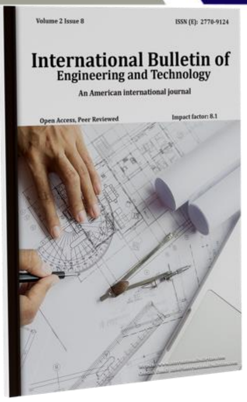

EVALUATING OPERATIONAL CONDITION RELIABILITY THROUGH LOAD CONDITION FORECASTING

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https://doi.org/10.5281/zenodo.14202057

ABSTRACT: This research investigates the operational reliability of transformers in the Qibray 35/6 substation by forecasting load conditions using Feed Forward Neural Networks (FNN). The study focuses on analyzing transformer load behavior over time and predicts when the load will exceed critical thresholds. Using primary data from 2021 to 2023, the study develops a forecasting algorithm based on FNN, which is used to predict when transformer loads exceed 85% of their nominal capacity. Results indicate that in the near future, the transformer load will enter a hazardous zone, reaching over 0.8 after 8 years and fully entering the critical range after 12 years. The study emphasizes the importance of load redistribution and the installation of new equipment to ensure the continuous and reliable operation of the electrical grid

Keywords*:* Transformer load forecasting, Feed Forward Neural Network (FNN), load distribution, operational reliability, Qibray substation, digital twin, load management, critical load thresholds.

INTRODUCTION

Currently, substations are equipped with modern metering, relay protection, and automated control systems. The integration of these modern metering, relay protection, and automated control systems in substations represents a significant advancement in the field of electrical energy distribution and management. This integration provides several key advantages that enhance the efficiency, reliability, and safety of the power network [45,46]. Modern metering systems integrated into substations offer real-time energy consumption data, which provides accurate information for better analysis of usage patterns, identifying peak usage times, and further optimizing load distribution planning [47,48,49]. Automated control systems in substations enable intelligent and automated management of energy distribution, ensuring power delivery to various areas based on demand, optimizing load distribution, and reducing losses [52]. However, these systems cannot forecast future load conditions accurately.

It is known that the normal load factor of a power transformer represents the average percentage of the transformer's nominal power used over a specific time period. Operating the transformer within its normal load factor range is crucial for ensuring efficient and reliable performance [53,54]. The load factor is typically expressed as a percentage of the transformer's nominal power. A common practice in energy systems is to operate transformers with a load factor between 70% and 80% of their nominal capacity to ensure optimal performance, efficiency, and extended lifespan [55,56]. Operating a transformer below 30% or above 90% of its nominal capacity can lead to inefficiencies and negatively impact the transformer's lifespan and reliability [56,58]. It is important for system operators and engineers to closely monitor transformer loads and manage load distribution to maintain the appropriate normal load factor, balancing reliability and economic efficiency with the transformer's condition and capabilities.

During the research, load variations of two 4000 kVA transformers at the Qibray substation (the research object) with a 35/6 kV configuration were analyzed. Initially, the total capacity of auxiliary transformers at the studied site was examined for load variation.

METHODS

To achieve the objectives of the study, a systematic approach was employed that combined empirical data collection, statistical analysis, and advanced forecasting using artificial intelligence techniques. The research methodology began with the collection of primary data on transformer loads at the Qibray 35/6 kV substation. Measurements were recorded using a radiometer system, capturing parameters such as three-phase currents, voltages, active and reactive power, and power factor levels for all months between January 2021 and April 2023. The data was preprocessed by calculating the minimum and maximum load coefficients for each transformer and analyzing their variations over time to identify trends and anomalies. The statistical adequacy of the load coefficient data was assessed using the Gaussian distribution law. This was implemented through IBM SPSS software, which confirmed the suitability of the primary data for further modeling without requiring additional fitting procedures. The load forecasting methodology utilized a Feed Forward Neural Network (FNN) configured with one hidden layer of 10 neurons, ReLU activation, and an output layer of a single neuron. The FNN was trained using an 80-15-5 split of the data into training, validation, and test sets, with 100 epochs and a batch size of 16. Pearson correlation analysis was applied during the training process to validate the model's accuracy, ensuring that the correlation between predicted and actual values exceeded 0.7 before proceeding with predictions.

