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MODELING RELIABILITY PARAMETERS OF THE OPERATIONAL CONDITION OF 6-10 KV RURAL POWER SUPPLY

Isakov A. J.[1],
Khojayorov F. E.[2*]
[1]Doctor of Technical Sciences, Dean of Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Uzbekistan,
[2] PhD Student of Tashkent State Technical University, Uzbekistan

Abstract
This study models and analyzes the reliability of 6-10 kV rural power supply systems, emphasizing the assessment of SAIDI and SAIFI reliability indices using a Feedforward Neural Network (FNN) model. Due to the absence of backup systems, unplanned outages in rural power grids can significantly disrupt electricity supply. Planned outages are managed through maintenance schedules, whereas unplanned outages arise from various factors, including equipment failure, natural events, and human error. The FNN model is employed to forecast SAIDI and SAIFI values based on historical data, allowing for predictive insights into system reliability. Results indicate a projected increase in outage indices over the next five years, underscoring the need for proactive measures to enhance system resilience.

Keywords: Rural power supply, SAIDI, SAIFI, reliability indices, unplanned outages, Feedforward Neural Network, FNN, predictive modeling, power system resilience

Introduction
The reliability of the power supply system is characterized by the number of interruptions [65]. Interruptions in the network are divided into planned and unplanned interruptions. Due to the absence of a backup network in the power supply networks of the research object, consumers are completely disconnected from the network during planned maintenance or inspections. Research shows that planned outages mainly occur for the following reasons [66] (Figure 2.1):

1. Routine and major repairs of 6/10 kV overhead lines
2. Routine and major repairs of 6/10 kV cable lines
3. Technical inspection of transformers
4. Major repairs of transformers
5. Repairs of 6/10 kV cells
6. Routine maintenance of switching devices
7. Technical inspection of measuring transformers

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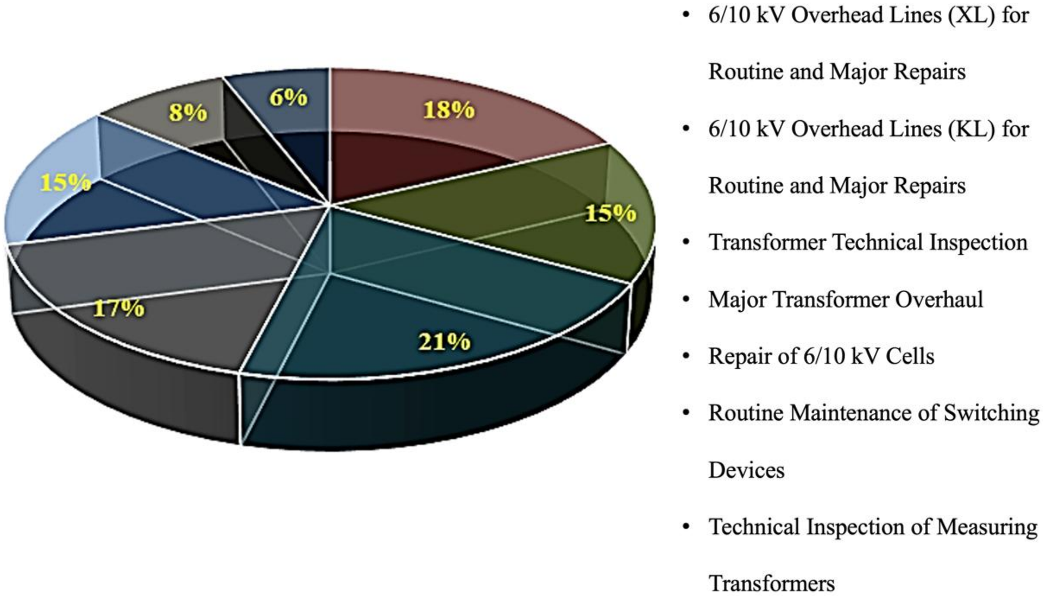

Figure 2.1. Quantitative Shares of Reasons for Planned Outages

For analysis, the number of planned and emergency outages in the research object from January 7, 2021, to July 7, 2023, was examined. The results indicate that planned outages are primarily observed between 9:00 AM and 5:00 PM during the day (Figure 2.2).

