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Identification of parameters of power transformer models using artificial intelligence methods

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Abstract. A large number of tasks for analyzing the state of power transformers are solved on the basis of mathematical models, the validity of which is undeniable. The disadvantage of standard methods for diagnosing current-carrying parts of transformers is the requirement to remove voltage. The applied diagnostic methods without stress relief require improvement in terms of increasing accuracy, speed and ensuring predictive response. The paper presents methods for identifying the parameters of mathematical models of power transformers using artificial neural networks.

1 Introduction

Power transformers are important components of electrical networks, and their failure can lead to significant economic losses. Predictive diagnostics of power transformers is an important tool in the maintenance and operation of the electrical network [1–3]. This technology provides early warning of potential problems that could lead to costly and time consuming repairs or replacements. By identifying problems before they occur, predictive diagnostics can help reduce downtime and improve overall system reliability [4].

Predictive diagnostics of power transformers is based on the use of advanced monitoring methods. This includes the use of current and voltage transformers, sensors to detect changes in temperature, vibration, and other factors that may indicate a potential problem [5–6]. The data collected by these sensors is then analyzed by specialized software to identify any anomalies that may indicate a problem. In some cases, data can be used to predict when a transformer will need maintenance or replacement. This allows for proactive maintenance and repair rather than waiting for a problem to occur and then reacting to it [7–10].

Power transformer predictive diagnostics can also be used to identify areas of the system that are vulnerable to failure. This information can be used to develop preventive maintenance plans that help reduce the risk of failure and improve system reliability. In addition, the data can be used to determine the best locations for new transformers and other equipment [11].

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Continuous predictive diagnostics of power transformers are essential to ensure accurate results. This will help ensure that any potential problems are identified and corrected before they result in serious damage or costly repairs. It is also important to keep sensors and software up to date so that they can detect any new problems that may arise [12].

In general, predictive diagnostics of power transformers is an important tool for the maintenance of the electrical network. By providing early warning of potential problems, this technology can help reduce downtime and improve system reliability. In addition, it can be used to develop preventive maintenance plans and identify vulnerable areas of the system. Regular monitoring of the system is essential to ensure accurate results and identify any new problems that may arise.

This article proposes a new approach to power transformer predictive diagnostics using machine learning methods. The use of machine learning methods to identify the parameters of mathematical models of power transformers is becoming increasingly important in modern electrical networks. Using advanced algorithms to analyze sensor data, parameters such as winding resistance, core loss, and transformer loss can be accurately determined. This data can then be used to develop an accurate mathematical model of the transformer that can be used to predict its performance and identify potential problems [13]–[14].

Using machine learning methods to determine these parameters is beneficial because it reduces the amount of manual labor required and improves accuracy. Traditional data collection methods require manual verification and measurements, which can be time consuming and error prone. On the other hand, machine learning algorithms are able to quickly and accurately process large amounts of data and determine parameters with high accuracy [15]. The use of machine learning methods also allows the development of more complex mathematical models. These models can take into account more factors than traditional models such as temperature, vibration, and other environmental conditions. This provides a more accurate view of the characteristics of the transformer and helps identify potential problems before they occur.

2 Materials and methods

The use of artificial neural networks (ANNs) in power transformer diagnostics is a new technology that has the potential to revolutionize power transformer maintenance practices. An ANN is a type of machine learning algorithm that can learn from data and identify patterns in order to make predictions and make decisions. This makes them well suited for diagnostic use as they can analyze data from a power transformer and detect any potential problems or problematic pieces of equipment.

In order to use ANNs to diagnose power transformers, the first step is to collect data. This data may include currents and voltages on the sides of the transformer, oil temperature, ambient temperature, and other parameters. This data is then used to train the ANN to recognize patterns and be able to make accurate predictions about the health and performance of the transformer.

The trained ANN can be used to monitor the transformer in real time. Artificial neural networks can detect any changes in the data that may indicate a problem and notify maintenance personnel to take action. In addition, ANNs can be used to predict future problems by looking at historical data and identifying negative trends.

The developed diagnostic algorithm includes the following steps:

- Collecting data from a power transformer to determine the current parameters of the transformer equivalent circuit.
- Adjustment of the weights and biases of the ANN to achieve the optimal parameters of the transformer equivalent circuit.

