown in Fig. 9 over the entire experimental period. The lower the bar in this graph, the higher the average rank, i.e., the higher the accuracy. This figure shows that the proposed method maintains higher accuracy than the other mother wavelets on average, not only during the period shown in Fig. 9 but also throughout the entire period. These results suggest that switching the mother wavelet may suppress the decline in forecast accuracy from week to week.

4. Conclusion

This paper proposed an electricity price forecasting model for energy management on the demand side under dynamic pricing. This is a significant improvement over the previously published hybrid model of

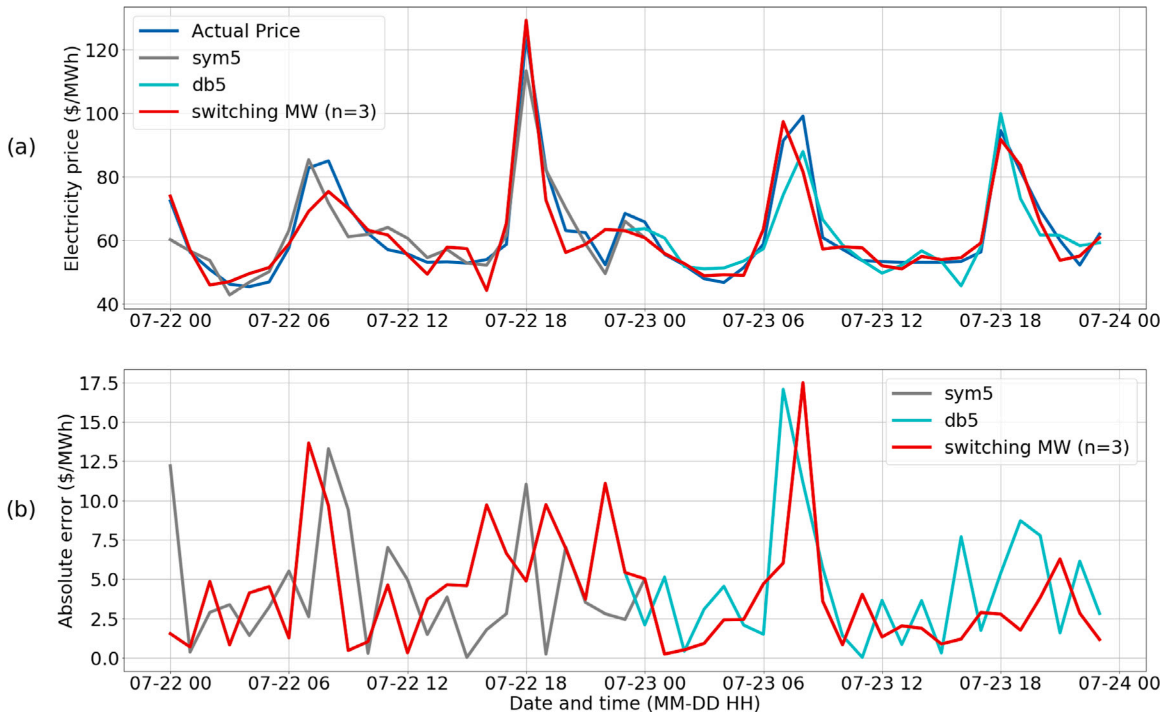

Fig. 8. Predicted and actual prices for July 22–23 and absolute error for each mother wavelet.