The forecasting algorithm focused on determining the time frame in which transformer loads would exceed the critical threshold of 0.85. By iteratively predicting load coefficients in three-value increments and averaging these values, the model identified critical load milestones. If the predicted average exceeded 0.85, it indicated the onset of a hazardous operational condition. This iterative forecasting method allowed for proactive identification of risks, enabling recommendations for load redistribution, infrastructure upgrades, and the development of a digital twin for real-time monitoring and management of the Qibray district's electrical grid.

RESULT AND DISCUSSION

Figure 1. Load variation of the first transformer over three days (in kva) at the research object (data from the radiometer system)

The load graphs of the transformers at the research object were very similar to each other. As seen in Figure 1.12, the transformer operates with more than 70% of its capacity for most of the observed times. Additionally, the maximum and minimum load values change from day to day. Therefore, it is necessary to continuously monitor the transformer's load and analyze its performance, determining these values (i.e., the maximum and minimum load limits) in order to bring them to the target values.

In the next stage, the future expected loads of the transformers at the Qibray substation were forecasted using artificial intelligence, specifically the Feed Forward Neural Network (FNN) approach. It should be emphasized that the initial step in forecasting the future expected loads of the transformers involves data collection and primary data processing [15].

For the research, data was collected from a radiometer system, recording the following parameters for each supplier (Figure 1.13):

Three-phase currents (A) in all phases.
Voltages in all phases (kV).
Active power (kW).
Reactive power (kVAR).
Power factor (level).

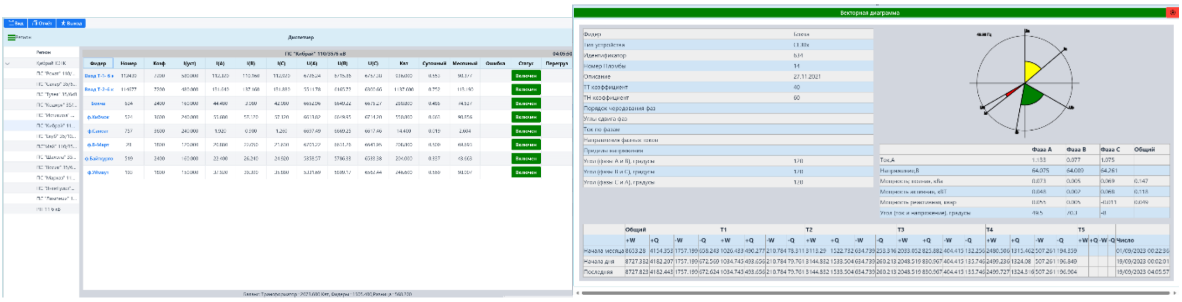


Figure 2. Interface of the radiometer digital system

As primary data, measurements were taken for all months of 2021, 2022, and the period from January to April 2023. The monthly average maximum and minimum load coefficients for the two 35/6 transformers were calculated using the following formula:

$$k = \frac{S_f}{S_0} \quad (1)$$

where, S_f – The actual value of the total power,, S_f – nominal power.
The average minimum ($k_{мин}$) and maximum (k_{max}) values of the load coefficient calculated using formula (1) were accepted as primary factors (Table 1.3). The load coefficient values of the two transformers located at the research object from January 2021 to April 2023 are shown below.

Table 1. Primary data for forecasting

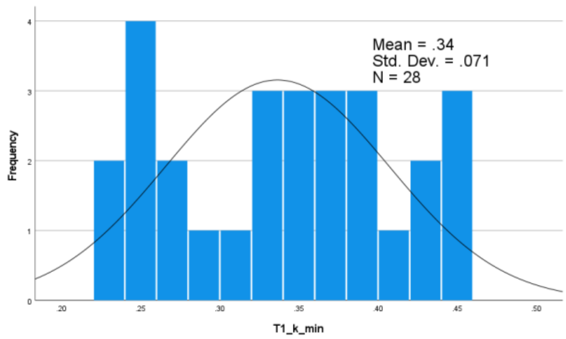
Ой.йил	T1			T2		
	$k_{мин}$	k_{max}	Δk	$k_{мин}$	k_{max}	Δk
1.2021	0,26	0,73	0,47	0,26	0,75	0,49
2.2021	0,25	0,82	0,57	0,27	0,87	0,60
3.2021	0,23	0,98	0,75	0,25	1,01	0,76
4.2021	0,23	0,98	0,75	0,24	1,06	0,82
5.2021	0,24	0,88	0,64	0,24	0,89	0,64
6.2021	0,24	0,78	0,54	0,26	0,85	0,59
7.2021	0,33	0,97	0,64	0,34	1,02	0,68
8.2021	0,32	0,95	0,63	0,35	1,02	0,67
9.2021	0,27	0,76	0,49	0,28	0,82	0,54
10.2021	0,25	0,96	0,71	0,25	1,04	0,78
11.2021	0,29	0,78	0,49	0,31	0,84	0,53
12.2021	0,31	0,95	0,64	0,34	1,02	0,68
1.2022	0,35	0,80	0,45	0,38	0,86	0,47

