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Utilizing Artificial Neural Networks for the Assessment of Technical Losses in Power Distribution Networks

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ABSTRACT: The estimation of electrical energy losses during the transmission and distribution of electricity is a challenging problem in power systems engineering. Traditional methods for loss calculation often rely on deterministic data and iterative steady-state analysis, incorporating several assumptions to approximate system behavior. However, these approaches may lack the accuracy and efficiency required for real-time applications. To address this issue, it is critical to employ advanced methodologies that can better capture the uncertainties inherent in operational data and provide faster computation times. This paper presents a set of models based on artificial neural networks (ANNs) for assessing electrical energy losses in distribution networks. The implementation of these models enhances the speed and precision of loss calculation, offering a more robust solution for operational management. The theoretical models are validated through application to actual 6-10 kV distribution network circuits.

I.INTRODUCTION

The amount of electrical energy losses is a key indicator in assessing the operational efficiency and economic viability of electrical networks. The task of identifying and minimizing energy losses in these networks remains both urgent and economically significant [1].

Frequently, when calculating electrical energy losses, one encounters incomplete and unreliable data, such as electrical load profiles, energy consumption amounts, and the switching states of network components [1-5]. However, the advent of modern automated information and measurement systems has made it possible to mitigate these issues effectively.

The calculation of electrical energy losses using automated information and measurement systems pertains to operational calculations and involves real-time assessment of energy losses [6]. Despite the availability of various methods for estimating energy losses, their application is often challenging. Traditional approaches to calculating energy efficiency losses rely on steady-state simulations based on network parameters and operating conditions. These calculations are complex, requiring high-dimensional data and significant computational time.

Recent studies [7, 8] have shown that more accurate and efficient solutions can be obtained through the use of "intelligent" methods, particularly artificial neural networks (ANNs) [9]. Currently, ANNs are widely employed in various power system applications, including loss analysis [10, 11], steady-state calculations [12, 13], and the prediction of electrical load and energy losses [14, 15], among others.

The key advantages of using ANNs in energy loss calculations include:

The ability to model complex processes effectively.

The potential to derive simplified models for practical applications.

High reliability in obtaining results through the explicit modeling of the relationship between input and output parameters.

Therefore, the primary aim of this paper is to conduct a comparative assessment of different types of ANNs for the rapid evaluation of electrical energy losses and to highlight their advantages over traditional methods.

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II.METHODOLOGY FOR CALCULATING TECHNICAL LOSSES OF ELECTRICAL ENERGY

To perform the required calculations based on the input data concerning the network topology and its components, an equivalent circuit is constructed, which is characterized by the resistances and conductances of the elements within the distribution network. When determining the active resistance of various sections of the network, it is essential to account for external factors, particularly the ambient temperature (t), as it significantly affects the electrical properties of the network components:

$$R_i = R_{i,20}[1 + \alpha(t - 20^{\circ})] \tag{1}$$

Technical losses of electrical energy in distribution networks are made up of load losses in the lines and windings of transformers, and losses in steel of transformers:

$$\Delta W_{6-9} = (\Delta W_{l.line} + \Delta W_{l.tr}) + \Delta W_{st.tr} \tag{2}$$

Depending on the available input data and the results of steady-state calculations, the determination of load losses in distribution networks can be performed using various methods: 1) operational calculations, 2) settlement days, 3) average loads, and 4) maximum losses [1, 16]. Among these, the average loads method is widely used in open distribution networks operating at 110 kV and below [16], and it serves as the basis for performing the loss calculations.

The average load at network nodes is determined based on the load factors of the transformers and the power factor of the primary node. Once these values are established, the network mode is calculated using an iterative method, which consists of two stages in each iteration.

In the first stage, initial voltage approximations (equal to the nominal voltage of the network) are assigned to all nodes of the electrical network. From there, the power losses, as well as the losses at the beginning and end of each network section, are calculated. This process continues iteratively until the total power is determined at the initial point of the network.In the second stage, the node voltages are refined sequentially from the beginning to the end of the network [17, 18].

Based on the results of this iterative process, the active and reactive power losses in the network are determined, considering the average loads over the calculated time interval:

$$\Delta P_{mid} = \frac{P_{mid,i}^2 + Q_{mid,i}^2}{U_i^2} \cdot R_i = \frac{P_{mid}^2}{U_i^2 \cdot cos\varphi^2} \cdot R_i \tag{3}$$

$$\Delta Q_{mid} = \frac{P_{mid,i}^2 + Q_{mid,i}^2}{U_i^2} \cdot X_i = \frac{P_{mid}^2}{U_i^2 \cdot cos\varphi^2} \cdot X_i \tag{4}$$

In addition to power losses, the power of the head node (P_{base}, Q_{base}) and the electricity supply (W_{base}) are also determined.

