TẠP CHÍ KHOA HỌC
TRƯỜNG ĐẠI HỌC QUY NHƠN

Nghiên cứu so sánh các phương pháp dự báo phụ tải ngắn hạn trong lưới điện phân phối

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TÓM TẮT

Dự báo phụ tải ngắn hạn đóng một vai trò cực kỳ quan trọng trong việc xây dựng kế hoạch vận hành cũng như đảm bảo độ tin cậy của bất kỳ hệ thống điện nào. Các phương pháp dự báo phụ tải ngắn hạn về cơ bản có thể được phân thành ba loại chính như sau: các phương pháp thống kê, các phương pháp sử dụng trí tuệ nhân tạo và các phương pháp kết hợp giữa hai phương pháp này. Mỗi phương pháp đều có những ưu điểm và nhược điểm riêng. Do đó, mục tiêu của bài báo này là khảo sát hiệu quả của mô hình thống kê ARIMA và sử dụng mạng nơ ron nhân tạo trong dự báo phụ tải ngắn hạn của lưới điện phân phối. Trước tiên, bài báo tiến hành phân tích phụ tải tiêu thụ của lưới điện phân phối Quy Nhơn và Phù Cát. Tiếp theo đó, hai phương pháp dự báo (Arima và mạng nơ ron) được áp dụng để dự đoán phụ tải ngắn hạn của hai lưới phân phối này. Cuối cùng, bài báo tiến hành phân tích, so sánh hiệu quả của hai phương pháp đã sử dụng dựa trên các kết quả có được.

Từ khóa: *Dự báo phụ tải ngắn hạn, mạng nơ ron nhân tạo, mô hình Arima, lưới điện phân phối.*

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A comparative study of short-term load forecasting methods in distribution network

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ABSTRACT

Short-term load forecasting plays an important role in building operation strategies and ensuring reliability of any electric power system. Generally, short-term load forecasting methods can be classified into three main categories: statistical approaches, artificial intelligence based-approaches and hybrid approaches. Each method has its own advantages and shortcomings. Therefore, the primary objective of this paper is to investigate the effectiveness of ARIMA model (e.g., statistical method) and artificial neural network (e.g., artificial intelligence based-method) in short-term load forecasting of distribution network. Firstly, the short-term load demand of Quy Nhon distribution network and short-term load demand of Phu Cat distribution network are analyzed. Secondly, the ARIMA model is applied to predict the load demand of two distribution networks. Thirdly, the artificial neural network is utilized to estimate the load demand of these networks. Finally, the estimated results from two applied methods are conducted for comparative purposes.

Keywords: *Short-term load forecasting, artificial neural network, ARIMA, distribution network.*

1. INTRODUCTION

Nowadays, the demand for electricity has increased noticeably due to the expansion of industrial and residential areas. In addition, the Vietnamese government has provided incentives for the huge development of wind and solar energy resources. Therefore, the load forecasting can be considered one of the most urgent issues in planning and development of power system. In power system operation, power load forecasting is an essential task of power companies in order to provide important decisions in operation and planning, load management, reliability evaluation of power system, and load dispatch. Short-term load forecasting ranging from hour, day, or week plays a significant role in daily and weekly operation modes. In the future, short-term load forecasting becomes more and more important as Vietnamese electricity market and renewable energy resources develop since these factors directly affects the spot price.

In order to perform short-term load forecasting, various prediction methods have been proposed such as multiple linear regression method,[1] regression based peak load forecasting using a transformation technique,[2] non-parametric short-term load forecasting,[3] ARIMA model,[4] ARMA model,[5] neural network,[6] fuzzy logic,[7] machine learning,[8] or hybrid method based on these methods.[9-10] Generally, these short-term forecasting methods can be classified into three main types, such as (1) statistical methods, (2) artificial intelligence-based methods and (3) hybrid methods. Each method has its specific

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characteristics, implementation and effects in power system forecasting. In this paper, ARIMA model (a statistical method) and neural network (an artificial intelligence based-method) are utilized in short-term load forecasting. In addition, the effectiveness of these forecasting methods is compared.

Binh Dinh power company has 9 electricity branches and one high-voltage grid operation management team, in which each electricity branch is managing a distribution network, such as Quy Nhon, Phu Tai, Tuy Phuoc, An Nhon, Phu Cat, Phu My, Bong Son, Hoai An and Phu Phong. Recently, the load demand has dramatically increased due to the rapid urbanization and expansion of industrial zones. Especially, the short-term load demand of both Quy Nhon and Phu Cat electricity branches has the fastest growth rate[11]. Therefore, the short-term load forecasting of these distribution networks is analyzed in this paper. Based on the forecasted results, the suitable operation strategies with high reliability can be proposed.

The remainder of this paper is organized as follows. The next section will discuss the forecasting methods used in this paper. Section 3 will discuss case studies. The final section will be the conclusion and further studies.

