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An ensemble method of full wavelet packet transform and neural network for short term electrical load forecasting

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ABSTRACT

Due to high penetration of distributed energy resources, integration of intermittent renewable energy resources and deployment of demand-side management, highly accurate short-term load forecasting becomes increasingly important. This paper proposes a full wavelet neural network approach for short-term load forecasting, which is an ensemble method of full wavelet packet transform and neural networks. The full wavelet packet transform model is used to decompose the load profile and various features into several components with different frequencies and these components are used to train the neural networks. To perform load forecasting, the full wavelet packet transform model decomposes features into various components that are fed into the trained neural networks, and the outputs of the neural networks are constructed as the forecasted load. The proposed model is applied for load prediction in the electric market of Ontario, Canada. Simulation results show that the proposed approach reduces the mean absolute percentage error (MAPE) by 20% in comparison with the traditional neural network method. The proposed approach can be used by utilities and system operators to forecast electricity consumption with high accuracy, which is highly demanded for renewable energy integration, demand-side management and power system operation.

1. Introduction

The power system operation and control are complex and challenging. The high penetration of distributed energy resources, integration of intermittent renewable energy resources, adoption of electric vehicles and deployment of demand-side management add more layers of complexity to the power system operation [1]. Under this context, short term load forecasting from one hour to one week becomes increasingly important since high accurate short term load forecasting can be used to improve power system reliability and energy efficiency while reducing the system operational cost [2–4].

Short term load forecasting methods can be mainly classified into two categories: statistical methods and artificial intelligence methods [5,6]. The statistical methods include time series forecasting [7,8], regression methods [9,10], Parsimonious stochastic methods [11,12] and exponential smoothing methods [13]. These methods have shown high accuracy for linear systems but suffered from the low performance if inputs and outputs are nonlinearly related [14]. Therefore, these methods are not suitable for highly complex and nonlinear electricity load prediction.

Artificial intelligence methods have been used to cope with the nonlinear load prediction including supervised or unsupervised neural networks [15,16], fuzzy logic [17], support vector machine [18,19] and data clustering [20,21]. However, the fluctuation of electricity load is highly complex due to users' electricity consumption patterns, special events and weather variations, which limits the accuracy of load prediction [22]. To further improve the performance of load forecasting, ensemble methods of the traditional wavelet transform and neural networks were developed [19–22]. In these studies, different levels of wavelet transform are performed, and various algorithms are applied to train the neural networks. For instance, trial and error method was used to determine the best level of wavelet transform and the modified bee colony optimization method was used to improve the learning accuracy [22]. A hybrid method of traditional 3-level wavelet transform and neural networks was proposed for day-ahead load prediction, in which the adaptive particle swarm algorithm was used to train the neural networks [23]. The MAPE was reduced to 1.9% (using the hybrid method) from 2.6% (using the basic particle swarm algorithm). The combination of 1-level wavelet transform and neural networks was developed to study the peak demand and the genetic algorithm is used to train the neural networks. [24]. In a different way, a 3-level wavelet transform with an echo state network technique was developed to

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predict hour-ahead and day-ahead load and temperature, in which the shuffled frog leaping algorithm was adopted to optimize the echo state network [25]. The MAPE for load prediction was 3.3%.

Since the full wavelet packet transform can reveal more information on load fluctuation than the traditional wave transform, it has been used in many applications such as noise reduction [26], optical communications [27], smart sensor utilization [28], and power system protection [29,30] However, the full wavelet packet transform combined with neural network has not been widely applied for electricity load forecasting.

In this study, we propose an ensemble method of full wavelet packet transform and neural networks for day-ahead load forecasting. Important features are identified for load forecasting. We divide these features and load profiles into training, testing and cross-validation sets. The training data and testing data are used to select hyperparameters. Finally, we use the cross-validation data set to evaluate the performance of the proposed model. In each stage, data are decomposed into various components and these components are fed into the neural networks. The outputs of the neural networks are then reconstructed. Simulation results show a high accuracy of load forecasting. The main contributions are summarized as follows.

1 A full wavelet packet transform model is developed to enhance the traditional wavelet transform. It is used to decompose the load profile into various components with different frequencies, which exploits electricity consumption patterns.
2 Multi-layer neural networks are designed, and the number of neurons is optimized.
3 A full wavelet neural network model is developed by combining the proposed full wavelet packet transform model and the neural networks, which dramatically increases the accuracy of short term load forecasting.
4 The proposed full wavelet neural network demonstrates great reliabilities under various conditions and the error statistic information provided confident levels of load forecasting.
5 The approach can be used for high accuracy short term load forecasting, which highly demanded in various smart grid applications.

The rest of the paper is organized as follows. Section 2 introduces the background of wavelet transform and neural networks. The methodology is illustrated in Section 3 followed by simulation results in Section 4. A discussion of the results is provided in Section 5. Section 6 concludes this work.

2. Background

2.1. Neural networks

As one of the most important techniques of artificial intelligence, neural networks can accurately predict the output of a complex and nonlinear system without explicitly modeling it. Fig. 1 shows a typical 3-layer neural network, in which the layers are input layer, hidden layer and output layer. Each layer consists of a set of neurons (shown in Fig. 2), and these neurons are connected by synaptic weights. These weights are initialized randomly and then adjusted by training algorithms (e.g., the Levenburg-Marquardt algorithm). Each neuron sums the weighted inputs and maps the summation by an activation function given as follows [13].

$$s_j(t) = \sum_{i=1}^{N} w_{ij}x_i(t) + b_j \tag{1}$$

where s_j is the weighted sum, w_{ij} represents weights, and b_j is the bias. $x_i$is the input.

The activation functions represent the nonlinear relationship between the inputs and outputs, which include Sigmoid (Logistic), Hyperbolic Tangent and ReLU functions. The neural network iteratively adjusts its parameters to reduce the error between the predicted outputs and the actual outputs until the error is minimized.