2.2022	0,37	0,90	0,53	0,37	0,98	0,61
3.2022	0,32	0,81	0,49	0,33	0,84	0,51
4.2022	0,38	0,81	0,43	0,41	0,87	0,46
5.2022	0,38	0,94	0,56	0,40	1,01	0,61
6.2022	0,35	0,95	0,60	0,37	1,02	0,64
7.2022	0,36	0,95	0,59	0,38	0,99	0,61
8.2022	0,43	0,93	0,50	0,43	0,95	0,51
9.2022	0,35	1,00	0,65	0,38	1,04	0,66
10.2022	0,40	0,85	0,45	0,40	0,92	0,51
11.2022	0,45	0,92	0,47	0,48	0,98	0,50
12.2022	0,45	0,95	0,59	0,39	0,97	0,58
1.2023	0,42	0,95	0,56	0,40	0,98	0,58
2.2023	0,46	1,00	0,56	0,45	1,02	0,57
3.2023	0,47	0,92	0,48	0,45	0,96	0,51
4.2023	0,47	0,85	0,42	0,46	0,88	0,42

In Table 1.3, in addition to the values $k_{мин}$ and k_{max} the difference Δk between them is also presented. From the reduction of this value, it can be inferred that as the years progress, the loads have increased, and the difference between the maximum and minimum loads has been decreasing. Additionally, considering that transformers begin to operate inefficiently when the load exceeds 90%, the load threshold can be set at 85%. c

When analyzing the maximum values presented in Table 1.3, it can be observed that they have already exceeded 85%. In Transformer T1, this situation occurred 18 times among the 28 observed time series data, and in Transformer T2, it occurred 23 times. This indicates that the transformers operated with an average load of 80%. From the 3-day time period shown in Figure 1.12, it can be seen that during over 70% of the observed time, the transformer loads were above 85%. Given that this situation is already abnormal, it is sufficient to forecast the issue based only on the minimum load values.

To do this, first, the adequacy of the $k_{мин}$ values for each transformer was determined using the Gaussian distribution law in IBM SPSS, as shown in Figures 3 and 4.



