Machine learning application for power systems reliability assessment

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Abstract. The paper presents the principles and features of the use of machine learning methods to assess the power system reliability. Based on the analysis of publications, the main approaches to the application of machine learning methods are given. A prototype of an automatic system has been developed to identify in real time potentially dangerous power system states, the occurrence of which can lead to the power system failures.

1 Introduction

Machine learning and artificial intelligence methods are among the key technologies of Industry 4.0 that underlie the digital transformation of the power systems [1]. The progress achieved over the past decades in the development of machine learning and artificial intelligence methods makes the use of these methods promising for solving many problems in various fields of science and technology. Such capabilities of machine learning methods as searching for patterns (characteristic sequences) in data, identifying various data features and characteristics, the ability to predict the appearance of certain values in data allow us to solve problems that either cannot be solved by classical methods, or have high computational complexity [2]. An additional driver for the development of machine learning methods (in addition to increasing the performance of computer technology and improving the machine learning methods) is the increasing availability and "quality" of big data (data reliability, structure, ability to process, etc.), which is the basis for training artificial intelligence models.

In power systems, machine learning methods show effectiveness in solving problems of short-term forecasting of electrical energy consumption [3, 4, 5], in problems of monitoring and predictive diagnostics of electrical equipment [6, 7, 8, 9], in problems of emergency control and relay protection [10], etc. It is also worth noting the experience of using machine learning methods in creating a software and hardware complex for recognizing the state and readings of electricity meters [11], the experience of developing electric power quality analyzers with a built-in artificial neural network [12], the development of the information system for identifying the power and electricity imbalances in electrical distribution networks [13]. This paper discusses the possibilities and features of using machine learning methods to solve the problem of ensuring the reliable functioning of electric power systems.

2 Review of the machine learning application to assess the power system reliability

There are quite a lot of publications devoted to assessing and ensuring the reliability of power systems based on the use of machine learning methods. A significant number of works have been published from the 2010s to the present. Publications present various aspects of the reliability of power systems (for example, from the point of view of power system adequacy [14], stability [15, 16], etc.). This paper provides a selection of references to publications devoted to assessing the reliability of power systems based on the parameters of steady-state (quasi-steady-state) electrical modes. A large number of publications have been analyzed and selected the papers that reflect the most common approaches to assessing the reliability of power systems. As a results, it is possible to identify the main approaches: using the Monte Carlo method to obtain a training sample and predicting the SAIDI, SAIFI indices [14, 17], assessing the power system state admissibility indices [18, 19, 20], assessing various aggregated indices taking into account the electrical network topology, including the L-index [21], SSI index (static security index) [22], the use of Markov chains for assessing the reliability of power systems, including to prevent cascading failures [23]. A number of publications reflect the features of the use of specific machine learning methods in assessing the reliability of power systems [24, 25]. Based on the results of the analysis of publications, the following general conclusions can be drawn:

1. The processes of creating machine learning models are fairly unified and, in general, consist of the following main stages: generating a training set from

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the parameters of power system states (voltages, currents, etc.), training the machine learning model, assessing the reliability of the power system based on test data (at the stage of the model operation – according to available data, for example, from SCADA systems, PMU, etc.).

2. To obtain a basic training set, mathematical models of power systems are used. To form the required power system states, in most cases the following criteria are used: N-1 criterion (in the general case – N-k), Monte Carlo methods, special power system states that simulate the required situations (for example, the voltage collapse, etc.).

3. The reliability of the power system is assessed in most cases based on the calculation of various indices. The use of indices has certain limitations and specific application area. In addition, the calculation of different indices requires different amounts of information about the power system. For example, to calculate the L-index, information about the topology of the electrical network, the impedances of the branches and the voltages in the nodes are required [26].

4. In most cases, various supervised learning methods are considered: support vector machines, random forest methods, decision trees, ensemble algorithms, neural networks, etc. From the results obtained in the publications reviewed, it is impossible to conclude that any one is superior or several machine learning methods for assessing the reliability of power systems.

5. In all the publications reviewed, a high accuracy of classification of power system states (prediction of the indices used) was obtained. In most cases, the performance assessment of the algorithms used by the authors of publications is obtained for mathematical power system models of a fairly small dimension (for example, IEEE power system models with 57, 96 and 118 nodes are often used).

3 Prototype of an automatic system for assessing the power system reliability

To study the features and possibilities of using machine learning methods, a prototype of an automatic system has been developed to identify potentially dangerous power system states in real time, i.e. states, the occurrence of which is associated with the possibility of developing emergency processes and failures in the power systems. The prototype of the system is based on the use of machine learning methods to solve the problem of classifying power system states according to the reliability index values.

The generalized process of creating machine learning models for assessing the reliability of power systems is shown in Fig. 1. At the first stage, a training set from power system parameters is generated. To generate this sample, the electrical parameters of the power system are used (voltages, currents, power flows, etc.), obtained from the results of calculations of the steady states in mathematical power system model. This paper examines states formed according to the N-1 criterion and states corresponding to different levels of power consumption in the power system.

The second step involves training several different machine learning models. Based on the training results, the best model is selected – the model with the best performance indicator values. At the third stage, the reliability of power systems is assessed using test or real data. Depending on the formulation of the problem, the result of the machine learning model operation can be either the classification of the power system state to one of the categories (for example, normal, emergency, etc.), or the determination (prediction) of reliability index value.