2. FORECASTING METHODS

2.1. ARIMA model

Box & Jenkins (1970) first introduced ARIMA model (autoregressive integrated moving average) in time series analysis, namely Box-Jenkins method. This statistical model is used for forecasting quantitative time series, in which the future value of the variable depends on the movement trend of that object in the past. ARIMA model consists of three main components: AR (auto regression), I (integrated), and MA (moving average). ARIMA model includes p, d and q parameters, non-negative integers, where p is the order (number of time lags) of the autoregressive model, d is the degree of differencing (the number of times the data have had past values subtracted), and q is the order of the moving-average model[12]. The effectiveness of using ARIMA model in forecasting depends on the estimation of p, d and q. The general equation of ARIMA (p, d, q) model can be represented as follows:

$$\begin{aligned} y_t = \delta + \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \beta_1 \\ + \varepsilon_{t-1} + \ldots + \beta_t \varepsilon_{t-q} + e_t \end{aligned} \quad (1)$$

where: α is auto regression coefficient; ε is moving average coefficient; $\delta = \mu\left(\beta_1 + \ldots + \beta_q\right)$; μ is the average of the time series; e_t is the forecast error, this error is the difference between the forecasted value and the actual value ($e_t = \hat{y}_t - y_t$).

2.2. Artificial neural network

2.2.1. Introduction

Recently, artificial neural network (or neural network) has been applied in various aspects of power system, especially in load forecasting. Neural network can be considered a "black – box". The structure of neural network includes three layers: input layer, hidden layer, and output layer. The general structure of a neural network is shown in Figure 1.

The external information is transferred to the input of the input layer. The output of the input layer with different weights and bias becomes the input of the hidden layer. Hidden layer has one or more layers. Each hidden layer has one or more hidden neurons. The output of hidden layer becomes the input of the output layer.

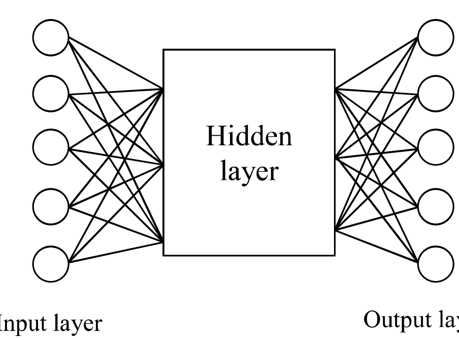

Figure 1. The general neural network structure

The mathematical equation of a neural network is presented as:

$$y(x) = f\left(\sum_{i=1}^{n} w_i x_i\right) \quad (2)$$

where: *y(x)* is the output value of x; f is activation function, w_i is connection weight of neuron x_i, x_i is the input value.

2.2.2. Training algorithm

The predicted results of neural networks depend on the application of training algorithms. An appropriate training algorithm will reduce the training time. The selection of training algorithm depends on various factors, including the complexity of the problem, the number of data in the training system, the weights and bias, and the error criteria. Some popular training algorithms commonly used in neural networks can be listed as follows:

- Levenberg-Marquardt (e.g. trainlm)
- BFGS Quasi-Newton (e.g. trainbfg)
- Resilient Backpropagation (e.g. trainrp)
- Scaled Conjugate Gradient (e.g. trainscg)
- Bayesian regularization backpropagation (e.g. trainbr).

The training process can be taken in several cycles (epoch) and repeated until the desired error value is reached.

2.3. Evaluation criteria

In forecasting problem, there is always an error between the actual value and the predicted value. This error is a criterion to evaluate the suitability of the forecasting model. Based on this error, the parameters of forecasting models can be adjusted.

In statistics, there are several criteria to evaluate the forecasting error. However, three typical evaluation criteria are used in this paper as follows:

a. Mean Absolute Error (MAE) criterion

$$MAE = \frac{\sum_{t=1}^{n} |e_t|}{n} = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n} \quad (3)$$

where: n is the number of forecasting points.

b. Mean Absolute Percent Error (MAPE) criterion

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{y_t}}{n} = \frac{\sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{y_t}}{n} \quad (4)$$

c. Mean Squared Error (MSE) criterion

$$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n} = \frac{\sum_{t=1}^{n} \left(y_t - \hat{y}_t\right)^2}{n}. \quad (5)$$

3. APPLICATION OF ARIMA MODEL AND ARTIFICIAL NEURAL NETWORK IN LOAD FORECASTING OF QUY NHON AND PHU CAT DISTRIBUTION NETWORKS

The load demand of Quy Nhon distribution network and Phu Cat distribution network in two different months (February and August 2020) is investigated in this paper. These are typical months of spring and summer periods. Data of maximum load demand (P_max, MW) and minimum load demand (P_min, MW) in February and August 2020 of Quy Nhon distribution network and Phu Cat distribution network is illustrated in Tables 1 and 2, respectively.[11]