Next, the load losses in the lines and windings of the transformers are determined:

$$\Delta W_l = k_l \cdot k_k \cdot \Delta P_{mid} \cdot T \cdot k_f^2 \tag{5}$$

where k_l is a coefficient that accounts for the impact of losses in overhead line fittings, and is set to 1.02 for lines with a voltage of 110 kV and above, and 1.0 for lower voltage lines; k_k is a coefficient that compensates for the difference in the configurations of the active and reactive load curves of different network branches, and is assigned a value of 0.99; T - represents the calculation interval (typically in months); k_f^2 - is the square of the shape factor of the load curve.

The square of the shape factor k_f^2 The square is determined based on the operational time at the maximum load T_{max} as follows:

$$k_f^2 = \left(\frac{1090}{T_{max}} + 0.876\right)^2 \tag{6}$$

The losses in steel of transformers (autotransformer) are determined on the basis of the no-load power losses given in the passport data, according to the formula:

$$\Delta W_{\mathrm{st.tr}} = \Delta P_{st} \cdot T \cdot \left(\frac{U_i}{U_{nom,i}}\right)^2 \tag{7}$$

III.ESTIMATION OF TECHNICAL LOSSES OF ELECTRICAL ENERGY BASED ON ARTIFICIAL NEURAL NETWORKS

To perform a comparative analysis of technical losses in electrical energy within distribution networks, two distinct types of Artificial Neural Networks (ANNs) are considered: the Fitting Neural Network (FNN) and the Cascade-Forward Neural Network (CFNN).

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Both of these ANN types are relatively simple feedforward networks, each consisting of a single hidden layer. In these architectures, information flows in a unidirectional manner—from the input layer, through the hidden layer, to the output layer—without the formation of feedback loops or recurrent connections. The Fitting Neural Network (FNN) represents the simplest form of a feedforward network, whereas the Cascade-Forward Neural Network (CFNN) introduces a distinctive feature: each subsequent layer is connected to all previous layers, differentiating it from the basic FNN structure.

The ANN-based modeling process is structured as follows:

1. Formation of Statistical Data for Modeling: This step involves the collection and preparation of relevant input data that will be used for training the ANN model.
2. Data Division: The dataset is divided into three subsets—training, testing, and validation samples. This division ensures that the model is evaluated and trained on diverse data to improve its generalizability.
3. Selection of Network Architecture and Parameters: In this step, the structure of the neural network is defined, including decisions regarding the number of layers, the number of neurons per layer, and the activation functions used in the network.
4. Training the ANN: The neural network is trained using the prepared training dataset. During this process, the model parameters are optimized to minimize error and improve prediction accuracy.
5. Model Evaluation: After training, the model is evaluated using the test and validation datasets. This step is critical to assess how well the trained model generalizes to unseen data.
6. Formation of Check Sample Data: A separate checking dataset is prepared for final evaluation, ensuring that the model's performance is thoroughly tested against new, untrained data.
7. Model Selection: Based on the performance of the model on the checking sample, the best-performing ANN model is selected for further use in estimating the technical losses of electrical energy.

In this methodology, steps 3, 4, and 5 are executed for each of the two ANN types mentioned above. Upon completing the algorithm, the most suitable ANN model is identified, providing an accurate estimation of the technical losses in the electrical energy distribution network.

IV.FORMATION OF STATISTICAL DATA AND THEIR BREAKDOWN INTO SAMPLES

To perform the required calculations of electrical energy losses, a 9-node distribution network configuration with four 6 kV voltage loads was selected (see Fig. 1), where the head node is designated as the one node. The time period for evaluating the electrical energy losses is one month, with a total duration of $T_{cal.p.}$ = 744 hours.

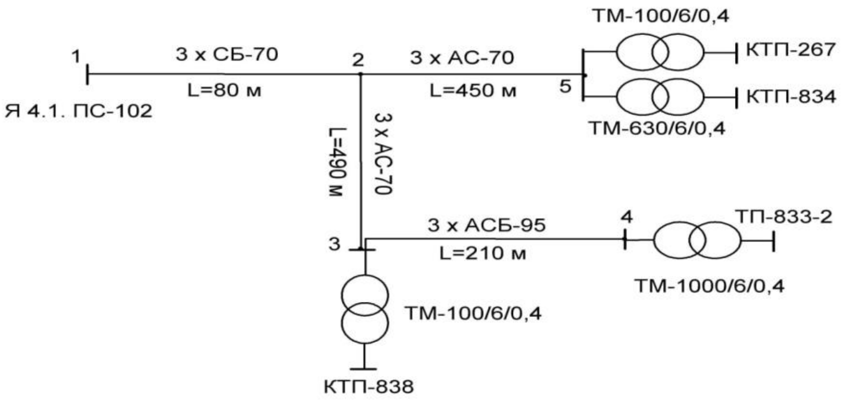

Fig. 1. Operational schema of the 6 kV distribution network

In order to generate statistical data, based on the above methodology, 1000 calculations were performed, in a wide range of changes in the following parameters:

