Transactions on Machine Intelligence 2(2) (219) 88-98

ISSN Online: 2821-1693

Transactions on Machine Intelligence

Journal Homepage: https://tmachineintelligence.ir/index.php/TMI

Short-Term Load Forecasting of Distribution Networks Using a Hybrid Method of Wavelet Transform and Neural Networks Based on Bacterial Foraging Optimization Algorithm

A. Zarif Loulouei[1,*], N. Kuchmeshki[2]

[1] Department of Electrical Engineering, Pardis Branch, Islamic Azad University, Tehran, Iran
[2] Department of Computer Engineering, Arak Branch, Islamic Azad University, Arak, Iran

ARTICLE INFO

Article History:
Received 7 March 2019
Received in revised form 24 May 2019
Accepted 11 June 2019
Available online 18 June 2019

Keywords:
Bacterial Foraging Optimization Algorithm, Distribution Network Load, Wavelet Transform, Short-Term Forecasting, Neural Network.

ABSTRACT

The effective application of consumption management in electrical distribution systems is expected to result in uniform load curves in the future, promoting the efficient utilization of resources. A critical aspect of consumption management is the precise prediction of electrical load in local networks, which consist of a diverse mix of residential, commercial, and industrial consumers. This paper proposes a hybrid approach combining neural networks and wavelet transform to accurately forecast the load of distribution networks. The model utilizes electrical load data from the Qom province distribution network to train and evaluate the prediction system. The wavelet transform is employed for multi-resolution analysis, enabling the model to capture both short-term and long-term patterns in the load data. The neural network's parameters, including the filter type, window length (the number of past data points used for forecasting), and the number of hidden layers, are optimized using the E. coli bacterial foraging algorithm. This optimization technique helps minimize forecasting errors by identifying the most effective configuration for the neural network model. The proposed hybrid model aims to improve forecasting accuracy compared to traditional methods by effectively addressing the complexities of load prediction in distribution networks. The results demonstrate the potential of this integrated approach for enhancing load forecasting and supporting more efficient consumption management in local electrical grids.

1. INTRODUCTION

Load forecasting is a crucial issue in the operation and design of electric power generation units. Electric power generation units utilize load forecasting to control the number of active units in order to reduce operational costs. Short-term load forecasting (STLF) is typically used for hour-by-hour predictions and is important for the daily maintenance of power plants. Additionally, load forecasting can lead to more effective performance in setting prices for the electricity market [1-14]. Various methods exist for forecasting, which can be broadly categorized into three main groups: time series, artificial intelligence-based methods, and hybrid methods.

* Corresponding Author: zarif@pardisiau.ac.ir
Department of Electrical Engineering, Pardis Branch, Islamic Azad University, Tehran, Iran

http://dx.doi.org/10.47176/TMI.2019.88

In the time series-based method, regression is initially used to estimate the parameters of the time series and obtain the residuals. Subsequently, various processes are employed to optimize the regression and minimize the error. Increasing the accuracy of forecasting with the time series method requires increasing the order of the series to ensure forecasting accuracy in cases where there are significant changes in the input signal, which leads to increased computational complexity [4, 5].

The use of artificial intelligence is also one of the methods explored for load forecasting. In [2], dynamic neural networks are employed for daily consumption forecasting. The proposed model is implemented on the French transmission network system, and the efficiency of the proposed algorithm is evaluated. Selecting appropriate data for training neural networks is one of the challenges of this forecasting method, particularly when there are significant variations in the input signal. To mitigate this issue, the number of hidden layers in the network can be increased or the neural network can be combined with fuzzy logic, both of which increase computational complexity [9-11].

In reference [6], methods for net load forecasting and its importance for power network operation and management with a high penetration rate of renewable energy sources are discussed. Load forecasting enables the integration of microgrids and macrogirds. Net load specifies the exact amount of loads transferred within the network, which is crucial for the connection of connectable networks. In this paper, two different approaches are examined: first, the integrated load forecasting model, and second, the incremental load forecasting model. The proposed method is tested in a microgrid with a 33% penetration rate for solar energy. In reference [14], a hybrid method utilizing an improved neural network based on a nonlinear structure for training and learning, and the combination of a bee colony algorithm for finding the best weights to minimize the mean squared error of the forecast is used.