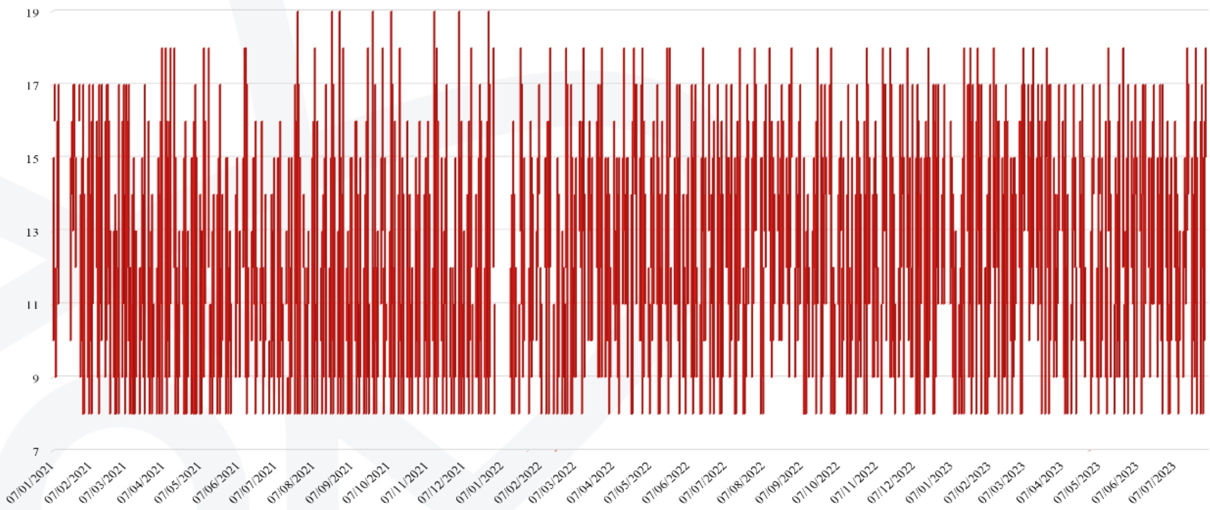

Figure 2.2. Indicators of Planned Outages

During the research, it was determined that emergency outages often occur due to the following reasons [67] (Figure 2.3):

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1. Natural disasters
2. Failure of equipment and machinery
3. Overloading
4. Human errors
5. Trees and vegetation
6. Impact of animals

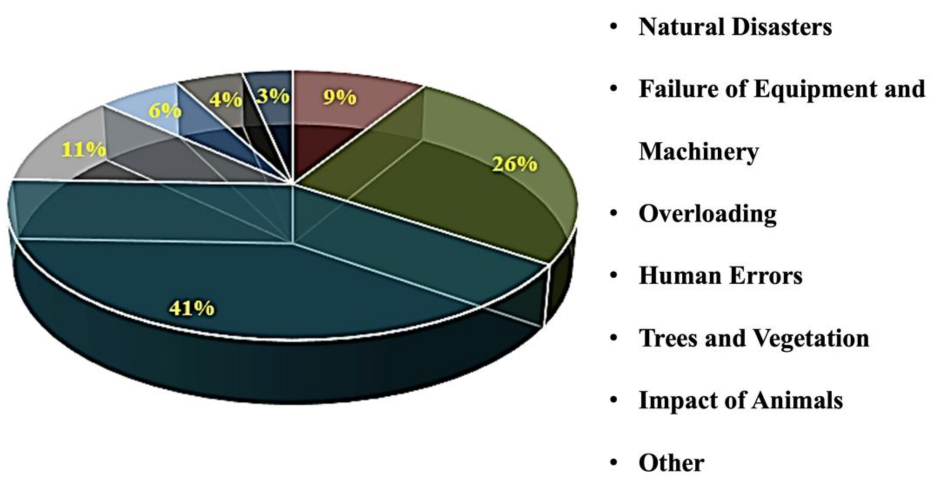

Figure 2.3. Quantitative Methods of Causes for Emergency Outages.