Table 1. Load data in February 2020

Date	Quy Nhon		Phu Cat	
	P_max	P_min	P_max	P_min
Sat, 01/02	56.2	32.9	15.2	6.9
Sun, 02/02	55.5	34.1	17.7	7.3
Mon, 03/02	58.1	33.8	21.7	7.8
Tue, 04/02	61.7	34.1	22.8	9.2
Wed, 05/02	62.6	38.7	22.9	10.8
Thu, 06/02	63.6	35.9	24.1	10.2
Fri, 07/02	68.1	36.9	23.8	11.5
Sat, 08/02	62.9	35.9	24.5	13.0
Sun, 09/02	59.9	36.4	22.6	11.6
Mon, 10/02	60.7	34.6	23.3	11.8
Tue, 11/02	60.3	33.3	25.2	10.3
Wed, 12/02	60.6	37.3	26.3	12.0
Thu, 13/02	60.5	35.5	31.6	13.9
Fri, 14/02	61.0	36.7	27.8	10.9
Sat, 15/02	60.8	38.6	26.8	12.3
Sun, 16/02	59.4	38.9	27.1	12.9
Mon, 17/02	56.1	35.8	25.2	11.7
Tue, 18/02	56.0	32.2	23.9	9.5

Wed, 19/02	61.8	32.6	24.7	12.5
Thu, 20/02	62.3	34.5	24.2	11.4
Fri, 21/02	59.3	37.2	24.7	13.1
Sat, 22/02	58.3	33.9	23.6	11.9
Sun, 23/02	56.3	34.5	23.9	11.7
Mon, 24/02	67.8	36.5	24.3	10.2
Tue, 25/02	64.1	39.5	26.4	11.0
Wed, 26/02	62.0	37.8	26.5	13.1
Thu, 27/02	59.9	37.3	27.5	13.3
Fri, 28/02	59.0	36.6	25.5	14.0
Sat, 29/02	57.5	37.1	25.8	13.9

Table 2. Load data in August 2020

Date	Quy Nhon		Phu Cat	
	P_max	P_min	P_max	P_min
Sat, 01/08	66.3	50.4	24.9	14.1
Sun, 02/08	67.4	46.8	21.7	14.6
Mon, 03/08	78.1	48.1	24.7	12.3
Tue, 04/08	77	49.9	26.8	13.2
Wed, 05/08	77.4	49.8	30.2	15.3
Thu, 06/08	79.6	48.8	26.2	14
Fri, 07/08	69.6	47.4	24.6	12.8
Sat, 08/08	70.3	43.6	25.5	13
Sun, 09/08	68.5	43.0	23.2	13.7
Mon, 10/08	79.2	46.8	26.8	12
Tue, 11/08	78.7	46.9	27.1	16.2
Wed, 12/08	77.7	51.7	27.9	15.9
Thu, 13/08	78.1	50.3	27.3	14.6
Fri, 14/08	79.5	50.7	22.1	14.4
Sat, 15/08	75.5	52.0	26.6	13.3
Sun, 16/08	72.3	46.8	21.2	12.2
Mon, 17/08	78.6	51.0	29.7	13.5
Tue, 18/08	82.2	49.0	26.3	15.5
Wed, 19/08	77.9	51.1	26.2	13.5
Thu, 20/08	73.6	49.5	24.7	15.2
Fri, 21/08	74.3	46.7	26.5	13.5
Sat, 22/08	71.7	39.6	24.9	13.8
Sun, 23/08	75.6	50.3	21.1	14.9
Mon, 24/08	86.9	55.5	27.1	12.4
Tue, 25/08	84.9	53.2	29.7	14.5
Wed, 26/08	88.9	59.8	26.6	16.6
Thu, 27/08	88.1	55.9	26.1	16.3
Fri, 28/08	94.4	59.7	28.3	15.2
Sat, 29/08	86.8	59.4	28.4	16.4
Sun, 30/08	73.7	54.6	24.2	14.2
Mon, 31/08	79.5	49.7	26.8	12.6

In order to estimate the short-term load demand of Quy Nhon distribution network and Phu Cat distribution network, statistical MINITAB software and the MATLAB software are used in this paper. The estimated parameters of ARIMA models by using MINITAB software for short-term load forecasting with P_max and P_min of Quy Nhon distribution network and Phu Cat distribution network in February and August 2020 are provided in Tables 3 and 4, respectively.

Table 3. The estimated parameters of ARIMA models for short-term load forecasting of Quy Nhon distribution network in February and August 2020

Load	Estimated parameters			
	p	*d*	*q*	Iteration
P_max (February)	1	0	3	19
P_min (February)	1	0	4	25
P_max (August)	4	0	3	21
P_min (August)	1	0	4	25

Table 4. The estimated parameters of ARIMA models for short-term load forecasting of Phu Cat distribution network in February and August 2020

Load	Estimated parameters			
	p	*d*	*q*	Iteration
P_max (February)	2	0	3	25
P_min (February)	2	0	3	19
P_max (August)	5	0	2	25
P_min (August)	4	0	2	25

Artificial neural networks with one input layer, one hidden layer, and one output layer are used to forecast short-term load demand of Quy Nhon distribution network and Phu Cat distribution network in this paper. The parameters of the trained neural networks by using MATLAB software for short-term load forecasting with P_max and P_min of Quy Nhon distribution network and Phu Cat distribution network in February and August 2020 are provided in Tables 5 and 6, respectively.

