Journal of Scientific Interdisciplinary
ISSN: 3063-0509

Daily Peak Load Forecasting At PT. PLN Uses Anfis (Adaptive Neuro-Fuzzy Inference System)

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Article Information	Abstract
Vol: 2 No : 3 2025 Page : 1-8 **Keywords:** *load forecasting,* *ANFIS* *daily peak load*	The demand for electrical energy continues to rise with the progression of time. This growth must be matched by a reliable and cost-effective supply of electricity, requiring power systems that are both dependable and economical. Since the amount of electricity consumed by users cannot be precisely predicted, balancing generation with consumption necessitates accurate electrical load forecasting. This study focuses on load forecasting using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. The forecast developed targets daily peak loads, which fall under short-term load forecasting. The data used for this forecasting consists of historical daily peak loads from January 1, 2017, to June 9, 2022. The forecasting process involves parameters such as radius, squash factor, accept ratio, reject ratio, and epoch. The forecast accuracy is evaluated using the Mean Absolute Percentage Error (MAPE) metric. The results are then compared with PLN's load forecasting, which employs the load coefficient method. The ANFIS-based forecasting achieved a MAPE of 1.879%, using networks Jaringan_24 and Jaringan_25. This MAPE value is slightly lower than PLN's load forecasting MAPE of 1.917%, indicating better accuracy by the ANFIS method.

Abstrak
Permintaan energi listrik terus meningkat seiring dengan perkembangan zaman. Peningkatan ini harus diimbangi dengan pasokan listrik yang andal dan ekonomis, sehingga dibutuhkan sistem tenaga listrik yang handal sekaligus efisien. Karena jumlah listrik yang dikonsumsi oleh pengguna tidak dapat diprediksi secara pasti, maka diperlukan peramalan beban listrik yang akurat agar produksi dan konsumsi dapat seimbang. Studi ini memfokuskan pada peramalan beban menggunakan metode Adaptive Neuro-Fuzzy Inference System (ANFIS). Peramalan yang dibuat adalah peramalan beban puncak harian, yang termasuk dalam kategori peramalan beban jangka pendek. Data yang digunakan dalam peramalan ini adalah data historis beban puncak harian dari 1 Januari 2017 hingga 9 Juni 2022. Parameter yang digunakan dalam proses peramalan meliputi radius, squash factor, accept ratio, reject ratio, dan epoch. Akurasi peramalan dievaluasi menggunakan metrik Mean Absolute Percentage Error (MAPE). Hasil peramalan kemudian dibandingkan dengan peramalan beban PLN yang menggunakan metode koefisien beban. Peramalan berbasis ANFIS mencapai nilai MAPE sebesar 1,879% dengan menggunakan jaringan Jaringan_24 dan Jaringan_25. Nilai MAPE ini lebih kecil dibandingkan dengan MAPE peramalan beban PLN sebesar 1,917%, yang menunjukkan bahwa metode ANFIS memberikan akurasi yang lebih baik.

Kata Kunci : *: peramalan beban, ANFIS, beban puncak harian,*

INTRODUCTION

As society progresses and science and technology continue to advance, the demand for electrical energy is steadily increasing. To ensure the stability of the electric power system and effectively meet the growing energy needs of consumers, this rising demand must be matched with adequate electricity supply from the provider, in this context, PT. PLN (Persero).

Djiteng emphasizes that the power generated must consistently equal the amount of power consumed by users, which is commonly referred to as the system load. If the generated and transmitted electrical energy falls short of consumer requirements, it may lead to overloading and consequently cause power outages, which can be harmful to consumers. On the other hand, generating significantly more electricity than needed leads to energy waste and potential financial losses for the electricity provider.

Therefore, it is essential to implement appropriate strategies and methodologies to maintain a balance between electricity production and consumption. To achieve this balance, providers must be able to estimate future electricity demand by forecasting the system's load.

In line with this need, the present study focuses on forecasting the daily peak load in the operational area of PT. PLN (Persero) for Central Java and the Special Region of Yogyakarta using the ANFIS (Adaptive Neuro-Fuzzy Inference System) method.

METHOD

The daily peak load forecasting system designed with ANFIS incorporates eight input variables: the peak load on the current day (D), as well as on the previous days—D-1, D-2, D-3, D-4, D-6, and D-7. The model outputs a single variable, which is the forecasted peak load for the next day (D+1).

The system design is carried out in three phases: the training phase, the network testing phase, and the forecasting phase.

a.Training Stage

During the training phase, the initial step involves gathering historical data and defining the input-target format to construct training datasets consisting of input and target values. Once this is completed, the training parameter values are configured, which include: radius, squash factor, accept ratio, reject ratio, epoch, and goal. The training process then begins, with the primary objective of enabling the system to learn and recognize target patterns.