In this research, the objective is to achieve a combination of wavelet transform and neural networks capable of accurately forecasting the load of distribution networks. The data used in this model is electrical load, and the wavelet technique is employed. The model consists of two stages: data preprocessing and data forecasting. The reason for using wavelet transform is to perform multi-resolution forecasting; data is divided into two parts with high variations (details) and low variations (approximation), and two different neural networks with varying computational complexities forecast these two signals, thus improving the accuracy of the details signal prediction. The neural network is utilized for data forecasting. To achieve an optimal response, the number of neural networks required for forecasting is determined by the number of wavelet transform stages, the type of high-pass and low-pass filters in the wavelet transform, using the bacterial foraging optimization (BFO) algorithm. To ensure the practical application of the research, load data from the Qom distribution network is used for this purpose.

2. FORECASTING METHODS

In this section, linear forecasting methods are examined as time series-based forecasting methods, and neural network methods are explored as artificial intelligence-based forecasting methods. The governing equations for these methods are derived, followed by the presentation of the proposed hybrid method.

2.1. Linear Forecasting

The linear forecasting method is a powerful technique for predicting time series in a time-varying environment. A time-varying process is one in which the function estimating its measured parameters changes over time. This means that the measured parameter of such a process cannot be represented by a single mathematical function over the entire period; instead, the equation must be updated over specific time intervals. Electricity price data are typically time-varying processes. The linear forecasting model represents the time series of signal samples over a specified time interval:

$$y(t+T) = a_1.y(t) + a_2.y(t-T) + \cdots + a_m.y(t-(m-1).T) \tag{1}$$

The coefficients $a_1, a_2, \ldots, a_m$ are the linear prediction coefficients, m is the order of the model, T is the sampling time, y(t+T) is the future sample, and y(t), y(t-T), …, y(t-mT) are the current and past observations. In Equation (1), the output function is a linear combination of the current and past samples; therefore, this function is called a linear prediction function. This equation is also referred to as a difference equation. Considering the error, Equation (1) can be expressed in matrix form as Equation (2).

$$\begin{bmatrix} y(t) \\ y(t-T) \\ \vdots \\ y(t-kT) \end{bmatrix} = \begin{bmatrix} y(t-T) & y(t-2T) & \cdots & y(t-m.T) \\ y(t-2T) & & \cdots & y(t-(m+1).T) \\ \vdots & & & \vdots \\ y(t-(k+1).T) & & \cdots & y(t-(m+k).T) \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} + \begin{bmatrix} e(t) \\ e(t-T) \\ \vdots \\ e(t-kT) \end{bmatrix} \tag{2}$$

The above equation can be represented in the following matrix form:

$$Y = \varphi \times A + E. \tag{3}$$

The elements of matrix A are coefficients that can be determined using the method of least squares error.

$$A = \left(\varphi^T . \varphi\right)^{-1} . \phi^T . Y. \tag{4}$$

In the above equation, φ^T is the transpose of matrix ϕ, and $(\varphi T.\varphi)^{-1}$ is the inverse matrix.

2.2. Neural Network Prediction

Artificial neural networks are models for information processing that are designed to mimic biological neural networks, such as the human brain. To train a neural network, it is sufficient to optimally calculate the values of weights and biases. Typically, the goal of training is to enable the network to produce the desired output for a given input. These networks are capable of curve fitting and pattern recognition. It is proven that a simple neural network can accurately model almost any arbitrary nonlinear function with a finite number of discontinuities.