- Checking the ANN output to ensure the required parameters of the transformer equivalent circuit.
- Control of voltages and currents (capacities) at the outputs of the power transformer over time to assess the success of setting up the ANN.
- Making the necessary adjustments to the weights and biases of the ANN to maintain optimal parameters of the transformer equivalent circuit.

The resulting array of data measurements is used to train an artificial neural network. In this case, the input parameters for training the artificial neural network is the data array *X*:

$$X = \begin{bmatrix} |U_{1,0}| & \delta_{1,0} & |U_{2,0}| & \delta_{2,0} & P_{1,0} & Q_{1,0} & P_{2,0} & Q_{2,0} \\ |U_{1,1}| & \delta_{1,1} & |U_{2,0}| & \delta_{2,1} & P_{1,1} & Q_{1,1} & P_{2,1} & Q_{2,1} \\ \cdots & \cdots & & & \cdots & & & \\ |U_{1,T}| & \delta_{1,T} & |U_{2,T}| & \delta_{2,T} & P_{1,T} & Q_{1,T} & P_{2,T} & Q_{2,T} \end{bmatrix} \quad (1)$$

Where $U_{1,i}$, $U_{2,i}$ – voltage modules on the winding side of the high and low voltage of the power transformer, respectively, kV; $\delta_{1,i}$, $\delta_{2,i}$ – voltage phase angles on the side of the high and low voltage winding of the power transformer, respectively, degrees; $P_{1,i}$, $P_{2,i}$ – active powers on the winding side of the high and low voltage of the transformer, respectively, kW; $Q_{1,i}$, $Q_{2,i}$ – reactive power on the winding side of the high and low voltage of the transformer, respectively, kvar; i=0..T, where T is the size of the training sample corresponding to the number of different initial measured modes.

The output parameters for training an artificial neural network is the data array *y*:

$$y = \begin{bmatrix} R_{T,0} & X_{T,0} & G_{T,0} & B_{T,0} & k_{T,0} \\ R_{T,1} & X_{T,1} & G_{T,1} & B_{T,1} & k_{T,1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ R_{T,T} & X_{T,T} & G_{T,T} & B_{T,T} & k_{T,T} \end{bmatrix} \quad (2)$$

Where $R_{T,i}$, $X_{T,i}$ - active and inductive resistances, reduced to the side of the higher voltage winding of the power transformer, Ohm; $G_{T,i}$, $B_{T,i}$ – active and inductive conductivities, reduced to the side of the higher voltage winding of the power transformer, μS; $k_{T,i}$ is the transformation ratio of the power transformer; i is the serial number of the mode in the data array *X*.

The power transformer damage prediction library is Scikit-learn, which is a free and open source Python library for machine learning. The Scikit-learn library provides a wide range of algorithms for classification, regression, clustering, and more. Scikit-learn also offers tools for data preprocessing, model selection, and scoring.

According to the author's conclusions, the best models for predicting the failure of a power transformer in Python are the RandomForestRegressor (random forest regressor) and MLPRegressor (multilayer perceptron) regressions. These models are powerful collaborative learning techniques that combine decision predictions to improve the accuracy and reliability of predictive analytics.

The fit function was used to train the power transformer model. This function is used to fit the model to the training data, which in our case is data related to the model and power transformer mode parameters.

The predict function was used to predict the parameters of the power transformer model. This function is used to make predictions based on the trained model and input data.

Often, when working with a data set and using a machine learning model, it is not known in advance which set of hyperparameters gives the best result. Iterating over the options of all sets of hyperparameters manually through the model and checking the result can be an impossible task.

The grid search method was used to obtain the best set of hyperparameters. The GridSearchCV function sequentially passes all combinations of hyperparameters to the model and checks the result. This allows you to set a set of hyperparameters that gives the best result of model tuning.

3 Results and Discussion

The evaluation of the forecasting results was carried out using numerical methods on the example of an electrical network, the scheme of which is shown in Figure 1.