Following the training, the network is saved to ensure it can be utilized during the testing and forecasting phases. If the user intends to perform training again with a different set of parameters, the system allows for a reset, enabling the parameter values to be redefined and the training process to be repeated.

b. Network Testing Stage

Following the training phase, the process continues with the network testing stage. The flowchart illustrating this phase is presented in Figure 4.

At the beginning of the testing stage, test data is first collected. Then, a previously trained network is selected for evaluation. The testing is then conducted, producing outputs in the form of daily peak load values (in MW) along with associated error metrics. After obtaining the test results, the predicted daily peak load is compared against the actual peak load values. The accuracy and reliability of the test can be assessed by examining the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values.

If the user wishes to perform another test using a different trained network, they may reset the current setup and select an alternative network. An example of the test simulation subprogram interface is shown in Figure 1

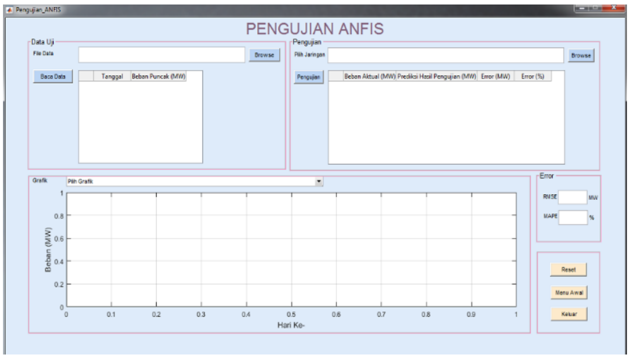


Figure 1. Display of the Network Testing GUI

c. Forecasting Stage

Once the network testing phase is completed, the process proceeds to the forecasting stage.

In this stage, the first step is to select a previously developed network to perform the forecasting. The input data used includes the peak load for the current day (D) and the preceding days—D-1 through D-7. After entering all the required input values, the forecasting operation is carried out. The output of this process is the predicted peak load for the next day (D+1).

If the user wishes to run the forecasting again, they can reset the system and reselect the desired network and input data. The user interface of the load forecasting simulation subprogram is shown in Figure 2.

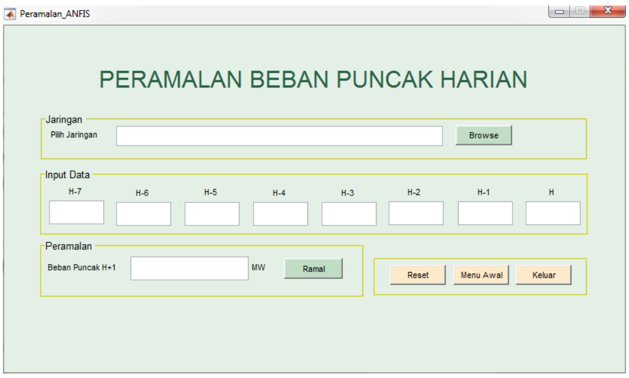


Figure 2. Load Forecasting GUI display

RESULTS AND DISSCUSION

a. Training

A total of 25 different network configurations were utilized in the development of this program. The training dataset comprised 2,183 data points, spanning the period from January 1, 2017, to

December 31, 2022. Table 1, along with Figures 3 and 4, illustrates the training outcomes, which include the error values recorded during the final epoch and the corresponding linear regression coefficient (R).

Table 1. Training Results with Varying Parameter Values

Nama Jaringan	Parameter Radius	Squash Factor	Accept Ratio	Reject Ratio	Epoch	Hasil Pelatihan Error	R
Jaringan_1	0,30	1,25	0,50	0,15	1.000	77,6454	0,97258
Jaringan_2	0,35	1,25	0,50	0,15	1.000	75,3411	0,97258
Jaringan_3	0,40	1,25	0,50	0,15	1.000	79,9219	0,97205
Jaringan_4	0,45	1,25	0,50	0,15	1.000	78,2384	0,97325
Jaringan_5	0,50	1,25	0,50	0,15	1.000	80,1499	0,97205
Jaringan_6	0,50	1,25	0,50	0,15	1.000	80,1499	0,97205
Jaringan_7	0,50	1,40	0,50	0,15	1.000	87,4125	0,96728
Jaringan_8	0,50	1,55	0,50	0,15	1.000	87,4125	0,96728
Jaringan_9	0,50	1,70	0,50	0,15	1.000	80,1499	0,97205
Jaringan_10	0,50	1,85	0,50	0,15	1.000	80,1499	0,97205
Jaringan_11	0,50	1,25	0,30	0,15	1.000	80,1499	0,97205
Jaringan_12	0,50	1,25	0,40	0,15	1.000	80,1499	0,97205
Jaringan_13	0,50	1,25	0,50	0,15	1.000	80,1499	0,97205
Jaringan_14	0,50	1,25	0,60	0,15	1.000	80,1499	0,97205
Jaringan_15	0,50	1,25	0,70	0,15	1.000	80,1499	0,97205