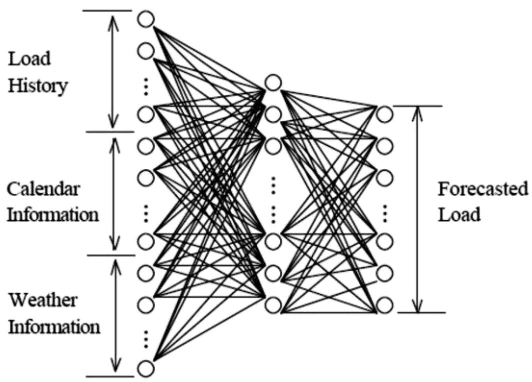


Fig. 1. Structure of the neural network for short-term prediction [5]

The selection of appropriate data for training the neural network is itself a challenge in the prediction method. The data must be chosen to ensure the optimal performance of the predictor. Other factors influencing the performance of this predictor include the number of hidden layers and the number of inputs (the number of previous data points used to predict the next step). Therefore, to ensure adequate accuracy when the input data changes significantly, it is necessary to consider a larger number of layers and inputs. However, this computational burden is not required when the changes are minimal. Consequently, this paper proposes a multi-resolution prediction method based on wavelet transform.

2.3. Neural Network Prediction

The proposed algorithm consists of two main parts: data preprocessing and data prediction. In the data preprocessing phase, the consumption load data of the distribution network is decomposed into approximate and detailed components using wavelet transform along with low-pass and high-pass filters. The approximate components contain the distribution network consumption data with less variation, while the detailed components capture the data with significant variations. During the data prediction phase, these different components are independently predicted using the neural network prediction algorithm. Finally, the predicted distribution network consumption load is obtained by summing these individually predicted data components. Figure 2 illustrates the structure of this proposed algorithm.

Wavelet transform is a variable-sized windowing technique. Wavelet analysis enables us to achieve high accuracy for low-frequency information over long time intervals and to meet the need for high-frequency data over shorter intervals. Multi-resolution analysis refers to the examination of a signal at different frequencies with varying resolutions. Unlike the short-time Fourier transform, multi-resolution analysis does not treat each frequency component uniformly. The objective of multi-resolution analysis is to provide suitable temporal resolution and coarse frequency resolution at high frequencies, and conversely, good frequency resolution and poor temporal resolution at low frequencies. The application of wavelet transform yields two versions of the initial signal, one high-pass and the other low-pass, each with a reduced (halved) length, obtained as follows:

$$\begin{aligned} y_{high}[k] &= \sum_{n} x[n].g[2k-n] \\ y_{low}[k] &= \sum_{n} x[n].h[2k-n] \end{aligned} \tag{5}$$

The output coefficients of the low-pass filter follow the initial shape of the signal; hence, these coefficients are referred to as approximations. Additionally, the output coefficients of the high-pass filter capture the high-frequency details of the signal, which is why these coefficients are called details. As the number of transformation stages increases, the amount of detail decreases.

The predicted data consists of two parts: the first part approximately predicts the consumption load of the distribution network for the next step, and the second part predicts the consumption load of the distribution network in detail. The wavelet transform filtering can be multi-staged. The type of wavelet transform filter is particularly important as it can affect the prediction system's performance.

The type of wavelet transform filter significantly impacts the separation of frequency components and can influence the accuracy of short-term predictions. Considering the existence of various filters in wavelet transform, both low-pass and high-pass, with common filters numbering around 50 types, and given the wavelet transform's decomposability up to several stages, there are many options for selection. Thus, it is necessary to use an intelligent search algorithm to determine the type of wavelet filter and its degree.