Table 5. The parameters of the trained neural networks for short-term load forecasting of Quy Nhon distribution network in February and August 2020

Load	Trained parameters		
	Hidden neuron	Training algorithm	Epoch
P_max (February)	22	trainlm	1
P_min (February)	25	trainrp	20
P_max (August)	25	trainbr	2
P_min (August)	30	trainbr	2

Table 6. The parameters of the trained neural networks for short-term load forecasting of Phu Cat distribution network in February and August 2020

Load	Trained parameters		
	Hidden neuron	Training algorithm	Epoch
P_max (February)	13	trainlm	3
P_min (February)	13	trainlm	3
P_max (August)	30	trainrp	29
P_min (August)	11	trainlm	28

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Quy Nhon distribution network in February are illustrated in Table 7.

Table 7. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Quy Nhon distribution network in February

Criteria	ARIMA model	Neural network
MAE	1.7099	0.8210
MAPE	2.8034	1.3409
MSE	4.7860	1.9393

In this case, the evaluation criteria values including MAE (1.7099), MAPE (2.8034), MSE (4.7860) of ARIMA model and MAE (0.6842), MAPE (1.3409), MSE (1.9393) of neural network are relatively small. These results showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_max of Quy Nhon distribution network by using ARIMA model and neural network in February is demonstrated in Figure 2.

In Figure 2, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Quy Nhon distribution network in February are illustrated in Table 8.

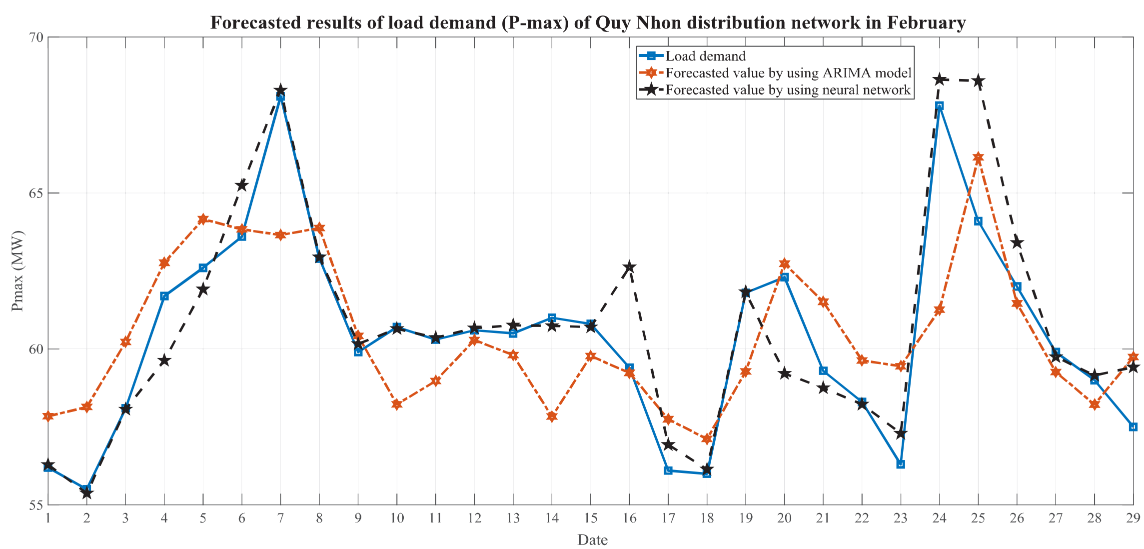

Figure 2. The forecasted results of load demand (P_max) of Quy Nhon distribution network by using ARIMA model and neural network in February