When emergency outages were distributed across each feeder, it was found that the highest number of outages occurred on the Qipchoq feeder (Figure 2.4). Therefore, the SAIDI and SAIFI values model is presented in the dissertation based on data from the Qipchoq feeder.

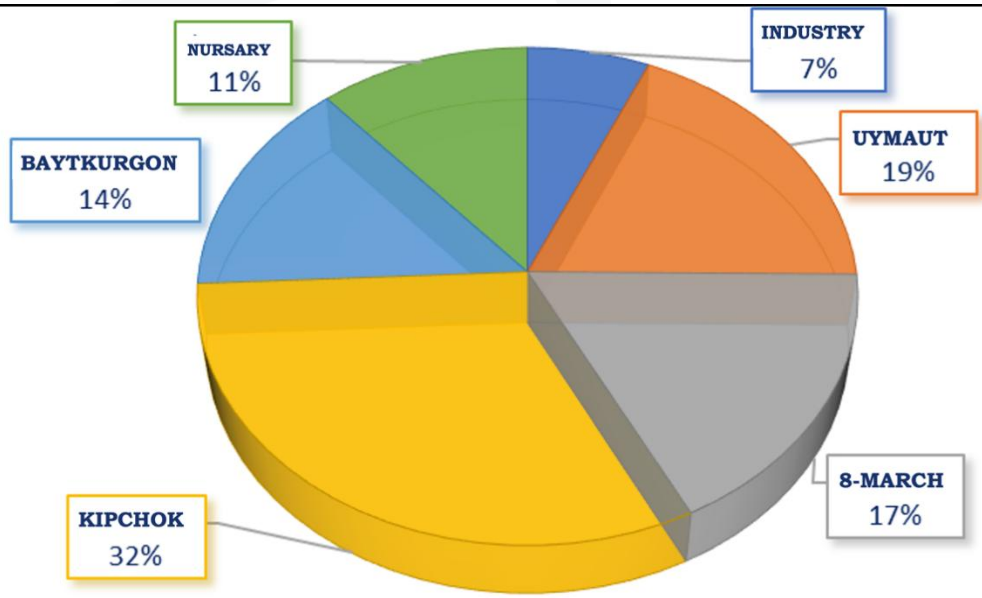

Figure 2.4. Quantitative Methods of Emergency Outages by Feeder

In normal conditions, SAIFI represents the number of outages per consumer within a specified time interval and is determined as follows:

1) $$SAIFI = \frac{\sum_{i=1}^{n} Ca(i)}{C_s} \quad (2.1)$$

In that case, *Ca(i)* – The number of disconnected consumers in the power supply system of the energy supply organization during the calendar year; *t(i)* – duration of the outage in the power supply, in hours; *Cs* - total number of consumers [68,69].
SAIDI represents the average outage duration per consumer in the power supply system under normal conditions, expressed in hours, and is determined as follows:

2) $$SAIDI = \frac{\sum_{i=1}^{n} Ca(i) \times t(i)}{C_S} \quad (2.2)$$

where, *Ca(i)* – The number of disconnected consumers in the power supply system of the energy supply organization during the calendar year; *Cs* – total number of consumers in the power supply system [70,71].
Data on *Ca(i), t(i), Cs* for the research object from 2000 to 2023 were analyzed, and the planned and unplanned SAIDI and SAIFI values were determined. The results, presented as average values, are shown in Table 2.1.

Table 2.1.