- Outside temperature t = 20 ÷ 40 ℃;
- Head node voltage U_0 = 6 ÷ 6.3 kV;
- Load factor of transformers k_z = 0.1 ÷ 0.8;
- Head unit power factor cosφ = 0.7 ÷ 0.9;
- Operating time with maximum load T_{max} = 2000 ÷ 7000;

On the basis of the entered data and the results of calculations, a general sample was formed consisting of 1000 pairs of statistical data “inputs-outputs”. In this case, the input data are the voltage of the head node, electricity supply, outdoor

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temperature, the square of the shape factor of the load graph and the power of the load nodes $(U_1, W_1, t, k_f^2, P_6, Q_6, P_7, Q_7, P_8, Q_8, P_9, Q_9)$, and the output data are the absolute values of electrical energy losses (ΔW_{6-9}, thousand kW * h).

The resulting dataset is divided into three subsets: training, control (test), and validation samples. The training dataset, which is used to adjust the synaptic weights of the neural network, comprises 70% of the total data. The test and validation datasets each account for 15% of the data. These subsets are not involved in the training process but are used to evaluate the performance and quality of the training for each ANN model.

In addition to these three primary subsets, a checking sample is also created. This checking sample, consisting of 100 input-output data pairs, is used to select the best-performing ANN model from the generated network models. The checking sample covers a wide range of variations in the following parameters:

- Outside temperature t = 40 ÷ 45 ℃;
- Head node voltage U_0 = 6 ÷ 6.3 kV;
- Load factor of transformers k_z = 0.8 ÷ 0.85;
- Head unit power factor cosφ = 0.9 ÷ 0.99;
- Operating time with maximum load T_{max} = 7000 ÷ 7500.

As illustrated above, the input data sets for the training, test, and validation samples are derived from the same overall dataset. In contrast, the input data set for the checking (control) sample is distinct from the others and does not belong to the aforementioned general dataset.

V.ANN ARCHITECTURE SELECTION AND TRAINING

One of the key challenges in designing an Artificial Neural Network (ANN) is selecting its architecture, including the depth, width, type of layers, and number of neurons. Each network type requires a tailored approach.

For feedforward networks, optimal performance is typically achieved using an ANN with a single hidden layer consisting of 8 neurons. The hyperbolic tangent function is employed as the activation function. The training process for these networks is carried out using the Levenberg–Marquardt method, which has been found to yield the best results compared to other training algorithms (see Fig. 2-3).

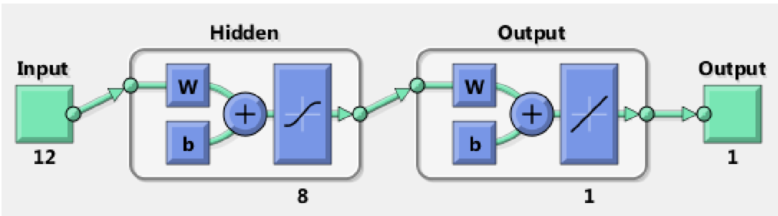

Fig. 2. Fitting neural network with one hidden layer consisting of 8 neurons

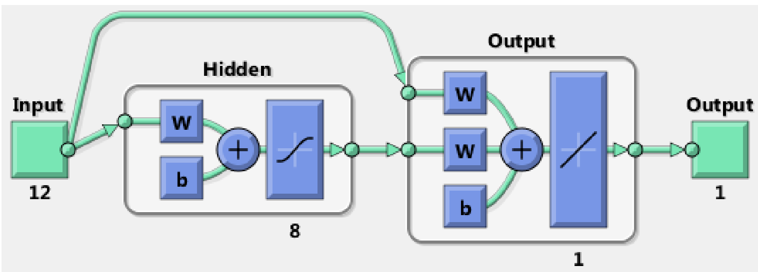

Fig. 3. Cascade-forward neural network with one hidden layer consisting of 8 neurons