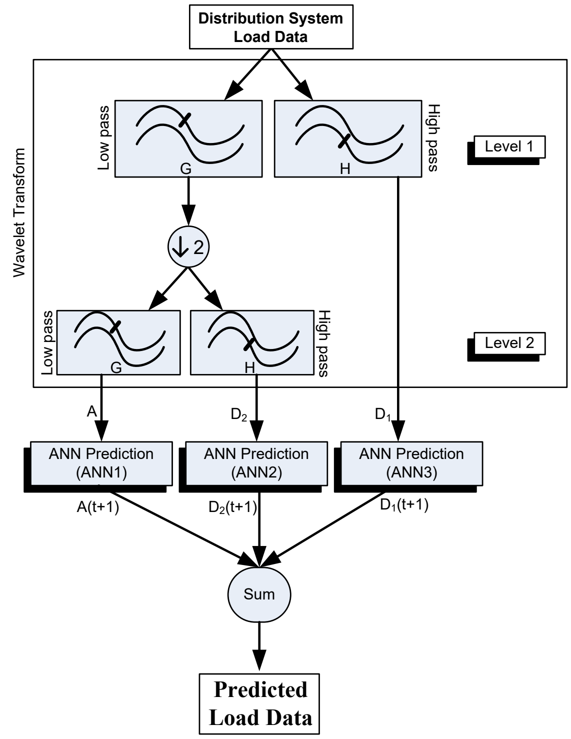


Fig. 2. The structure of the proposed algorithm (short-term prediction using wavelet transform and neural network).

3. OPTIMIZATION BY E. COLI BACTERIAL FORAGING ALGORITHM

The Bacterial Foraging Optimization (BFO) algorithm is a type of dynamic simulation of the optimization behavior of E. coli bacteria within the human body, discovered by Kevin Passino. This has enabled scientists to model biological activity as an optimization process. The optimization strategy can be explained through four processes: chemotaxis, swarming, reproduction, and elimination/dispersal. Compared to other optimization methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), the E. coli Bacterial Foraging Algorithm has lower computational complexity and faster convergence speed, making it a suitable option for this purpose [5].

In this paper, the objective is to optimize the type of low-pass and high-pass filters and the decomposition level of the wavelet transform using the Bacterial Foraging Algorithm to achieve minimum prediction error in the consumption load of the distribution network. The selectable filters include 50 different types, which are referenced in Chapter Four. Additionally, for better analysis, the types of low-pass and high-pass filters are considered independently and are selected based on the Bacterial Foraging Algorithm. Figure 3 illustrates the overall optimization system algorithm.

4. SIMULATION

To evaluate and compare the performance of the proposed predictor, the following methods have been simulated: 1) linear predictor, 2) neural network predictor, 3) neural network-wavelet transform predictor. These predictors have been used for short-term prediction of the consumption load of the distribution network. The data used for the prediction is the daily consumption load data of the Qom province distribution network, sampled at an hourly rate. Figure 4 shows the chart of these data.