Neural networks have been widely applied to predict time series electricity load [31]; however, the electricity load is highly complex and nonlinearly depends on features such as temperature, month and day types. On the other hand, the load profile is aggregated from many individual loads such as factory machines, commercial lighting and residential appliances, whose load profiles have different inherent patterns (e.g., frequency). Therefore, the load profile can be preprocessed (e.g., decomposed based on the frequency) and then applied to neural networks. This combination can significantly improve the accuracy of prediction.

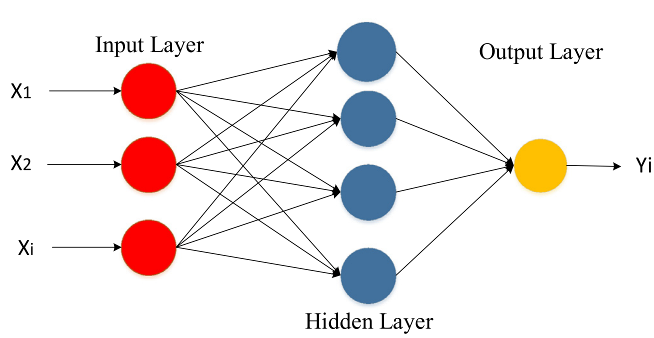

Fig. 1. The diagram of neural network [5].

2.2. Wavelet transform

Wavelet transform converts the signal from the time domain into a time-scaled frequency domain. This method can decompose a nonstationary and nonlinear signal profile to a group of profiles with different frequencies. High-frequency signals containing short-term fluctuation can be extracted and used to improve the accuracy of short-term prediction [32].

Wavelet transform decomposes the original signal into two categories: approximation (A) data that have low-frequency coefficients, and detail (D) data that have high-frequency coefficients. The original signal is decomposed in multiple levels; however, the traditional wavelet transform only decomposes approximation data (with low frequencies). Fig. 3 shows the 3-level signal decomposition. In $A_{\alpha;\beta}$ and $D_{\alpha;\beta}$, α represents levels and β resents the index of the signal in level-α [33].

Different levels of decomposition (e.g., 1-5) can be conducted [3]; however, research shows that in traditional wavelet transform, the 3-level shows the best performance in time series load forecasting [23].

In general, there are two types of wavelet transform: continuous wavelet transform and discrete wavelet transform defined in Eq. (2)–(5) [34].

$$CWT_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{2}$$

$$DWT_{(m,k)} = \frac{1}{\sqrt{a_0^m}} \sum_{n}^{N} x(n)\psi\left(\frac{k-nb_0a_0^m}{a_0^m}\right) \tag{3}$$

$$a = a_0^m \tag{4}$$

$$b = nb_0a_0^m \tag{5}$$

where a and b are the scale and time shift, respectively. $x(t)$ represents the original signal and $\psi(t)$ represents the mother function. m and k is the scale and shift parameter respectively, and they are integers. n represents the discrete-time. a_0 *and* b_0 are constant values.

Performing continuous wavelet transform is complex and time-

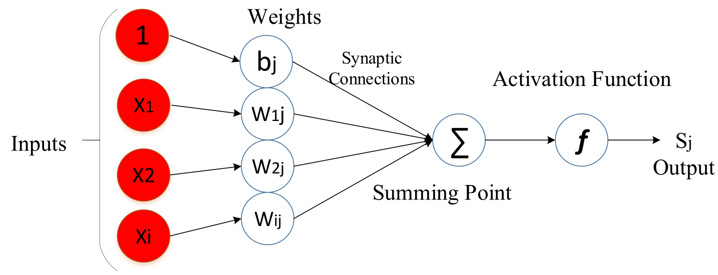

Fig. 2. The diagram of a neuron.

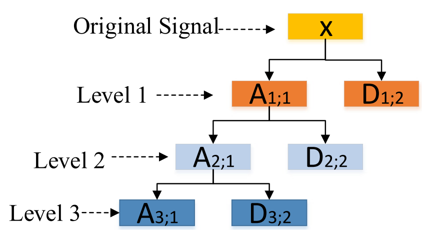

Fig. 3. 3-level wavelet transform. In $\boldsymbol{A}_{\alpha;\,\beta}$ and $\boldsymbol{D}_{\alpha;\,\beta}$, $\boldsymbol{\alpha}$ represents levels and $\boldsymbol{\beta}$ resents the index of the signal in level-$\boldsymbol{\alpha}$.

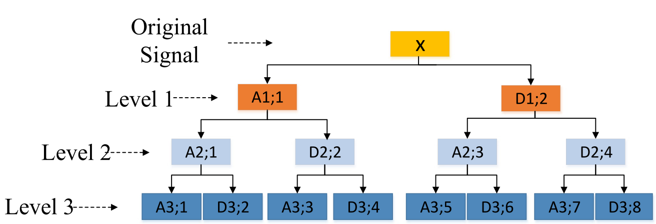

Fig. 4. Level-3 full wavelet packet transform. In $\boldsymbol{A}_{\alpha;\,\beta}$ and $\boldsymbol{D}_{\alpha;\,\beta}$, $\boldsymbol{\alpha}$ represents levels and $\boldsymbol{\beta}$ resents the index of the signal in level-$\boldsymbol{\alpha}$.

Table 1
Data on December 26, 2015.

Hours	Day	Day type	Load (MW)	Temp (°C)	Humidity (%)
1	7	0	13,820	11.4	89
2	7	0	13,319	12.1	85
3	7	0	13,045	12.6	81
4	7	0	12,930	10.3	90
5	7	0	12,858	10.3	98
6	7	0	13,077	11.3	99
7	7	0	13,589	11.5	95
8	7	0	14,186	11.5	92
9	7	0	14,830	10.6	86
10	7	0	15,375	9.3	85
11	7	0	15,823	6.6	67
12	7	0	16,117	4.4	69
13	7	0	16,229	3.8	65
14	7	0	16,108	3.6	62
15	7	0	15,856	2.9	65
16	7	0	15,967	2.8	66
17	7	0	16,591	2.8	67
18	7	0	17,554	2.6	70
19	7	0	17,266	2.7	69
20	7	0	16,714	2.5	69
21	7	0	16,138	2.4	70
22	7	0	15,678	2.1	72
23	7	0	14,937	2	71
24	7	0	13,965	1.8	72

*In day type, 0 represents holiday and weekend while 1 represents weekday.