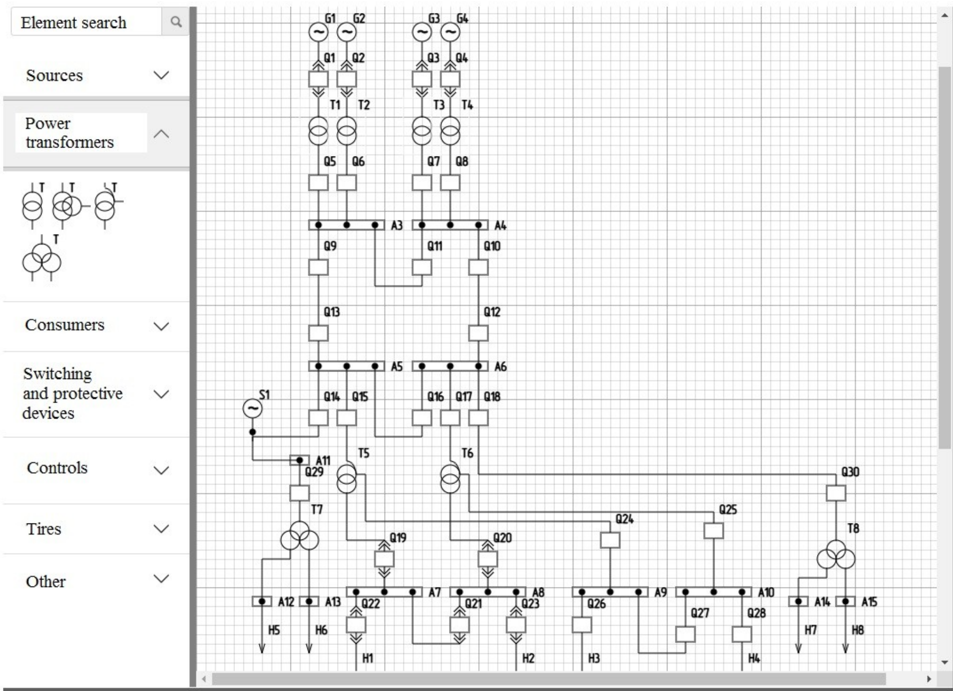

Fig. 1. Calculation scheme of the electrical network section in the editor "Online Electric".

With the help of the Pandapower library, numerous steady-state modes of the network section were calculated by varying the generation capacities, consumer loads, and the positions of power transformer tap-changers.

Further use of the obtained artificial neural network is to feed to its input a set of data recorded on the power transformer X. The result of the regression are layers y, which are matrices, each row of which is part of the results of calculating the required parameters of the equivalent circuit of the transformer R_T, X_T, G_T, B_T and K_T . In the future, the found parameters of the equivalent circuit can be used to determine the resistance Z_K and short-circuit losses P_K, current I_0 and no-load losses P_0. According to the deviation of the values Z_K, P_K, I_0, P_0 from the corresponding reference values, one can judge the technical condition and operability of the transformer.

The results of applying the obtained datasets *X* and *y* to train the ANN model showed an increase in accuracy with the growth of the training set. The accuracy of calculating the parameters of the power transformer equivalent circuit using RandomForestRegressor has reached 91%.

To further increase the accuracy of power transformer predictive diagnostics, the following RandomForestRegressor settings can be applied:

- Increase the number of trees in the model.
- Increasing the depth of each tree.
- Increasing the minimum number of samples required for a leaf node.
- Increasing the number of objects used in each tree.
- Using characteristic selection methods to determine the most important characteristics for predicting transformer failure.
- Using cross validation to tune hyperparameters such as tree depth and number of trees in the model.
- Use relevant metrics such as accuracy, precision, recall, and F1 metric to evaluate model performance.

Thus, the results of numerical experiments have shown that the proposed machine learning method can be used to identify the parameters of the power transformer model. The proposed approach can be applied to real-time diagnostics of a power transformer. In addition, ANN can be used to control the diagnostic parameters of other types of electrical equipment.

4 Conclusion

In general, the use of ANNs for power transformer diagnostics is a promising technology that has the potential to improve the efficiency and accuracy of the maintenance and operation of electrical networks and substations. By using ANNs, service personnel can quickly detect any potential problems and take action before they become serious. In addition, ANNs can be used to predict future problems, allowing maintenance personnel to plan ahead and ensure optimal operation of the transformer substation.

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