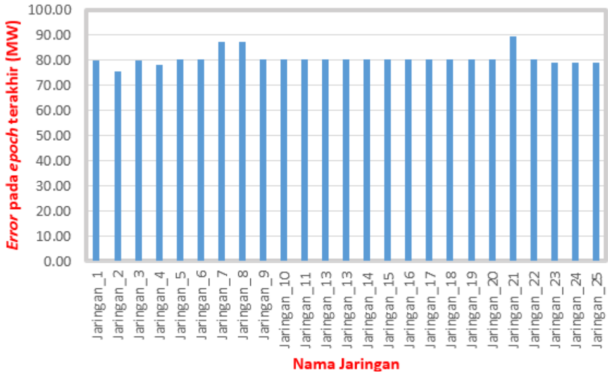


Figure 3. Graph of Error Values at the last Epoch

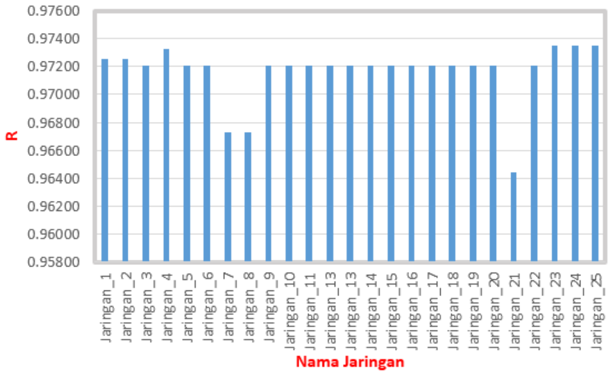


Figure 4. Graph of R Value of Training Results

Based on the data presented in Table 1 and Figures 3 and 4, the training process using 25 different parameter configurations revealed that Network_24 and Network_25 delivered the highest R value, reaching 0.97353. These networks also showed an error of 97.0331 MW at the final epoch. Given these results, Network_24 and Network_25 are selected for use in the forecasting phase. However, before proceeding, it is essential to evaluate both networks using unseen data to determine the error rate when applied to data outside the training set.

b. Testing

The test dataset utilized in the development of the daily peak load forecasting program consisted of 152 data points collected between January 1 and May 31, 2022. The evaluation was conducted using the most accurate networks identified during training—Network_24 and Network_25. The outcomes of this testing process are presented in Table 2.

Table 2. Test Results for Network_24 and Network_25

Network Name	Test Results	
	RMSE (MW)	MAPE (%)
Network_24	101,0677	2,0418
Network_25	101,0677	2,0418

Table 2 reveals that both networks yield identical RMSE and MAPE values, specifically 101.0677 MW for RMSE and 2.0418% for MAPE. These results indicate satisfactory performance, allowing the networks to proceed to the subsequent forecasting phase. Networks that produce the same RMSE and MAPE values during testing are expected to generate identical forecasting outcomes.

c. Forecasting

The forecasting process utilizes peak load data from May 24 to June 8, 2022, in order to predict the peak load for the period between June 1 and June 9, 2022. The forecasting is carried out using either Network_24 or Network_25, as both networks generate identical forecasted values. The daily peak load forecasting outcomes produced by this network are presented in Table 3.

Table 3. Forecasting Results using Network_24 and Network_25

Date	Peak Load Forecast Results (MW)
1 June 2022	3899,84
2 June 2022	3897,43
3 June 2022	3897,93
4 June 2022	3720,01
5 June 2022	3629,35
6 June 2022	3690,74
7 June 2022	3718,66
8 June 2022	3899,65
9 June 2022	3828,56

Based on Table 3, you can see the results of daily peak load forecasting using Network_24 or Network_25 which are expressed in MW units.

d. Comparison of ANFIS Forecasting Results with PLN Forecasting

The forecasting results from ANFIS will be evaluated against PLN's forecasts and the actual load data to assess the extent of forecasting errors. Tables 4 and 5 display the ANFIS and PLN forecasting results alongside the actual loads, including the errors identified in the forecasts.