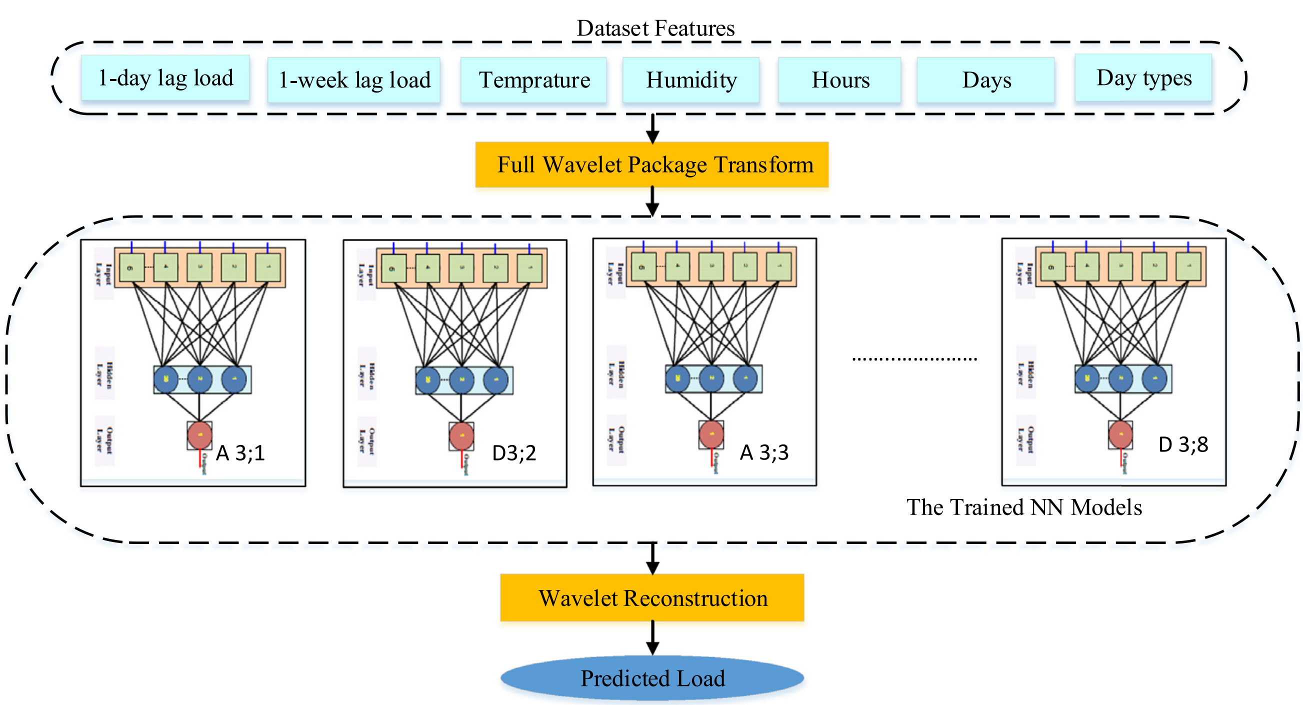

Fig. 5. The diagram of full wavelet neural network.

Table 2
Holidays in Ontario, Canada, 2015.

Stationary Holiday	Date
New Year's Day	January 1
Family Day	February 16
Good Friday	April 3
Easter	April 6
Victoria Day	May 18
Canada Day	July 1
Civic Holiday	August 3
Labor Day	September 7
Thanksgiving	October 12
Christmas Day	December 25
Boxing Day	December 26

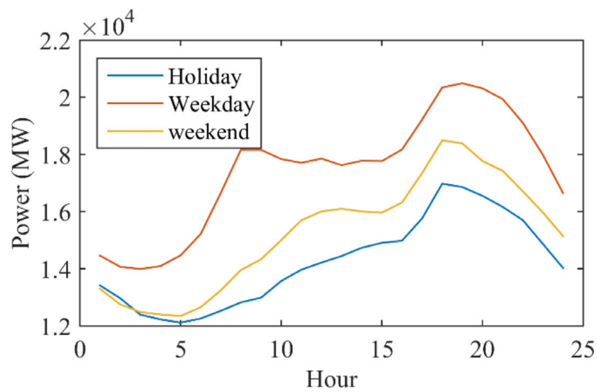

Fig. 6. Load profiles in three different types of day. Holiday (Jan. 1st 2016), weekday (Jan. 11th 2016), and weekend (Jan. 10th 2016).

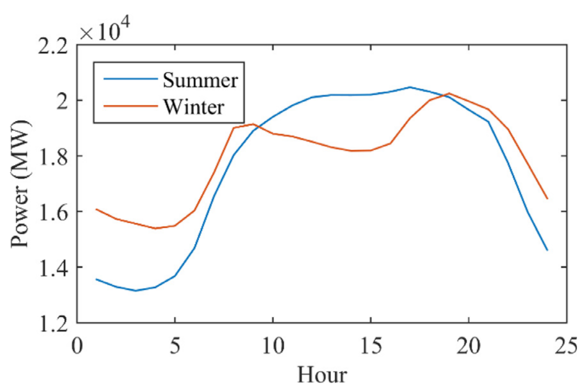

Fig. 7. Load profiles in summer and winter.