Year	Planned		Unplanned	
	SAIDI	*SAIFI*	*SAIDI*	*SAIFI*
2000	4,17	6,22	6,67	12,05
2001	4,35	6,13	6,96	12,26
2002	4,53	6,26	7,25	12,52
2003	4,71	6,39	7,54	12,78
2004	4,89	6,52	7,83	13,04
2005	5,07	6,65	8,12	13,30
2006	5,25	6,78	8,41	13,57
2007	5,43	6,91	8,70	13,83
2008	5,62	7,04	8,99	14,09
2009	5,80	7,17	9,28	14,35
2010	5,98	7,30	9,57	14,61
2011	6,16	7,43	9,86	14,87
2012	6,34	7,57	10,14	15,13
2013	6,52	7,70	10,43	15,39
2014	6,70	7,83	10,72	15,65
2015	6,88	7,96	11,01	15,91
2016	7,07	8,09	11,30	16,17
2017	7,25	8,22	11,59	16,43
2018	7,43	8,35	11,88	16,70
2019	7,61	8,48	12,17	16,96
2020	7,79	8,61	12,46	17,22
2021	7,97	8,74	12,75	17,48
2022	8,15	8,87	13,04	17,74
2023	8,33	9,23	13,33	18,01

Planned outages are carried out by the regional power grid company employees according to a specific schedule. In such cases, it is not feasible to model SAIDI and SAIFI values for planned outages; they can only be regulated through digital twin technology. However, since unplanned outages are uncontrolled, it is advisable to model these situations to forecast SAIDI and SAIFI values in advance, enabling problem resolution based on the forecast results.

Modeling uses an FNN neural network. Through FNN, the mathematical model below demonstrates how data transformation occurs across network layers and how final forecast values are calculated:

Let us define:

Layer 1 (From Input to Hidden Layer 1):

For each neuron i in the first hidden layer:

$$a_i^{(1)} = \sigma\left(W_i^{(1)} \cdot x + b_i^{(1)}\right) \quad a_j^{(2)} = \sigma\left(\sum_i W_{ji}^{(2)} \cdot a_i^{(1)} + b_j^{(2)}\right) \tag{2.3}$$

where,

- x — Input feature (year)
- $W^{(l)}$— l- Weight matrix for the layer..
- b^l — l - Bias vector for the layer
- a^l— l - Activation value of the layer.
- σ — Activation function (in this case, linear) [72,73].

Since the activation function is linear, it simplifies as follows:

$$a_i^{(1)} = W_i^{(1)} \cdot x + b_i^{(1)} \tag{2.4}$$

Layer 2 (From Hidden Layer 1 to Hidden Layer 2):

For each neuron jj in the second hidden layer [74]:

$$a_j^{(2)} = \sigma\left(\sum_i W_{ji}^{(2)} \cdot a_i^{(1)} + b_j^{(2)}\right) \tag{2.5}$$

Also, with a linear activation function [75]:

$$a_j^{(2)} = \sum_i W_{ji}^{(2)} \cdot a_i^{(1)} + b_j^{(2)} \tag{2.6}$$

Layer 3 (From Hidden Layer to Output Layer):

For the output neuron kk:

$$a_k^{(3)} = \sigma\left(\sum_j W_{kj}^{(3)} \cdot a_j^{(2)} + b_k^{(3)}\right) \tag{2.7}$$

With a linear activation function:

$$a_k^{(3)} = \sum_j W_{kj}^{(3)} \cdot a_j^{(2)} + b_k^{(3)} \tag{2.8}$$

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3. Final Output:

The final output of the model, i.e., the forecasted SAIDI or SAIFI value for a given year, is calculated as follows [76]:

$$\text{Прогноз Қиймат} = a_k^{(3)} \qquad (2.9)$$

4. Loss Function:

The model minimizes the Mean Squared Error (MSE) loss function using backpropagation [77]:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (2.10)$$

Where:

- y_i — Actual value.
- $\hat{y}_i$ — Forecasted value.
- n — Number of training data points.

5. Optimization:

The model updates weights and biases during each epoch by calculating the gradients of the loss function and applying the Adam optimizer. Initially, the epoch value for the model is varied from 0 to 500, and the optimal epoch value is determined by measuring validation error (Figure 2.5).