VI.COMPARATIVE ANALYSIS OF SIMULATION RESULTS

To evaluate the quality of the obtained models for assessing technical losses of electrical energy, all the previously mentioned samples (training, test, validation, and checking samples) are utilized. The performance of the models is assessed using two key evaluation criteria: the Mean Squared Error (MSE) (see Table 1) and the Coefficient of Determination (R^2) (see Table 2):

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$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - Y_{mod,i}\right)^2 \quad (8) \qquad R^2 = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - Y_{mod,i}\right)^2}{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \frac{\sum_{i=1}^{N} Y_i}{N}\right)^2} \quad (9)$$

where, Y_i - the actual value of technical losses of electrical energy calculated using the method of average loads; $Y_{mod,i}$ - the value of technical losses of electrical energy obtained by the ANN model.

Table 1. The mean square error (MSE) of simulation

Data samples	unit	ANN type	
		CFNN	FNN
Training	thousand kW * h	0,0003673	0,00000012
Control		0,0004713	0,00000031
Validation		0,0004764	0,00000022
Checking		0,1370613	0,00009921

Table 2. The determination coefficient (R^2) and calculation time

Data samples / calculation time	ANN type	
	CFNN	FNN
Training	0,99991473	0,99999997
Control	0,99954990	0,99999984
Validation	0,99963510	0,99999987
Checking	0,69840612	0,99980014
Calculation time, sec	2,64	4,18

To select the best model, the Mean Squared Error (MSE) and the Coefficient of Determination (R^2) on the checking sample are used as evaluation criteria. As shown by the results, the Fitting Neural Network (FNN) proves to be the most accurate model for estimating technical power losses. The evaluation results for this model are presented in Fig. 6.

Using this algorithm, ANN models were also developed for other 6-10 kV distribution network configurations, where the Fitting Neural Network consistently performed as the best model. The assessment results for these networks are summarized in Table 3, based on the checking sample.

Table 3. Results of evaluations on the checking sample for fitting neural network

№	Scheme data	MSE	R^2	Calculation time, sec
1	3 branches 1 load	0,00004	0,999	3,25
2	6 branches 2 loads	0,0021	0,998	3,52
3	27 branches 11 loads	0,1526	0,992	7,88
4	43 branches 16 loads	4,2428	0,992	11,93

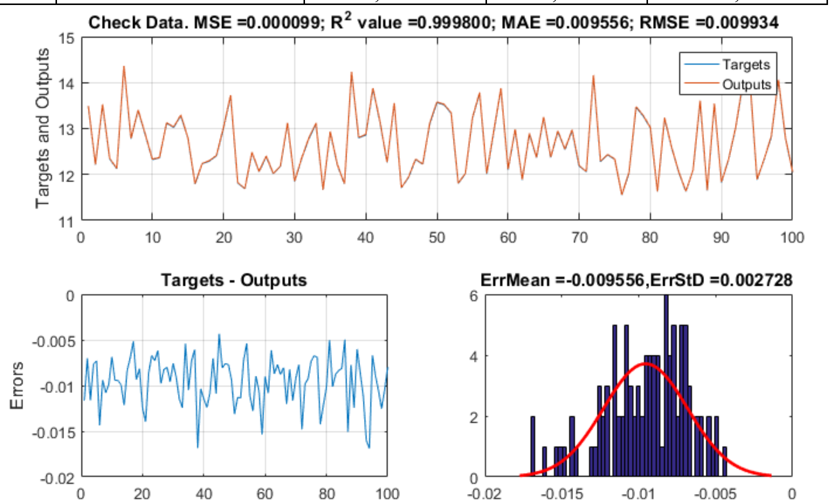

Fig. 6. Results of evaluations on the control sample for fitting neural network

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VII.CONCLUSION

The use of feedforward artificial neural networks (ANNs) for assessing technical losses of electrical energy in distribution networks represents a promising alternative to traditional calculation methods.

Compared to classical techniques, the calculation of technical losses using a trained ANN requires minimal computational and time resources, which is particularly advantageous for performing real-time operational calculations.

Among the four types of feedforward ANNs considered, the Fitting Neural Network (FNN) with a single hidden layer consisting of 8 neurons yielded the best results for assessing technical losses, based on evaluations with the checking sample. The performance metrics for this model include a Mean Squared Error (MSE) of 0.000099 MW·h and a Coefficient of Determination (R^2) of 0.9998.

As the results demonstrate, the calculation error is very small in networks with fewer branches and loads. In networks with a larger number of branches and loads, the error slightly increases, but it remains relatively small. This suggests that the ANN has been successfully trained and is correctly structured, providing reliable estimates for technical losses.

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