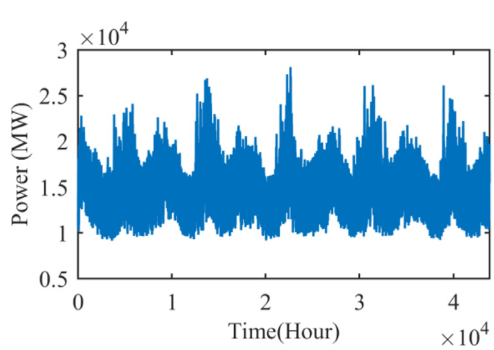

Fig. 8. The actual load profile from January 2011 to December 2016.

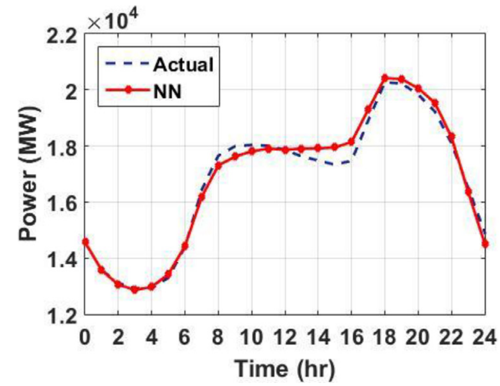

Fig. 9. The actual load and predicted load. NN represents the predicted load using the neural network.

consuming since the continuous wavelet transform analyzes the mother function continuously and produces huge amount of data. By contrast, discrete wavelet transform computes parameters in discrete values, which is much more efficient. Therefore, in this study, we use a discrete wavelet transform.

3. Methodology

In this work, we enhance the traditional wavelet transform by developing a full wavelet packet transform. We also developed a full wavelet neural network method by combining the full wavelet packet transform and neural networks. This section discusses the proposed full wavelet packet transform and full wavelet neural network. In addition, we describe the data preparation and feature selection method.

3.1. Full wavelet packet transform

The proposed full wavelet packet transform model can decompose not only the approximation components with low frequencies but also the detail components with low frequencies at each level. Therefore, more information can be exploited from the original signal. For example, the original signal is decomposed into 4 sets of signal: ($A_{3;\,1}$, $D_{3;\,2}$), ⋯, ($A_{3;\,7}$, $D_{3;\,8}$) in the level-3 shown in Fig. 4.

3.2. The proposed full wavelet neural network

Fig. 5 shows the diagram of the full wavelet neural network, in which the following procedure is performed. We first prepare the data including 1-day lag load, 1-week lag load, temperature, humidity, hours, days, and day types (including weekdays, weekends and holidays). The method of data preparation is described in Section 3.3.

The data are divided into three sets: training, testing, and cross-validation. In the training stage, the training set is decomposed into a number of components with different frequencies. The number of components depends on the level of decomposition. For example, there are 8 components for 3-level decomposition. These components are used to train the neural networks.

In the testing stage, the testing data set is decomposed into various components. The trained neural networks are used to predict the load profile for each component. These load profiles are reconstructed for the final load prediction. In this study, we optimize the numbers of neurons in the hidden layer to maximize the prediction accuracy. Finally, we use cross-validate data to evaluate the accuracy.

3.3. Data preparation and feature selection

The historical data used for the case studies are from Ontario's independent electricity system operator (IESO), Canada, from 2011 to