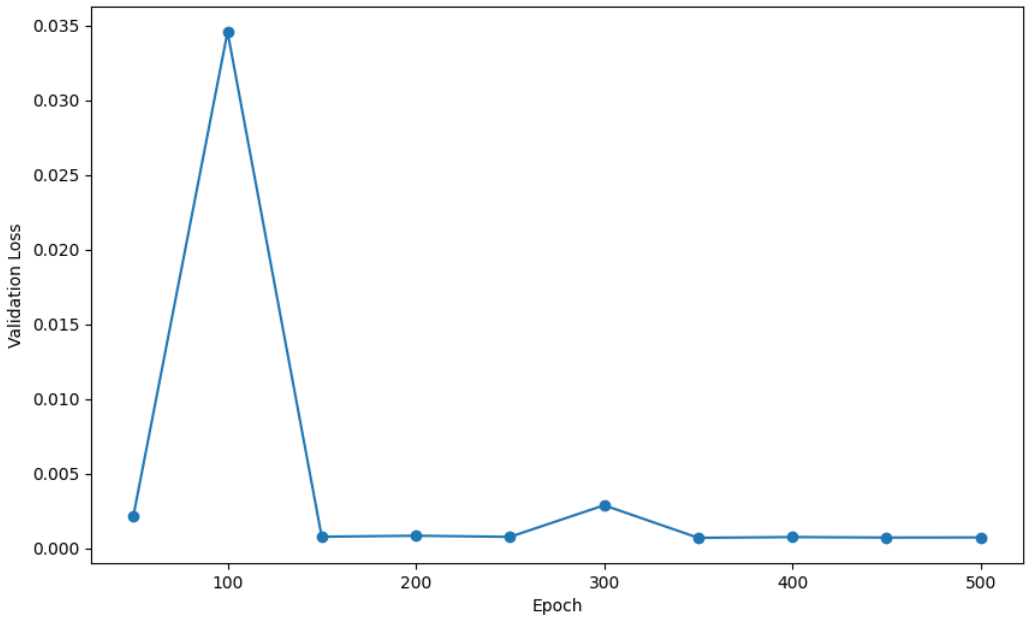

Figure 2.5. Result of Laboratory Analysis for Determining the Optimal Epoch Value

Based on the data in Figure 2.5, the optimal epoch value is found to be 350.

The optimal values for the neurons in the input, hidden, and output layers are determined by testing various combinations (Figure 2.6).

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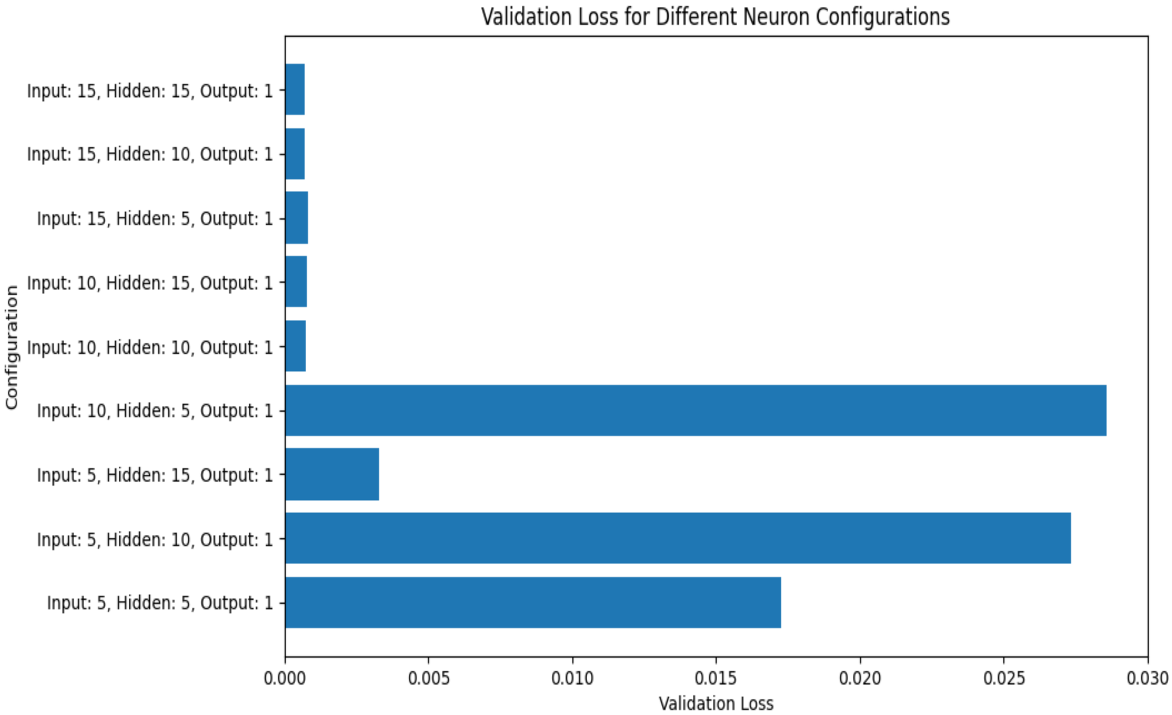