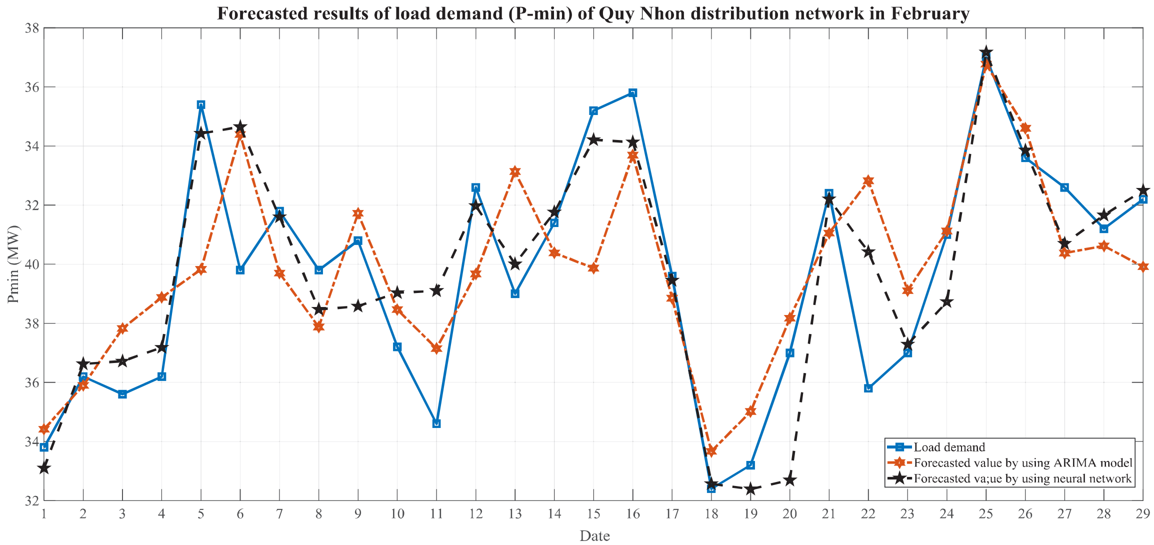

Figure 3. The forecasted results of load demand (P_min) of Quy Nhon distribution network by using ARIMA model and neural network in February

Table 8. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Quy Nhon distribution network in February

Criteria	ARIMA model	Neural network
MAE	1.0723	0.6842
MAPE	2.9915	1.9396
MSE	1.8565	0.9734

In this case, the evaluation criteria values including MAE (1.0723), MAPE (2.9915), MSE (1.8565) of ARIMA model and MAE (0.6842), MAPE (1.9396), MSE (0.9734) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_min of Quy Nhon distribution network by using ARIMA model and neural network in February is demonstrated in Figure 3.

In Figure 3, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Quy Nhon distribution network in August are illustrated in Table 9.

Table 9. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Quy Nhon distribution network in August

Criteria	ARIMA model	Neural network
MAE	3.6034	1.7853
MAPE	4.6312	2.2412
MSE	20.0097	6.0907

In this case, the evaluation criteria values including MAE (3.6034), MAPE (4.6312), MSE (20.0097) of ARIMA model and MAE (1.7853), MAPE (2.2412), MSE (6.0907) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_max of Quy Nhon distribution network by using ARIMA model and neural network in August is demonstrated in Figure 4.

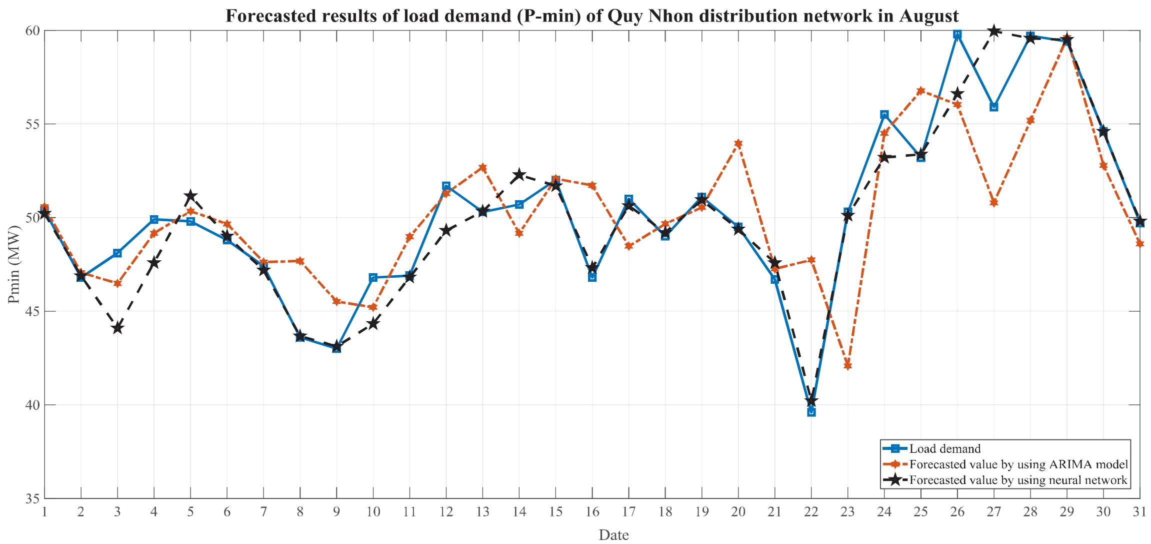

Figure 4. The forecasted results of load demand (P_max) of Quy Nhon distribution network by using ARIMA model and neural network in August