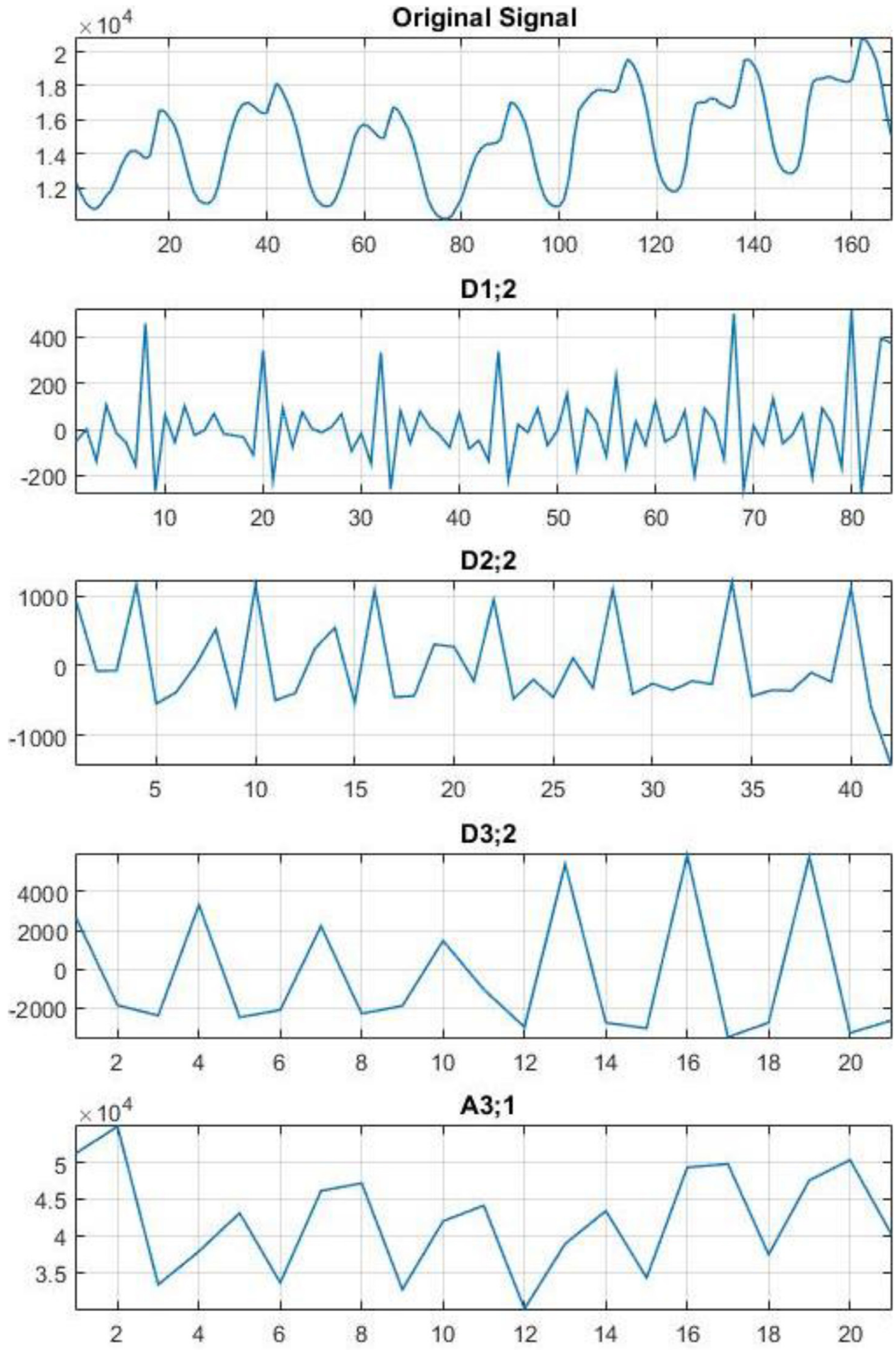

Fig. 10. Load profiles of one week decomposed by a 3-level traditional wavelet transform.

2016 [35]. Table 1 provides the data on December 26th, 2015 and Table 2 shows the holidays in the same province in the same year.

Many missing data are identified in the input dataset. These missing data are replaced by the average load of the same day in the previous years.

Since preparing the feature matrix is paramount in load forecasting, the features must be carefully selected. To select the best features, we observe the data by plotting them in different ways. For example, we plot the load profiles for various day types such as weekdays, weekend and holidays. Fig. 6 shows load profiles in three different day types. We can see that the day types have a significant impact on electricity consumption. For instance, the electricity consumption on weekdays is the highest followed by the ones on weekends, while the electricity load is the lowest during the holidays.

In addition, weather variations have a big influence on the load profile. As shown in Fig. 7, the load profile is different between winter and summer. More specifically, the peak demands occur in evenings and mornings in winter season while in summer, the peak demand is at noon. Based on these observations, the following factors are identified as the most important features: temperature, humidity, hours, days, and day types. The temperature and humidity are collected from Canada Historical Climate Data [36].

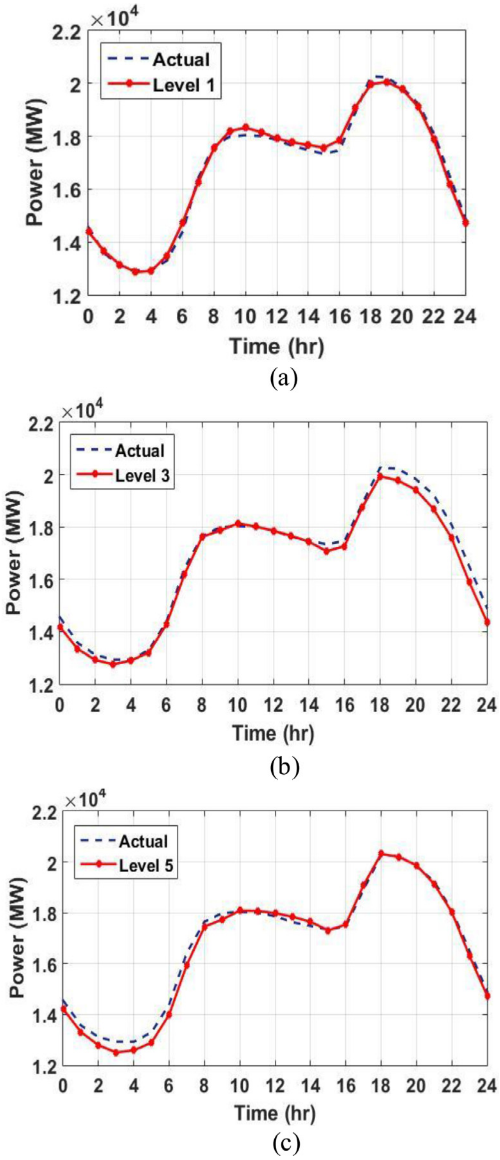

Fig. 11. Day-ahead predicted load profiles using traditional wavelet neural network techniques (a) 1-level wavelet transform. (b) 3-level wavelet transform. (c) 5-level wavelet transform.

4. Simulation results

We conduct a number of simulations in different scenarios as follows.

1 Using only neural networks;
2 Using traditional wavelet transform with neural networks;
3 Using the proposed full wavelet neural network, which assembles the full wavelet package transform and neural networks;
4 Evaluation of the proposed full wavelet neural network.

4.1. Experimental setup

In this study, we use MAPE as the measurement to compare the accuracy among different scenarios. In this section, we also describe the method to divide the data set. The Levenberg-Marquardt algorithm [37] is used to train the neural networks.

4.1.1. Mean absolute percentage error

MAPE and mean absolute error (MAE) shown in Eqs. (6) and (7) are used to evaluate the accuracy of different approaches [38].

$$MAE = \frac{1}{n}\sum_{i=i}^{n}|X_i - \dot{X}_i| \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - \dot{X}_i}{X_i}\right| \times 100\% \tag{7}$$

where n is the number of data. X_i and $\dot{X}_i$ are the actual and forecasted values respectively.

4.1.2. Data division

Fig. 8 shows the load profile used in the simulation. In all the scenarios, the data are divided into three sets: training, testing, and cross-validation. We randomly select 80% of the data as the training set that contain 35,064 hourly data. The remaining 20% (8784 hourly data) were treated as the testing set. From the training set, we select one-week data as the cross-validation data set. The training data are used to train the neural networks, the testing data are used to select hyperparameters (e.g., the number of neurons and the number of wavelet transform levels), and the cross-validation is used to presents the prediction accuracy.