Figure 2.6. Result of Laboratory Analysis for Determining Neuron Values in Input, Hidden, and Output Layers

The laboratory results in Figure 2.6 indicate the optimal neuron parameters: 15 neurons in the input layer, 15 neurons in the hidden layer, and 1 neuron in the output layer, achieving the smallest error $Validation\ Loss = 0.000706$.

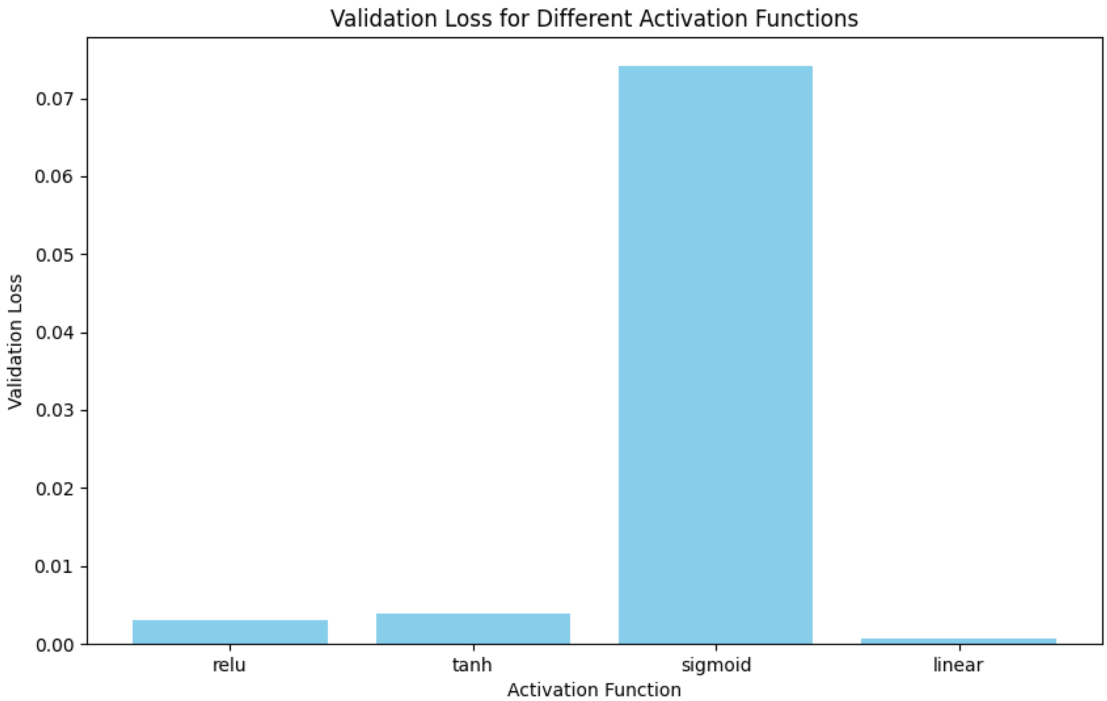

Figure 2.7. Laboratory Result for Determining the Activation Function

Another key parameter is the activation function. Based on the characteristics of the input data, activation functions such as ReLU, tanh, sigmoid, and linear are tested to identify the function that yields the lowest error. As shown in Figure 2.7, the linear activation function was selected as it achieved the lowest error of 0.00071.
Based on the selected values, the training and test model values are compared with the actual values using a regression method, and a correlation coefficient is calculated to characterize the model error (Figure 2.8).