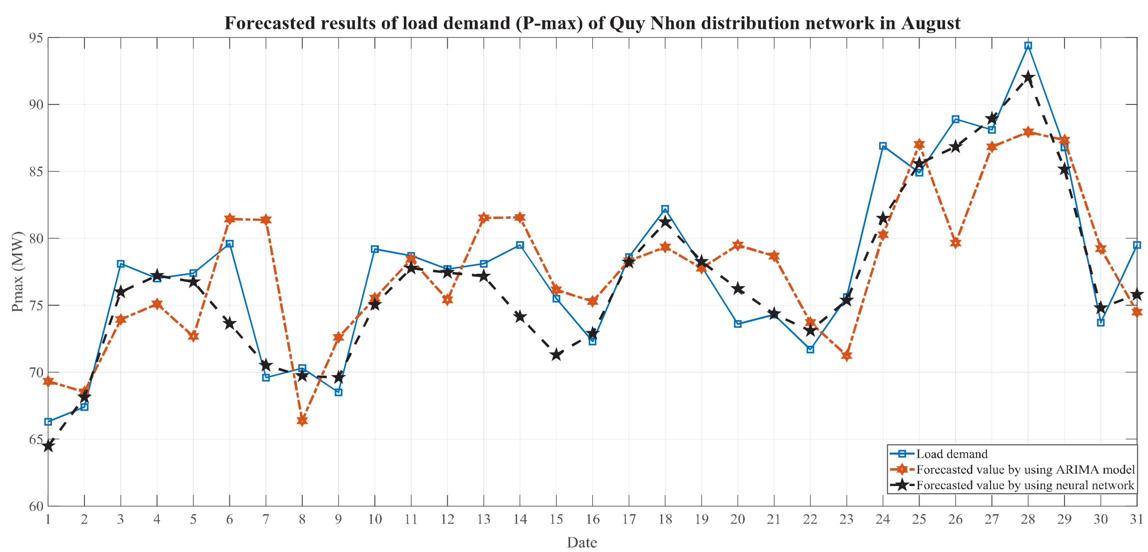

Figure 5. The forecasted results of load demand (P_min) of Quy Nhon distribution network by using ARIMA model and neural network in August

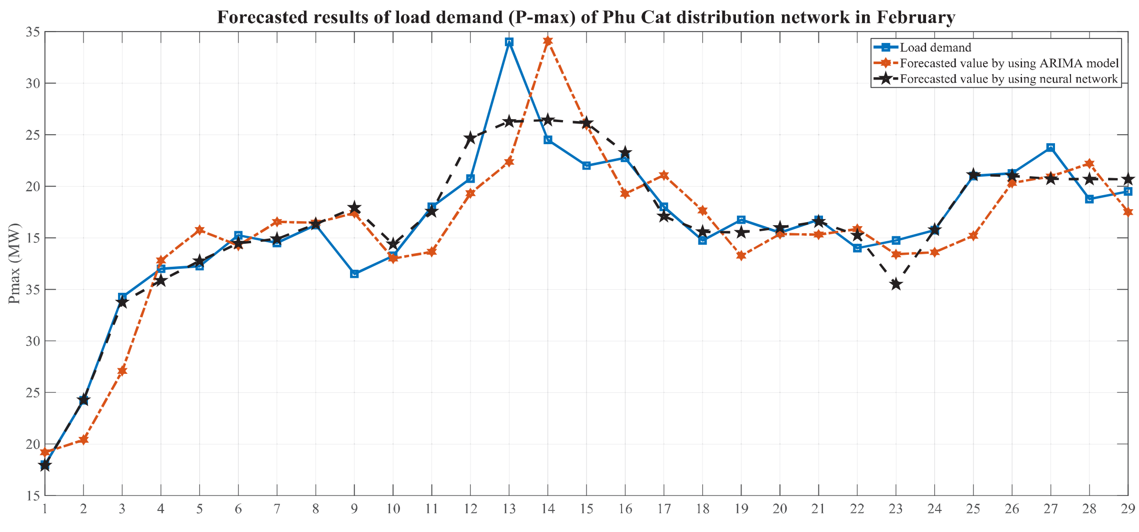

Figure 6. The forecasted results of load demand (P_max) of Phu Cat distribution network by using ARIMA model and neural network in February

In Figure 4, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Quy Nhon distribution network in August are illustrated in Table 10.

Table 10. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Quy Nhon distribution network in August

Criteria	ARIMA model	Neural network
MAE	2.4062	0.9738
MAPE	4.9078	1.8997
MSE	10.5720	2.4585

In this case, the evaluation criteria values including MAE (2.4062), MAPE (4.9078), MSE (10.5720) of ARIMA model and MAE (0.9738), MAPE (1.8997), MSE (2.4585) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_min of Quy Nhon distribution network by using ARIMA model and neural network in August is demonstrated in Figure 5.

In Figure 5, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Phu Cat distribution network in February are illustrated in Table 11.

Table 11. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Phu Cat distribution network in February

Criteria	ARIMA model	Neural network
MAE	1.2655	0.6257
MAPE	5.0768	2.4340
MSE	2.7436	0.9866

In this case, the evaluation criteria values including MAE (1.2655), MAPE (5.0768), MSE (2.7436) of ARIMA model and MAE (0.6257), MAPE (2.4340), MSE (0.9866) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_min of Quy Nhon distribution network by using ARIMA model and neural network in August is demonstrated in Figure 6.