4.2. Scenario #1 using only neural networks

We use the data to train a neural network, in which, the hidden layer contains 20 neurons. Tanh-Hyperbolic tangent function is used as an activation function. Since the Levenberg–Marquardt algorithm has a fast rate of convergence, we use it to train the parameters of the neural networks in this study. The MAPE for this method is 1.91%. Fig. 9 depicts the actual load and predicted load using the neural network.

4.3. Scenario #2: using traditional wavelet transform with neural networks

In this scenario, we replaced the full wavelet packet transform shown in Fig. 5 by the traditional wavelet transform. We use various levels of decomposition including 1-level, 3-level and 5-level. In the neural networks, we use 20 neurons in the hidden layer.

Fig. 10 shows the load profiles of one week decomposed by a 3-level traditional wavelet transform. The load profile of the week was decomposed into four components with different frequencies including A3;1, D3;2, D2;2, and D1;2. The A3;1 is the approximation component in which the high-frequency fluctuation is removed but the trend is sustained. The D3;2, D2;2, and D1;2 are the detail components that contain the irregular fluctuations of the original signal. Therefore, the electricity consumption patterns encoded in signals with various frequencies can be exploited.

Fig. 11 day-ahead predicted load profiles using traditional wavelet neural networks with different levels of decomposition. The MAPE of the load forecasting with the 3-level wavelet transform was 1.72% while the MAPEs were 1.85% (with 1-level decomposition) and 1.82 % (with 5-level decomposition). As can be seen, the load forecasting with 3-level wavelet transform showed the best performance.

4.4. Scenario #3: using the proposed full wavelet neural network

In this scenario, we evaluate the proposed model, which ensemble full wavelet package transform and multi-level neural networks.

The full wavelet packet transform decomposes not only the approximation components but also the detail components so more information can be exploited. 3-level decomposition was selected to decompose the original data into 4 sets of components: $(A_{3;\,1}, D_{3;\,2})$, ⋯, $(A_{3;\,7}, D_{3;\,8})$. Fig. 12 shows the waveform of the original one-week load profile and its decompositions. These components are used to train the neural networks.

In the prediction stage, features with the same index and level are

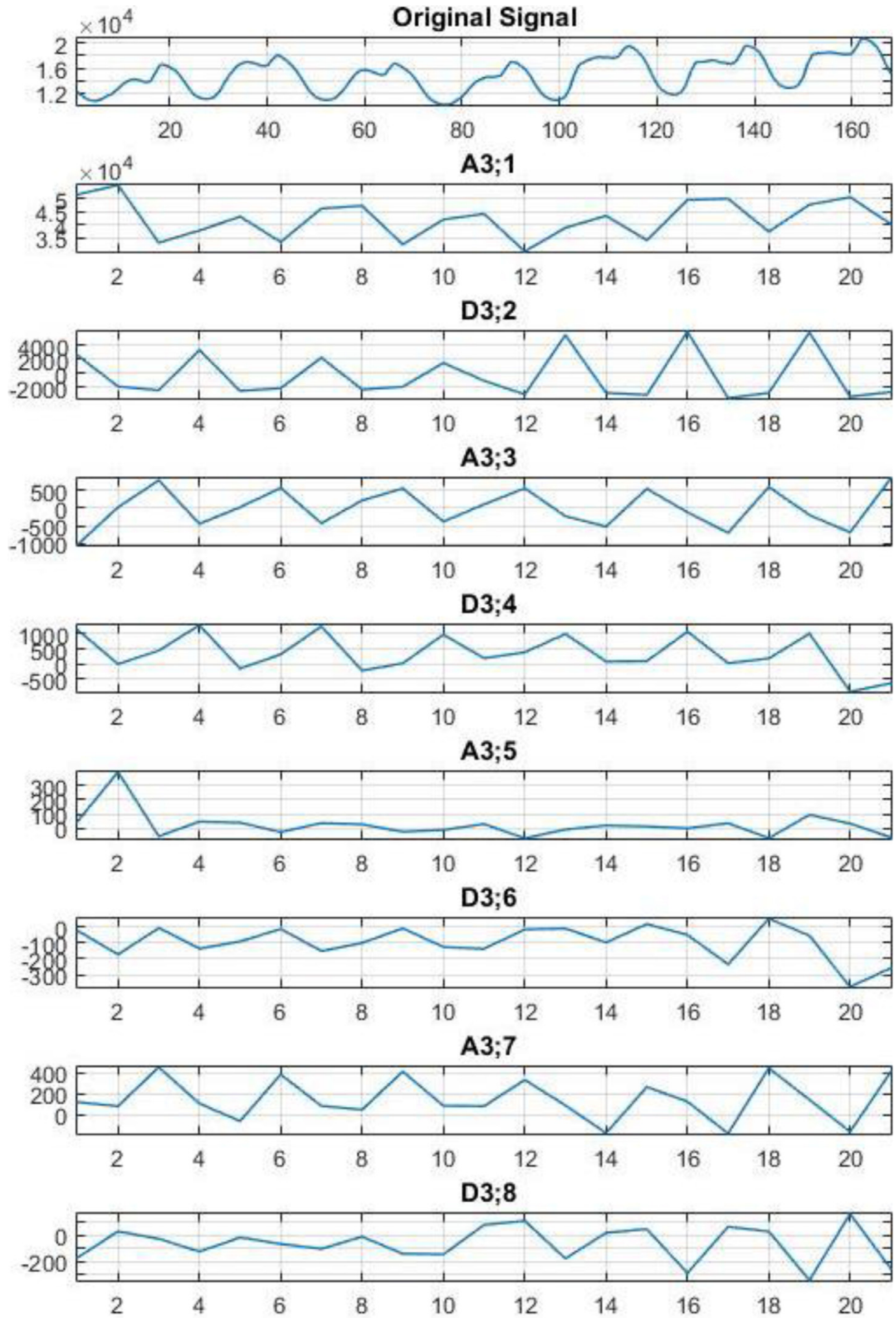

Fig. 12. One-week load data samples decomposed by a 3-level full wavelet packet transform approach.

fed into the trained neural networks to predict the load profile for each component. Finally, the predicted load profile is constructed. Fig. 13 shows the actual and predicted load profile using full wavelet neural networks The MAPE was 1.52%.