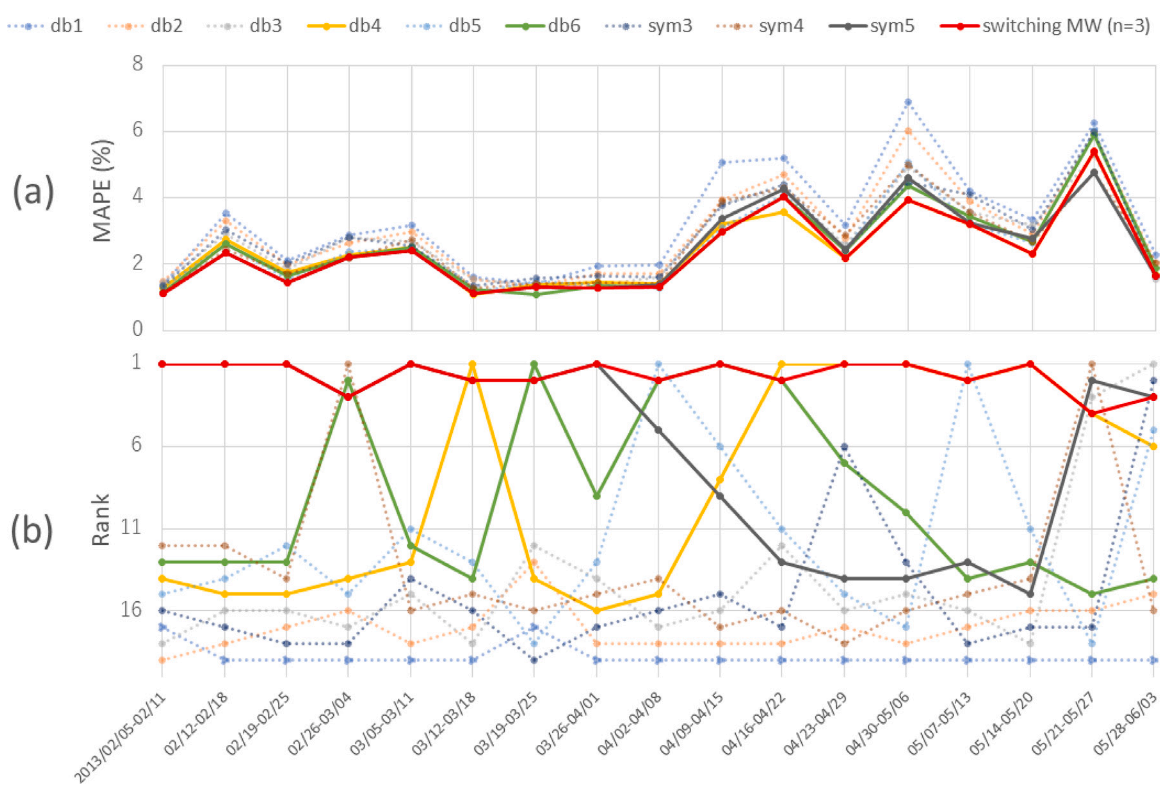

Fig. 9. Prediction accuracy MAPE and rank for each mother wavelet by week.

wavelet transform and Long Short-Term Memory using the constitutive series of electricity price and demand. Specifically, we aimed to achieve prediction with stable accuracy by periodically switching the mother wavelet, one of the parameters included in the wavelet transform. We conducted an evaluation experiment of the proposed model using hourly electricity price and demand data from New South Wales, Australia in 2013. We compared the forecasting accuracy of a total of 19 patterns of time series decomposition: nine ways that are fixed to any one of the mother wavelets and ten ways in the proposed method of switching mother wavelets. As a result of one-step-ahead prediction, which predicts the electricity price of the next hour every hour, the proposed method is more stable and accurate than the method with a

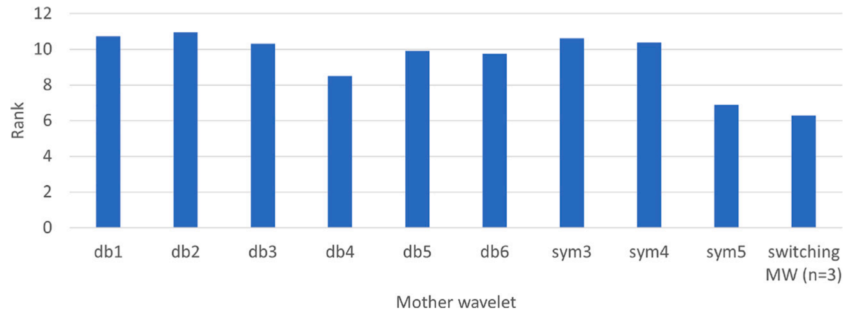

Fig. 10. Average rank of accuracy over experimental period.