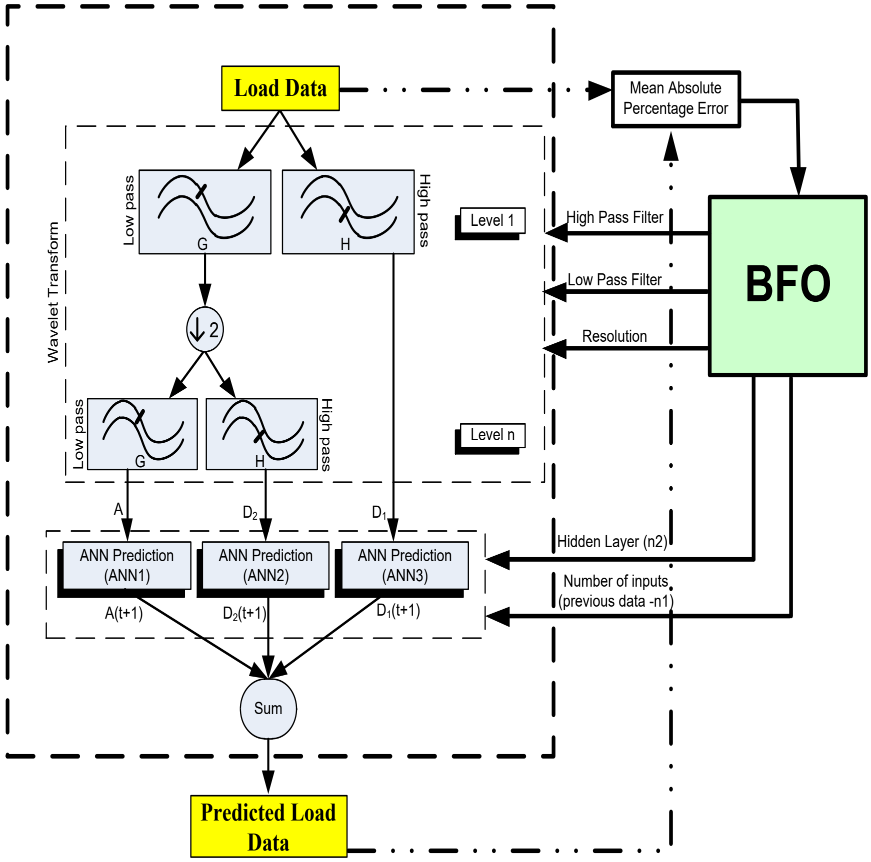


Fig. 3. The structure of the optimization algorithm for the proposed wavelet-neural system.

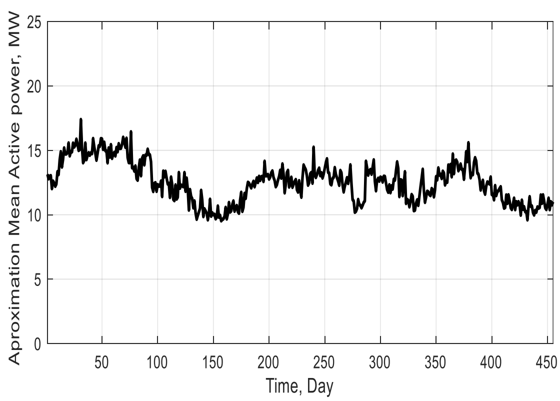


Fig. 4. Average daily consumption load data of the Qom distribution network over 15 months.

To evaluate the performance of the prediction methods, the following four metrics are assessed:

1. Maximum Error (ME).

2. Maximum Percentage Error (MPE).

3. Mean Absolute Percentage Error (MAPE).

4. Mean Squared Error (MSE).

The Maximum Error is the largest prediction error for the test dataset, defined as follows in Equation (6):

$$ME = \max(Load_{actual} - Load_{predicted}) \tag{6}$$

The Maximum Percentage Error (MPE) is defined as follows:

$$MPE = \max(\frac{Load_{actual} - Load_{predicted}}{Load_{actual}}) \times 100 \tag{7}$$

The Mean Absolute Percentage Error (MAPE) is defined as follows in Equation (8):

$$MAPE = \frac{1}{N} \sum_{k=1,\ldots,N} \left| \frac{Load_{actual} - Load_{predicted}}{Load_{actual}} \right| \times 100 \tag{8}$$

Additionally, the Mean Squared Error (MSE) is defined as follows:

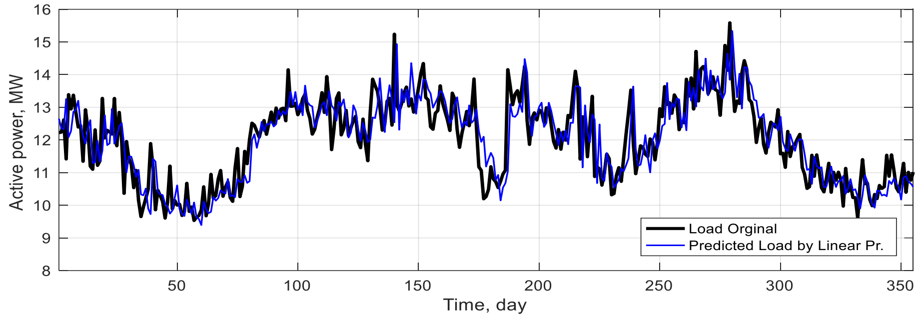
$$MSE = \sqrt{\frac{1}{N} \sum_{k=1,\ldots,N} \left| Load_{actual} - Load_{predicted} \right|^2} \tag{9}$$

The results of the optimization are presented in Table (1). Based on these optimization results, it can be seen that the number of signal decomposition stages is determined to be a single stage. This implies that further decomposition of the signal into more details does not increase prediction accuracy. Additionally, considering the number of hidden layers and the previous data obtained from optimization for the two neural networks—one for predicting the approximate signal (ANN1) and the other for predicting the detailed signal (ANN2)—it is evident that the neural network for the detailed signal has a higher computational load due to accommodating more variations in the input signal.