4.5. Scenario #4: evaluation of the proposed full wavelet neural network

In this scenario, the proposed full wavelet neural network is evaluated in different months and different day types.

4.5.1. Evaluation in different months

Fig. 14 shows the MAPE in the months of 2016. As can be seen, the MAPEs were small and slightly fluctuate among the months. The minimum of the MAPE was 1.2% in May and the maximum MAPE was in June and December with 2%. The average was 1.5%.

4.5.2. Evaluation in different day types

Table 3 shows the MAPEs in working days, weekends and holidays. As can be seen, the MAPE in working day was the lowest with 1.03% while the MAPE was 2.14% on holidays that was the highest. The MAPE of the load forecasting on weekends was 1.33%.

5. Discussion

The proposed model is applied for day-ahead load forecasting in case studies for the Ontario electric market, Canada. Simulation is

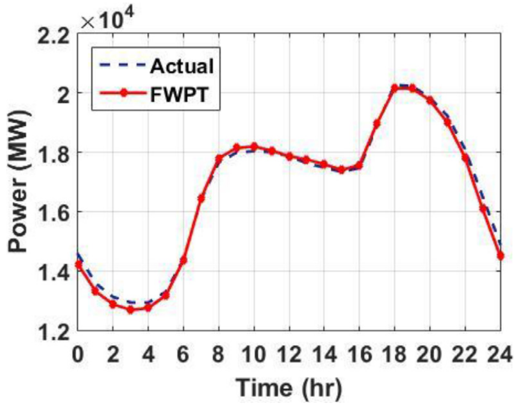

Fig. 13. The actual and predicted load profile using full wavelet neural networks.

conducted in scenarios using various methods including neural networks, a combination of traditional wavelet transform and neural networks, and the proposed full wavelet neural network. In addition, different levels of traditional wavelet transform are evaluated.

Table 4 shows the MAE and MAPE using these methods. The proposed wavelet packet transform and neural networks perform the best with the lowest MAE (232.8 MW) and MAPE (1.52%). By contrast, the neural networks show the highest MAE (287.2 MW) and MAPE (1.91%). The performance of the combination of traditional wavelet transform and neural networks stays in the middle, among which, the 3-level decomposition appears the best with MAE (254.1 MW) and MAPE (1.72%). As can be seen, the proposed full wavelet neural network improves the accuracy by 20% from using the neural network method and 11.6% from using 3-level traditional wavelet transform combined with neural networks.

Fig. 15 shows the actual load and predicted load using the testing data set of the year 2016, which shows the reliability of the proposed approach with good accuracies of load forecasting in different months. The accuracy of load forecasting for June and December appears lower than the other months. This is because the demand variation is large due to the irregular usage of air conditioners in June or space heaters in December.

Fig. 16 shows the actual load, forecasted load and the MAE using the cross-validation data set of one week. The MAPE is as low as 1.04%.

Fig. 17 illustrates the statistics of the MAPE of load forecasting using the testing data set (8784 hourly data). On each box, the central mark indicates the median of the data. The bottom edge of the box indicates the 25th percentile and the top edge of the box indicates the 75th percentile. The whiskers extend to the maximum and the minimum data points without considering outliers. For instance, at 1:00, the median

Table 3
Load prediction accuracy using full wavelet neural network in different day types.

Day type	MAPE%
Working day	1.03
Weekend	1.33
Holiday	2.14

Table 4
MAE and MAPE using different methods.

Error type	Neural network	1- level	3-level	5-level	FWNN
MAE (MW)	287.2	278.2	254.1	268.8	232.8
MAPE (%)	1.91	1.85	1.72	1.82	1.52

MAPE was 1% indicated by the central mark. The maximum and minimum MAPE were 4% and 0% respectively.

Furthermore, load forecasting using the proposed full wavelet neural network show that the human factors have significant impact on the load variation and hence influence the accuracy of load prediction. More specifically, load forecasting in working day has a higher accuracy than weekends and holidays since people have a regular routine during weekdays while the activities during weekends and holidays are more random.

6. Conclusion

This paper proposes a full wavelet neural network model that can be used for high accuracy short term load forecasting. This model ensembles two approaches: the full wavelet packet transform and multilayer neural networks. The full wavelet packet transform decomposes the original load profile into components with different frequencies to exploit electricity consumption patterns. The neural networks are trained to predict load for each wavelet component using the Levenberg–Marquardt algorithm. The predicted load profiles are constructed as the final load prediction. This method is applied for load prediction in the electricity market of Ontario, Canada in case studies. Simulation results show that the proposed full wavelet neural network approach has the lowest prediction error of 1.52% (MAPE) in comparison with neural networks and traditional ensemble methods. Furthermore, the approaches demonstrate a high prediction accuracy and great reliability under various conditions such as different months and day types (e.g., weekday, weekend and holiday).