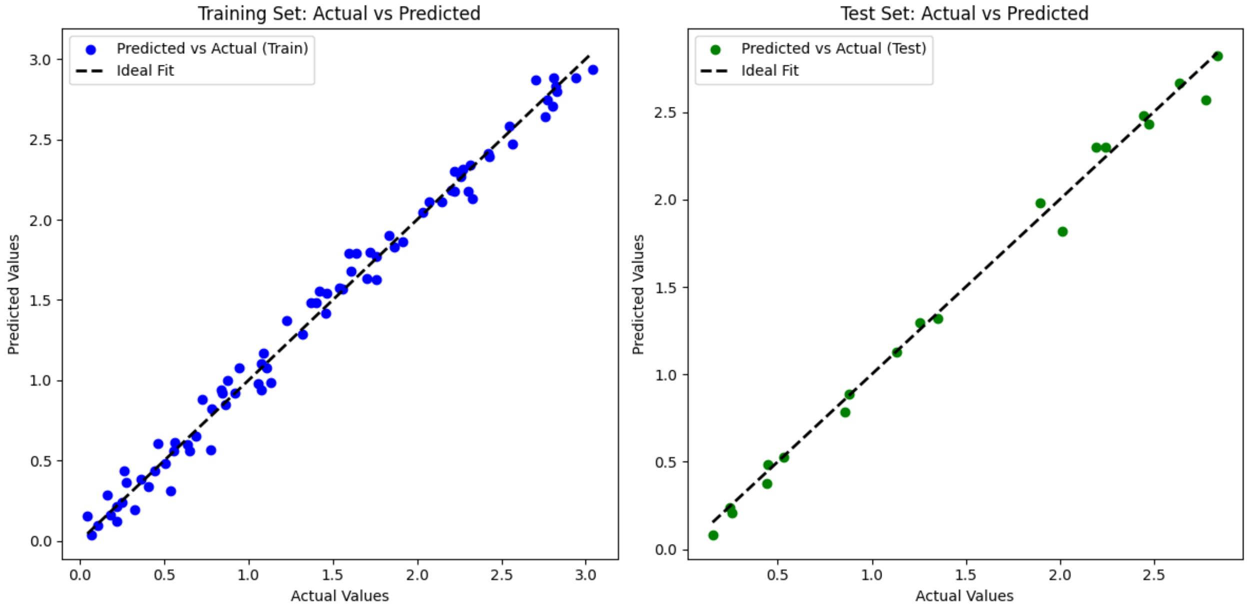

Figure 2.8. Regression Analysis of Train and Test Model vs. Actual Values

The correlation coefficients for the training and test values are 0.9943 and 0.9965, respectively, indicating that the model's results are reliable for use. The SAIDI and SAIFI values forecasted for the next 5 years based on this model are presented in Table 2.2.

Table 2.2. 5-Year SAIDI and SAIFI Indicators Obtained from the FNN Model for Determining SAIDI and SAIFI

Йил	SAIDI	SAIFI
2024	13.613	18.259
2025	13.902	18.520
2026	14.191	18.780
2027	14.481	19.041
2028	14.770	19.301

The results obtained from the FNN model for determining SAIDI and SAIFI in Table 2.2 indicate that the SAIDI and SAIFI values are expected to increase further in the coming years.

Conclusion

This research highlights the significant impact of unplanned outages on rural power supply reliability, with SAIDI and SAIFI indices projected to increase in the coming years. By implementing an FNN model, this study successfully forecasts reliability trends, offering valuable insights for proactive maintenance and system improvements. The findings underline the potential of digital twin technology and machine learning models in managing and predicting reliability parameters. Future work should consider integrating real-time monitoring and optimization techniques to reduce outage durations and improve overall system robustness, ensuring better service for rural consumers.

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