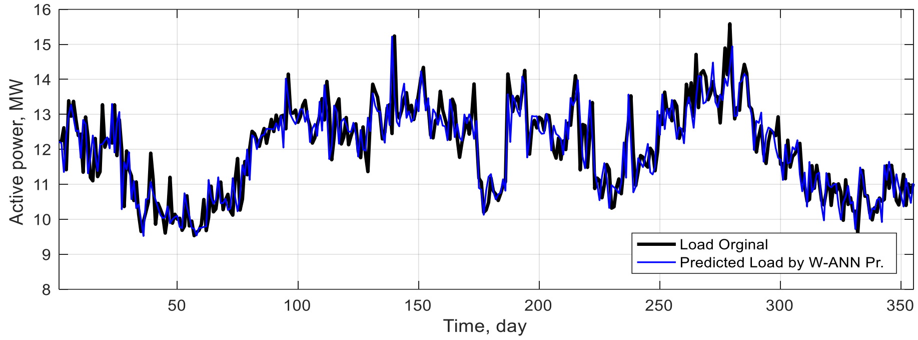
The results of linear prediction, neural network prediction, and optimized neural network-wavelet prediction are shown in Figure (5). Based on these results, it can be seen that the proposed method has the least error and the highest similarity to the distribution network load as the input signal. The prediction errors are shown in Figure (6), and the error values based on the four tests are presented in Table (2). According to the results in Table (2), it can be concluded that the proposed method provides a more desirable response compared to the other two methods.

Table 1. Configurations and Optimization Results for the Proposed Wavelet-Neural System.

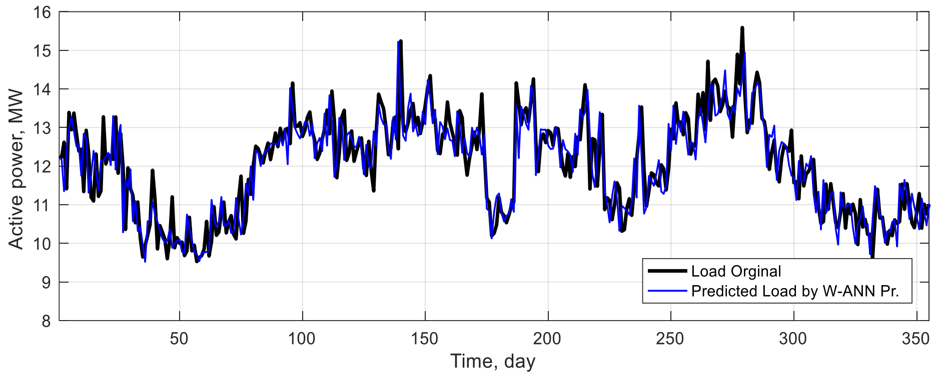
Number of Bacteria	Nb	50
Number of Repetitions	Iteration	150
Probability of Population Elimination	Mutaion	5%
Number of Signal Decomposition Stages	nLevel	1
Number of Prior ANN Data for Detailed Signal	nInp for ANN2	7
Number of Prior ANN Data for Approximate Signal	nInp for ANN1	4
Number of Hidden Layers in ANN for Detailed Signal	nH for ANN2	18
Number of Hidden Layers in ANN for Detailed Signal	nH for ANN1	11
High-pass and Low-pass Wavelet Transform Filter	High & Low filter	Dubanchi



(a)



(b)



(c)

Fig. 5. Distribution network load prediction results by: (a) Linear prediction, (b) Neural network prediction, (c) Wavelet-neural network prediction.