fixed mother wavelet. In particular, the best accuracy was obtained by switching the mother wavelet based on the forecast results of the past three weeks. In this experiment, compared to the case where the mother wavelet is fixed, the proposed method can reduce the prediction error by up to 42.8%. In the future, we will integrate the developed electricity price prediction model with existing energy management systems to verify how well energy management can be performed with the current prediction accuracy. Furthermore, it is important to implement the proposed electricity price forecasting model in a real system together with an energy management framework. In such a real system, we plan to empirically verify that the consistently accurate price forecasting provided by the proposed model is useful for optimizing energy use on the demand side and has an impact on the electricity market.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Huang W, Zhang N, Kang C, Li M, Huo M. From demand response to integrated demand response: Review and prospect of research and application. Prot Control Mod Power Syst 2019;4(1):1–13.
[2] Zhao X, Gao W, Qian F, Ge J. Electricity cost comparison of dynamic pricing model based on load forecasting in home energy management system. Energy 2021;229:120538.
[3] Zhao Z, Wang C, Nokleby M, Miller CJ. Improving short-term electricity price forecasting using day-ahead LMP with ARIMA models. In: Proc. of IEEE power energy society general meeting. 2017, p. 1–5. http://dx.doi.org/10.1109/PESGM.2017.8274124.
[4] 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):3606–10.
[5] Mohsenian-Rad A, Leon-Garcia A. Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans Smart Grid 2010;1(2):120–33. http://dx.doi.org/10.1109/TSG.2010.2055903.
[6] Wei D. Prediction of stock price based on LSTM neural network. In: Proc. of international conference on artificial intelligence and advanced manufacturing. 2019, p. 544–7.
[7] Durganjali P, Pujitha MV. House resale price prediction using classification algorithms. In: Proc. of international conference on smart structures and systems. 2019, p. 1–4. http://dx.doi.org/10.1109/ICSSS.2019.8882842.
[8] Lu R, Hong SH, Yu M. Demand response for home energy management using reinforcement learning and artificial neural network. IEEE Trans Smart Grid 2019;10(6):6629–39. http://dx.doi.org/10.1109/TSG.2019.2909266.
[9] Lago J, De Ridder F, De Schutter B. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Appl Energy 2018;221:386–405.
[10] Xu J, Baldick R. Day-ahead price forecasting in ERCOT market using neural network approaches. In: Proc. of ACM international conference on future energy systems. 2019, p. 486–91.
[11] Peng L, Liu S, Liu R, Wang L. Effective long short-term memory with differential evolution algorithm for electricity price prediction. Energy 2018;162:1301–14.
[12] Lago J, Marcjasz G, Schutter BD, Weron R. Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. 2020, arXiv:2008.08004.
[13] Su H, Zio E, Zhang J, Xu M, Li X, Zhang Z. A hybrid hourly natural gas demand forecasting method based on the integration of wavelet transform and enhanced deep-RNN model. Energy 2019;178:585–97.
[14] Barzegar R, Adamowski J, Moghaddam AA. Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay river, Iran. Stoch Environ Res Risk Assess 2016;30(7):1797–819.
[15] Liu Y, Guan L, Hou C, Han H, Liu Z, Sun Y, et al. Wind power short-term prediction based on LSTM and discrete wavelet transform. Appl Sci 2019;9(6):1108.
[16] Aggarwal SK, Saini LM, Kumar A. Electricity price forecasting in ontario electricity market using wavelet transform in artificial neural network based model. Int J Control Autom Syst 2008;6(5):639–50.
[17] Singh N, Tiwari S, Mohanty S, Yadav D. A modified cost function generalized neuron for electricity price forecasting in deregulated power markets. In: Proceedings of the sixth international conference on computer and communication technology 2015. 2015, p. 120–6.
[18] Chang Z, Zhang Y, Chen W. Electricity price prediction based on hybrid model of adam optimized LSTM neural network and wavelet transform. Energy 2019;187:115804.
[19] Babu CN, Reddy BE. A moving-average filter based hybrid ARIMA-ANN model for forecasting time series data. Appl Soft Comput 2014;23:27–38. http://dx.doi.org/10.1016/j.asoc.2014.05.028, URL http://www.sciencedirect.com/science/article/pii/S1568494614002555.
[20] Iwabuchi K, Kato K, Watari D, Taniguchi I, Catthoor F, Shirazi E, et al. Demand-aware electricity price prediction based on LSTM and wavelet transform. In: Proc. of 38th European photovoltaic solar energy conference and exhibition. 2021, p. 1668–70. http://dx.doi.org/10.4229/EUPVSEC20212021-7DV.1.4.
[21] Kingma DP, Ba J. Adam: A method for stochastic optimization. 2017, arXiv:1412.6980.
[22] Bergstra J, Bardenet R, Bengio Y, Kégl B. Algorithms for hyper-parameter optimization. In: Advances in neural information processing systems, Vol. 24. 2011.
[23] Ozaki Y, Tanigaki Y, Watanabe S, Onishi M. Multiobjective tree-structured parzen estimator for computationally expensive optimization problems. In: Proceedings of the 2020 genetic and evolutionary computation conference. 2020, p. 533–41.
[24] Nourani V, Baghanam AH, Adamowski J, Kisi O. Applications of hybrid wavelet–artificial intelligence models in hydrology: a review. J Hydrol 2014;514:358–77.
[25] Math Works. Introduction to the wavelet family. 2022, Online https://jp.mathworks.com/help/wavelet/gs/introduction-to-the-wavelet-families.html. (Accessed 5 Jan 2022).
[26] AEMO. Aggregated price and demand data. 2021, Online https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/aggregated-data. (Accessed 25 Jan 2021).