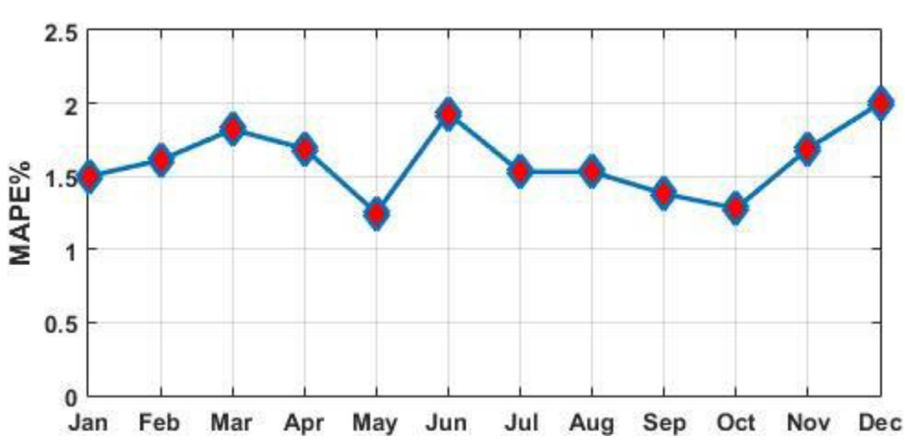

Fig. 14. Monthly MAPE % through the year 2016.

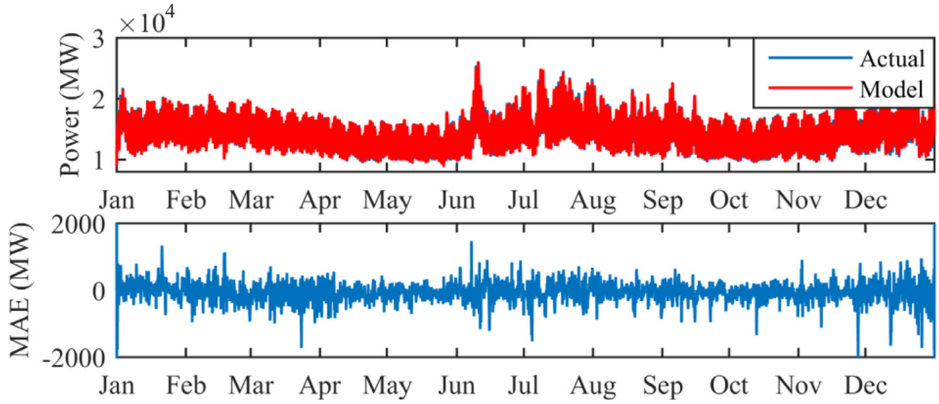

Fig. 15. The actual load and predicted load using testing data set of one year of 2016.

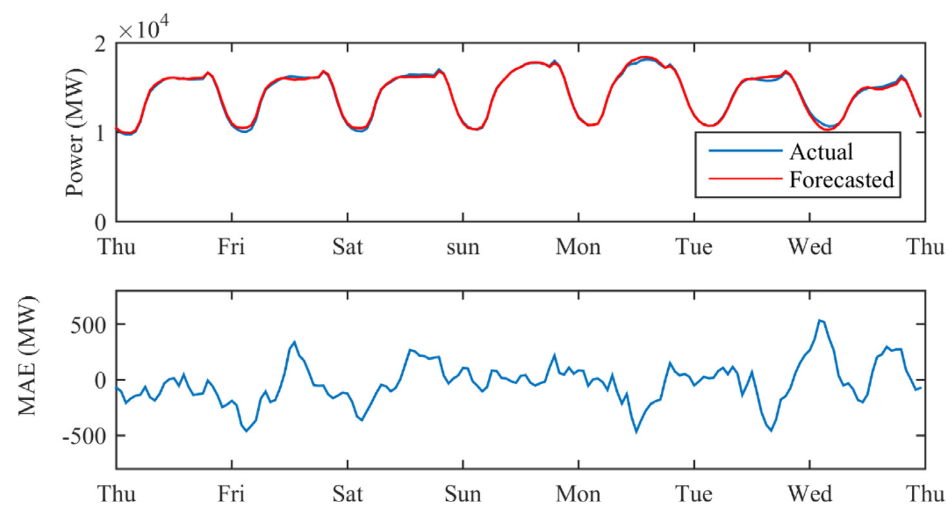

Fig. 16. The actual load, the forecasted load and the MAE using cross-validation data set.

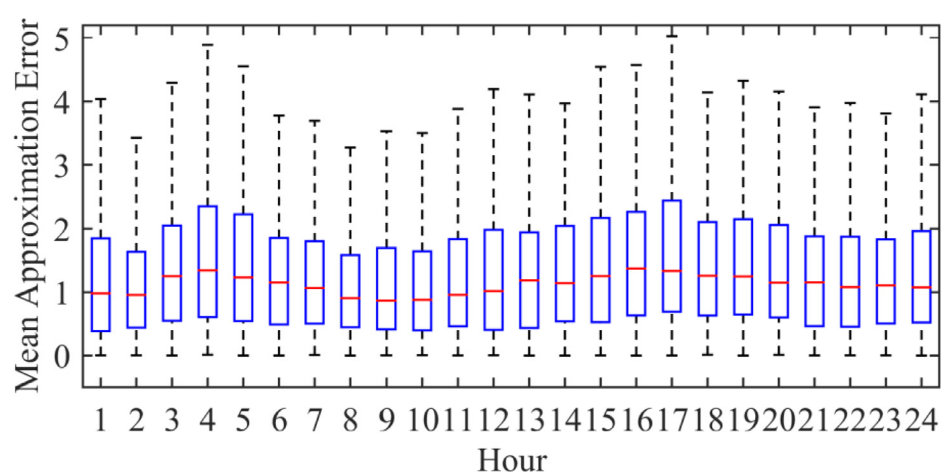

Fig. 17. Statistics of the MAPE. On each box, the central mark indicates the median of the data. The bottom edge of the box indicates the 25th percentile and the top edge of the box indicates the 75th percentile. The whiskers extend to the maximum and the minimum data points without considering outliers.

CRediT authorship contribution statement

Mohamed El-Hendawi: Conceptualization, Data curation, Formal analysis, Software, Writing - original draft. **Zhanle Wang:** Funding acquisition, Investigation, Methodology, Supervision, Writing - review & editing.

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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