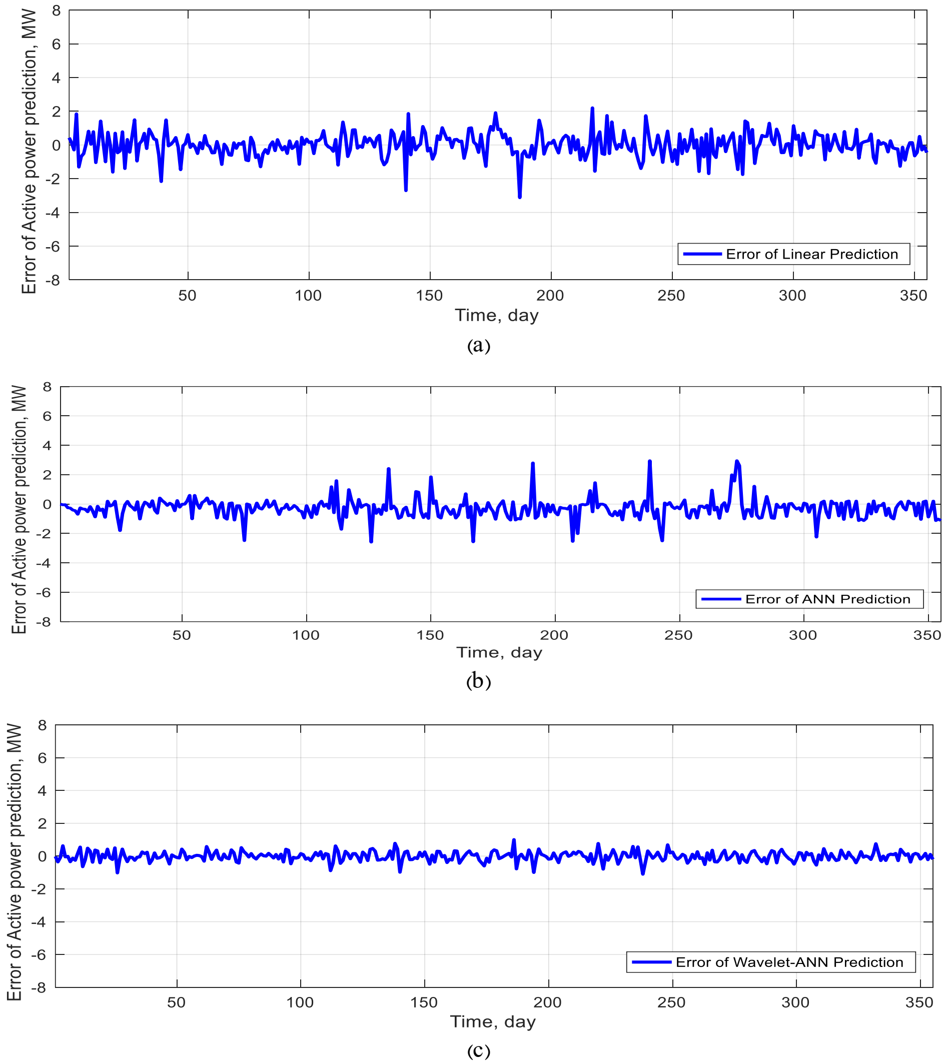


Fig. 6. Prediction error of the distribution network load by: (a) Linear prediction, (b) Neural network prediction, (c) Wavelet-neural network prediction.

Table 2. Comparison of the Error Resulting from Load Forecasting in the Distribution Network Using the Three Examined Methods.

	MAPE	MSE	Maximum Error	Maximum Error Percentage
Linear Prediction	4.423	0.199	3.120	22.04%
Neural Network Prediction	4.203	0.210	2.951	22.00%
Optimized Neural Network-Wavelet Prediction	2.188	0.096	1.443	13.43%

5. CONCLUSION

In this paper, linear forecasting methods and neural networks were presented as various short-term forecasting approaches. These methods were employed to forecast the load data of the distribution network, which served as input data. Subsequently, wavelet transform was utilized as a method for multiresolution analysis of the distribution network load signal. To enhance performance, the neural network was combined with the wavelet transform. To achieve minimal forecasting error, the bacterial foraging algorithm was used for optimal filter selection and neural network adjustments. By analyzing the results obtained for forecasting the distribution network load in Qom province, it is evident that employing the wavelet-neural forecasting method combined with the bacterial foraging algorithm leads to improved performance compared to using the neural network forecasting method alone.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

Acknowledgments

We would like to express our gratitude to all individuals who contributed to this project.