In Figure 6, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

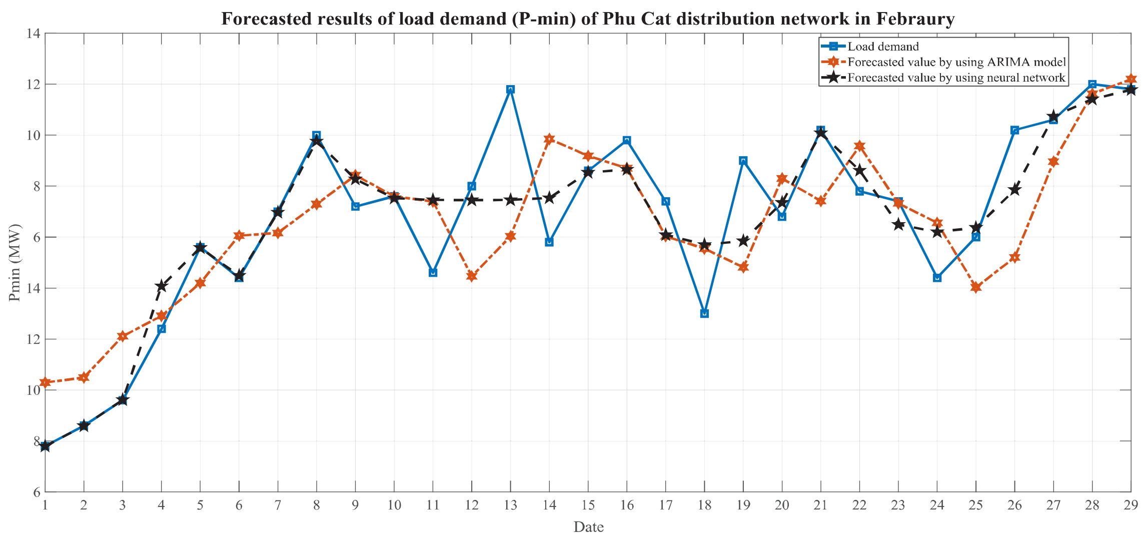

Figure 7. The forecasted results of load demand (P_min) of Phu Cat distribution network by using ARIMA model and neural network in February

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Phu Cat distribution network in February are illustrated in Table 12.

Table 12. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Phu Cat distribution network in February

Criteria	ARIMA model	Neural network
MAE	1.0147	0.4955
MAPE	9.1955	4.3096
MSE	1.5324	0.5663

In this case, the evaluation criteria values including MAE (1.0147), MAPE (9.1955), MSE (1.5324) of ARIMA model and MAE (0.4955), MAPE (4.3096), MSE (0.5663) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_min of Phu Cat distribution network by using ARIMA model and neural network in February is demonstrated in Figure 7.

In Figure 7, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Phu Cat distribution network in August are illustrated in Table 13.

Table 13. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_max) of Phu Cat distribution network in August

Criteria	ARIMA model	Neural network
MAE	1.3281	1.1770
MAPE	5.2385	4.6501
MSE	2.6991	2.6431

In this case, the evaluation criteria values including MAE (1.3281), MAPE (5.2385), MSE (2.6991) of ARIMA model and MAE (1.1770), MAPE (4.6501), MSE (2.6431) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_max of Phu Cat distribution network by using ARIMA model and neural network in August is demonstrated in Figure 8.