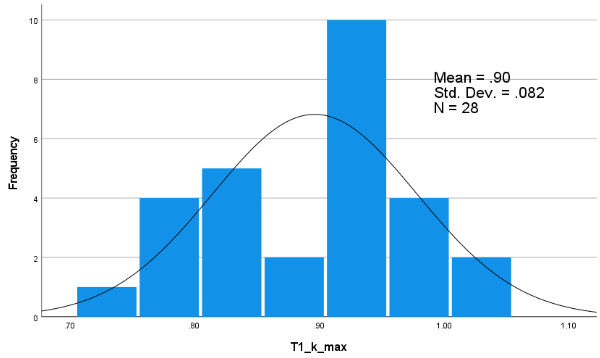


Figure 3. Checking the First Data Using the Gaussian Normal Distribution Law

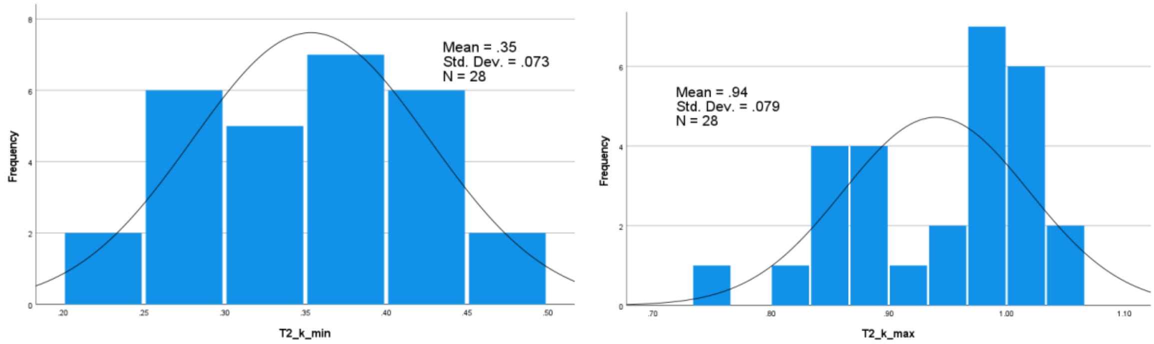


Figure 4. Checking the second data using the gaussian normal distribution law

The values shown in Figures 2 and 3 indicate that the primary data accepted can be used in the next stage. This suggests that there is no need to build a Fit model in this case. For forecasting, it is recommended to split the primary data into 80% train set, 15% validation set, and 5% test set.

In the calculation of load coefficients, Feed Forward Neural Network (FNN) was used. It has 2 layers, 1 hidden layer, and 1 output layer. The FNN parameters were set to 100 epochs and a batch size of 16. The hidden layer contains 10 neurons, and the activation function used is ReLU (Rectified Linear Unit). The output layer consists of a single neuron with no activation function.