Declaration of Interest

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

REFERENCES

[1] Tarsitano, A., & Amerise, I. L. (2017). Short-term load forecasting using a two-stage SARIMAX model. Energy, 133(1), 108-114. https://doi.org/10.1016/j.energy.2017.05.126

[2] Mordjaoui, M., Haddad, S., Laouafi, A., & Medoued, A. (2017). Electric load forecasting by using dynamic neural network. International Journal of Hydrogen Energy, 42(28), 17655-17663. https://doi.org/10.1016/j.ijhydene.2017.03.101

[3] Haben, S., Giasemidis, G., Ziel, F., & Arora, S. (2019). Short term load forecasting and the effect of temperature at the low voltage level. International Journal of Forecasting, 35(4), 1469-1484. https://doi.org/10.1016/j.ijforecast.2018.10.007

[4] Hong, T., & Fan, S. (2016). Probabilistic electric load forecasting: A tutorial review. International Journal of Forecasting, 32(3), 914-938. https://doi.org/10.1016/j.ijforecast.2015.11.011

[5] Sepasi, S., Reihani, E., Howlader, A. M., Roose, L., & Matsuura, M. M. (2017). Very short term load forecasting of a distribution system with high PV penetration. Renewable Energy, 106(1), 142-148. https://doi.org/10.1016/j.renene.2017.01.019

[6] Kaur, A., Nonnenmacher, L., & Coimbra, C. F. M. (2016). Net load forecasting for high renewable energy penetration grids. Energy, 114(1), 1073-1084. https://doi.org/10.1016/j.energy.2016.08.067

[7] Panapakidis, I. P. (2016). Clustering based day-ahead and hour-ahead bus load forecasting models. Electrical Power and Energy Systems, 80, 171-178. https://doi.org/10.1016/j.ijepes.2016.01.035

[8] Duan, Q., Liu, J., & Zhao, D. (2017). Short term electric load forecasting using an automated system of model choice. International Journal of Electrical Power & Energy Systems, 91(1), 92-100. https://doi.org/10.1016/j.ijepes.2017.03.006

[9] Vogler-Finck, P. J. C., Bacher, P., & Madsen, H. (2017). Online short-term forecast of greenhouse heat load using a weather forecast service. Applied Energy, 205(1), 1298-1310. https://doi.org/10.1016/j.apenergy.2017.08.013

[10] Raza, M. Q., Nadarajah, M., Hung, D. Q., & Baharudin, Z. (2017). An intelligent hybrid short-term load forecasting model for smart power grids. Sustainable Cities and Society, 31(1), 264-275. https://doi.org/10.1016/j.scs.2016.12.006

[11] Zhai, M. Y. (2015). A new method for short-term load forecasting based on fractal interpretation and wavelet analysis. International Journal of Electrical Power & Energy Systems, 69(1), 241-245. https://doi.org/10.1016/j.ijepes.2014.12.087

[12] Sani, F., Shahgholian, G., & Zamani-Far, M. (2012). Short-Term Load Forecasting for Distribution Feeders Using Neural Networks. First National Conference on Innovative Ideas in Electrical Engineering, Isfahan.

[13] Nosrati Marallo, M., Karolux, & Tashnehlab, M. (2009). Electric Load Consumption Forecasting Using the Neuro-Fuzzy Intelligent Method. Seventh National Energy Conference, 2009.

[14] Seyyed Shenava, S., Ghasemi, A., Shayegi, H., & Noshiyar, M. (2009). Presenting a Combined Model for Load Forecasting in the Restructured Electricity Market. Iranian Journal of Electrical Industry Quality and Productivity, 2(3), 19-28.