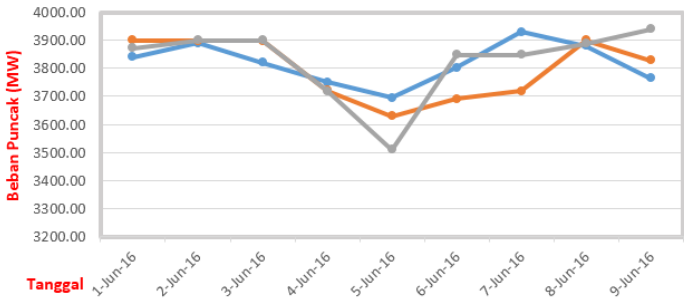
Table 4. Comparison of ANFIS Forecasting Results and PLN Forecasting of Actual Loads

Datel	**Forecasting Results (MW)**		**Actual Load (MW)**
	ANFIS	**PLN**	
1 June 2022	3899,84	3872,00	3841,05
2 June 2022	3897,43	3900,00	3890,19
3 June 2022	3897,93	3900,00	3819,59
4 June 2022	3720,01	3718,00	3750,67
5 June 2022	3629,35	3509,00	3694,83
6 June 2022	3690,74	3849,00	3802,80
7 June 2022	3718,66	3848,00	3930,30
8 June 2022	3899,65	3888,00	3879,19
9 June 2022	3828,56	3940,00	3764,81

Table 5. Comparison of Errors in ANFIS Forecasting Results and PLN Forecasting of Actual Loads

Date	***Forecasting Results Error* (%)**	
	ANFIS	**PLN**
1 June 2022	1,531	0,806
2 June 2022	0,186*	0,252*
3 June 2022	2,051	2,105
4 June 2022	0,818	0,871
5 June 2022	1,772	5,029**
6 June 2022	2,947	1,215
7 June 2022	5,385**	2,094
8 June 2022	0,527	0,227
9 June 2022	1,693	4,653
MAPE	1,879	1,917

From Tables 4 and 5, the comparison between ANFIS forecasting results and PLN's forecasts of actual loads is evident. ANFIS achieves a lower MAPE of 1.879% compared to PLN's MAPE of 1.917%. Nevertheless, both forecasting methods meet PLN's quality standards, where the acceptable MAPE for short-term forecasts is approximately ± 2%. Figure 5 illustrates the comparison between ANFIS and PLN forecasting results against the actual loads.



	1-Jun-16	2-Jun-16	3-Jun-16	4-Jun-16	5-Jun-16	6-Jun-16	7-Jun-16	8-Jun-16	9-Jun-16
Aktual	3841.05	3890.19	3819.59	3750.67	3694.83	3802.80	3930.30	3879.19	3764.81
ANFIS	3899.84	3897.43	3897.93	3720.01	3629.35	3690.74	3718.66	3899.65	3828.56
PLN	3872.00	3900.00	3900.00	3718.00	3509.00	3849.00	3848.00	3888.00	3940.00

Figure 5. Graph comparing ANFIS forecasting and PLN forecasting with actual loads

The comparison chart above shows that the peak load predictions from both ANFIS and PLN forecasting closely follow the trend of the actual peak load. The most noticeable discrepancy in the ANFIS forecast occurs on June 7, 2022, whereas PLN's forecasts show larger differences on June 5 and June 9, 2022.

CONCLUSION

A daily peak load forecasting system was developed using ANFIS, incorporating variations in parameters such as radius, squash factor, accept ratio, reject ratio, and epoch. The design is divided into three phases: training, testing, and forecasting. During the training phase, daily peak load data from January 1, 2017, to December 31, 2022, was used. Among 25 parameter variations tested, Network_24 and Network_25 emerged as the best-performing models, achieving a correlation coefficient (R) of 0.97353 and an error of 79.0331 MW at the final epoch. The parameter settings for these networks were a radius of 0.5, squash factor of 1.25, accept ratio of 0.5, reject ratio of 0.15, with epoch counts of 25,000 and 50,000 respectively.

In the testing phase, data from January 1 to May 31, 2022, was employed. Testing Network_24 and Network_25 yielded a root mean square error (RMSE) of 101.0677 MW and a mean absolute percentage error (MAPE) of 2.0418% for both networks. These results indicate satisfactory performance, allowing the models to proceed to the forecasting phase.

During forecasting, Network_24 and Network_25 were utilized to predict daily peak loads for June 1 to June 9, 2022. The forecasting produced a MAPE of 1.879%, which is slightly lower than PLN's forecasting MAPE of 1.917%, obtained using the load coefficient method. Both forecasting methods comply with PLN's standard, where the acceptable MAPE for short-term forecasts is approximately ± 2%.

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