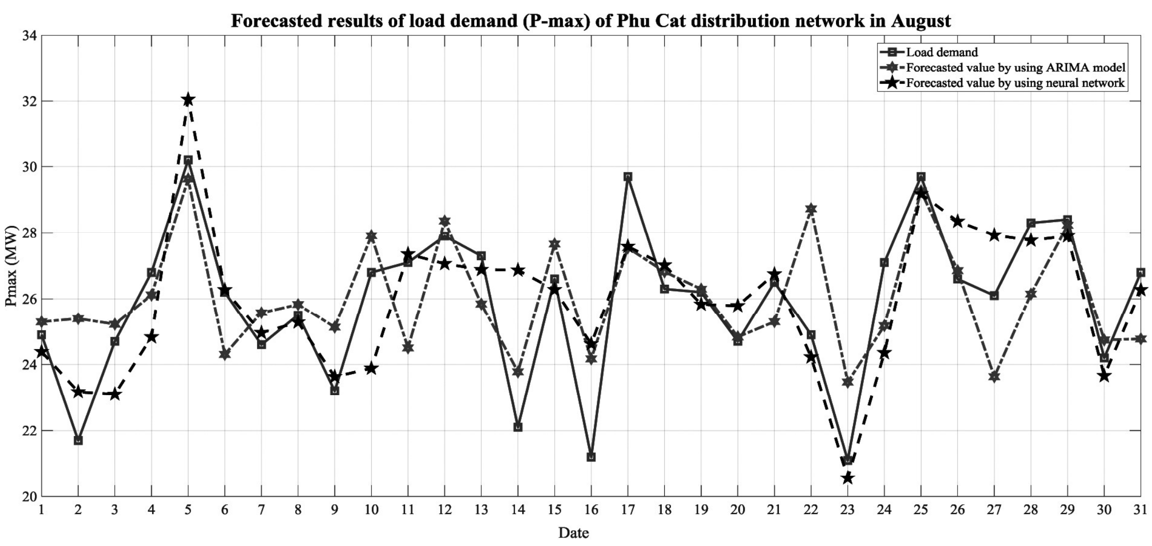

Figure 8. The forecasted results of load demand (P_max) of Phu Cat distribution network by using ARIMA model and neural network in August

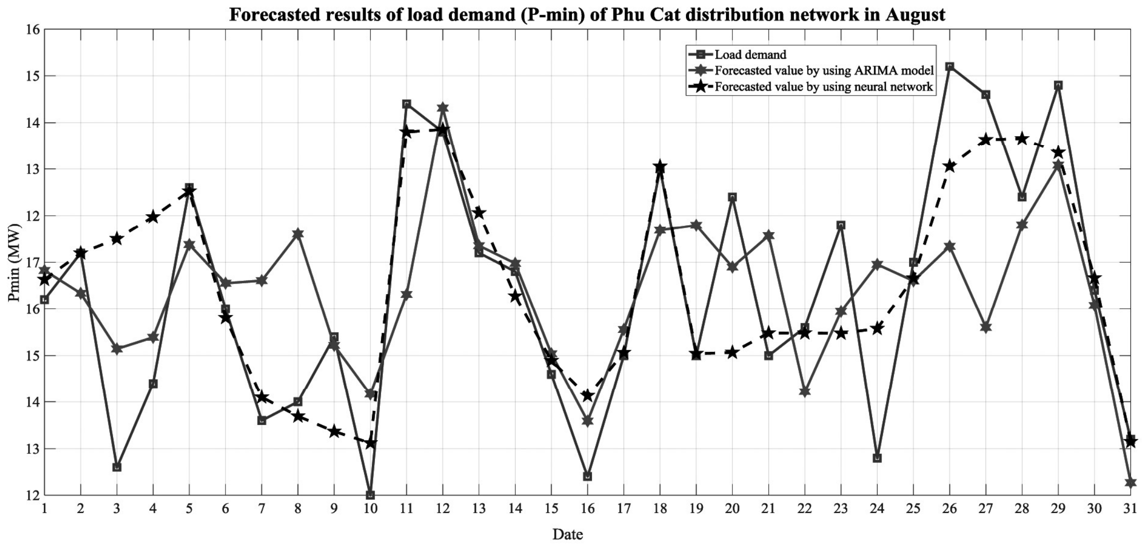

Figure 9. The forecasted results of load demand (P_min) of Phu Cat distribution network by using ARIMA model and neural network in August

In Figure 8, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

The evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Phu Cat distribution network in August are illustrated in Table 14.

Table 14. Evaluation criteria of ARIMA model and neural network in short-term load forecasting (P_min) of Phu Cat distribution network in August

Criteria	ARIMA model	Neural network
MAE	0.8583	0.5591
MAPE	6.0931	4.0552
MSE	1.2093	0.6976

In this case, the evaluation criteria values including MAE (0.8583), MAPE (6.0931), MSE (1.2093) of ARIMA model and MAE (0.5591), MAPE (4.0552), MSE (0.6976) of neural network are relatively small. These results also showed the effectiveness of both methods using short-term load forecasting. However, the neural network-based forecasting method provided the better solution compared to the ARIMA model based on the statistical criteria. The difference between the actual values and the forecasted values of P_min of Phu Cat distribution network by using ARIMA model and neural network in August is demonstrated in Figure 9.

In Figure 9, the solid line shows the load values, the dashed – dot line indicates the forecasted values by using ARIMA model and the dashed line indicates the forecasted values by using neural network. In this figure, the forecasted values by using neural network are closer to the load values than the forecasted values by using ARIMA model. This demonstrates the effectiveness of neural network in short-term load forecasting in this case.

Generally, neural network-based forecasting method provides better solutions in short-term load forecasting compared to ARIMA model in all case studies.

3. CONCLUSION

In this paper, two forecasting methods including ARIMA model and neural network were utilized in short-term load forecasting of Quy Nhon and Phu Cat distribution networks. These networks have the fastest load growth rates of Binh Dinh Power Company. Maximum load demand and minimum load demand in February and August are used in this paper. The results show that the neural network-based method provides better short-term load forecasting solutions compared to ARIMA model.

For further studies, the two methods can be combined in order to provide better solutions. In addition, the optimal design of neural network structure and ARIMA model is also a fruitful research direction.

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