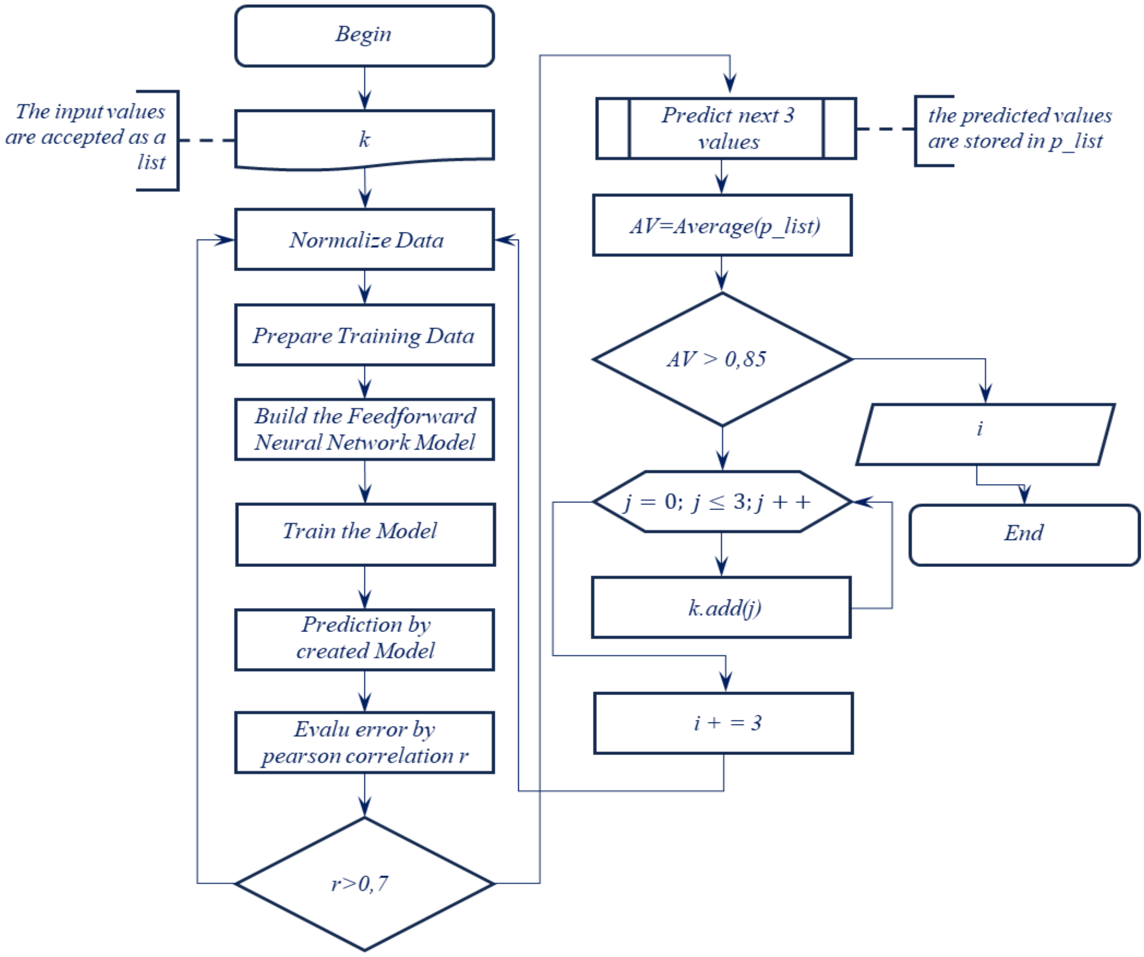


Figure 5. Algorithm for forecasting the time when transformer load exceeds the allowed value

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Forecasting is carried out based on the algorithm shown in Figure 1.16. In this algorithm, the model is first trained using the train data, and results corresponding to the training data are obtained. The obtained results are evaluated for their correspondence with the input values using Pearson correlation. If the Pearson correlation is less than 0.7, the algorithm is returned for retraining. Otherwise, the next 3 load coefficients are predicted. It should be emphasized here that what is important is not the state of the exact next values, but when the transformer load exceeds 0.85.

The main objective was to calculate how long it would take for the transformer load to increase in order to make the necessary adjustments. Based on this, the next 3 values are predicted, and their average values are calculated. If the average value is below 0.85, the predicted values are re-entered into the initial data list, and the next 3 values are forecasted. This process continues until the time when the load exceeds the 0.85 value is determined.

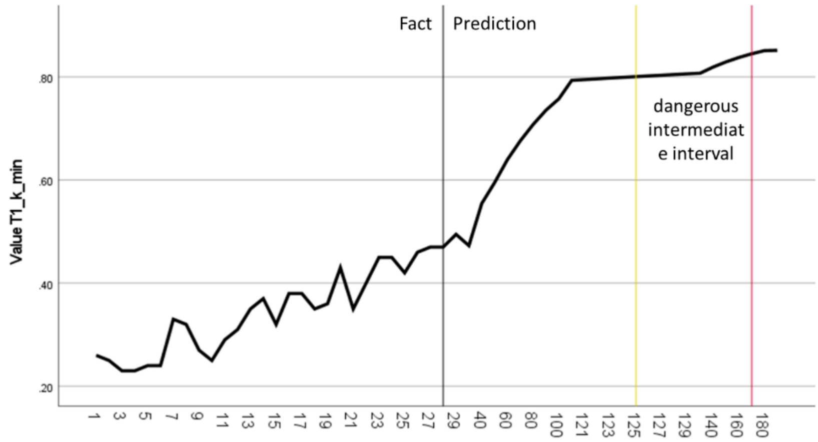

Figure 6. Forecast results of the first transformer load using the fnn neural network (only the results for the first transformer are shown as the load of both transformers is nearly identical)

The results obtained using the FNN neural network, as shown in Figure 5, demonstrate that if the load dynamics of the transformers continue in the same manner, the minimal load will exceed 0.8 after 8 years, and after 12 years, it will fully enter the hazardous zone. Considering that the aging coefficient of the transformers and the occurrence of minimal loads is 20% based on Figure 1, this situation is already critical. The maximum load has already reached its peak. In this case, it is essential to urgently review the issue of redistributing the load in the Qibray 35/6 substation and its distribution networks, install new equipment, and develop a digital twin of the Qibray district's electrical grid for constant monitoring.

.CONCLUSION

The study highlights the importance of forecasting transformer loads to ensure operational reliability and prevent overloads. The results show that the load on transformers at the Qibray 35/6 substation is expected to increase significantly over the next decade, potentially reaching hazardous levels. It is crucial to address this issue promptly through load redistribution, the installation of new equipment, and the development of a digital twin for constant monitoring. The findings underline the significance of predictive models, such as FNN, in maintaining the stability and efficiency of electrical networks, particularly as the demand for electricity grows over time.

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