At the stage of testing the final performance of the proposed machine learning models, the reliability of power systems is assessed for a test sample, i.e. according to data obtained from the results of power system simulation. At the stage of operation of the proposed algorithms in real time, the prediction of the reliability index value is carried out using available data (for example, received from SCADA systems, PMU, etc.).

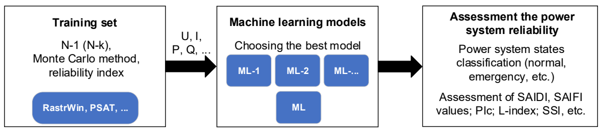

Fig. 1. A generalized process for generating machine learning models for assessing the power system reliability.

It should be noted that the presented prototype of the automatic system is a convenient tool (framework) for testing technologies for applying machine learning methods in electrical power systems. If necessary, the system prototype can implement various reliability indices, various scenarios for generating training samples, and apply various machine learning models to identify the model that is most appropriate for solving the specific problem.

4 Power system reliability indices

The aggregated index PI_c, defined as follows [19]:

$$PI_c = [\sum_i (q_{U_i}^{\max})^{2n} + \sum_i (q_{U_i}^{\min})^{2n} + \sum_j (q_{I_j})^{2n}]^{\frac{1}{2n}} \quad (1)$$

$$q_{U_i}^{\max} = \begin{cases} \dfrac{U_i - H_i^{\max}}{A_i^{\max} - H_i^{\max}}, \text{ if } U_i > H_i^{\max}; \\ 0, \textit{otherwise}. \end{cases} \quad (2)$$

$$q_{U_i}^{\min} = \begin{cases} \dfrac{H_i^{\min} - U_i}{H_i^{\min} - A_i^{\min}}, \text{ if } U_i < H_i^{\min}; \\ 0, \textit{otherwise}. \end{cases} \quad (3)$$

$$q_{I_j} = \begin{cases} \dfrac{I_j - I_{H_j}}{I_{A_j} - I_{H_j}}, \text{ if } I_j > I_{H_j}; \\ 0, \text{otherwise}. \end{cases} \quad (4)$$

where i, j – the numbers of nodes and branches,
n – parameter that determines the exponent,
$q_{U_i}^{\max}$, $q_{U_i}^{\min}$ – voltage deviation indices,
q_{I_j} – current deviation indices,
I_j – current in the branch,
I_{A_j} – permissible current in the branch,
I_{H_j} – warning value of the current in the branch,
U_i – voltage in the node,

$A_i^{\min}$, $A_i^{\max}$ – minimum and maximum permissible voltage levels in the node,
$H_i^{\min}$, $H_i^{\max}$ – warning permissible voltage level in the node.

Index PI_c values are used to classify power system states. The paper presents two methods of classification: into two and three categories.

Classification of power system states into two categories:

1. PI_c<1 – for power system states, the parameters of which do not exceed the permissible ranges (normal state);
2. PI_c≥1 – for power system states, whose parameters have either reached or are outside the permissible ranges (emergency state).

Classification of power system states into three categories:

1. PI_c=0 – normal state;
2. 0< PI_c <1 – for power system states, the parameters of which are outside the established warning ranges, but have not yet exceeded the permissible limits (normal state (warning));
3. PI_c≥1 – emergency state.

Thus, the value of the index PI_c value determines the admissibility of the power system state and is an indicator of the operational reliability of electric power system. Using the specified index, all electrical states can be classified into two classes: normal or emergency states, which allows the use of machine learning methods that carry out binary classification. Additionally, one more category of classification of states can be identified – potentially dangerous electrical states, the parameters of which go beyond the expertly established warning ranges, but have not yet exceeded permissible limits.

5 Power system model

To generate a training set and evaluate the performance of the machine learning models discussed in the paper, the IEEE-57 power system model was used. The model contains 57 nodes (including 7 generator nodes) and 80 branches. The following principles were used when selecting a test model of the power system. The power system model must be of a sufficiently large dimension, which makes it possible to obtain a large number of different electrical states and corresponds to models of real power systems. At the same time, based on the research nature of this paper, obtaining machine learning models should occur within an acceptable time and should not require the use of special hardware and software for storing and processing very large data sets. A single-line diagram of the power system model is shown in Fig. 2. The model was developed in the software RastrWin.

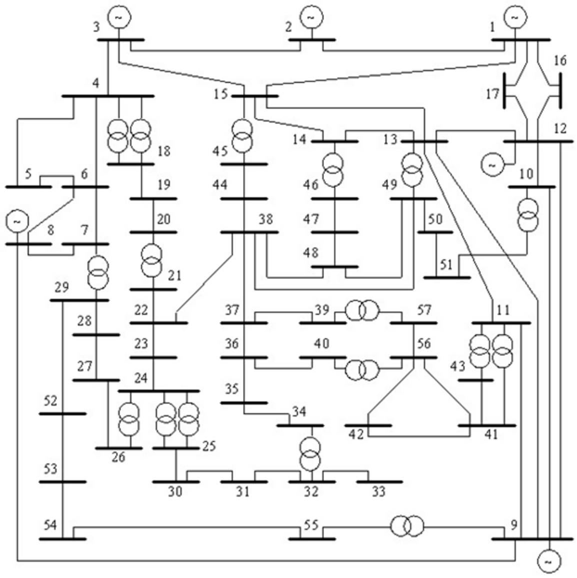

Fig. 2. IEEE-57 power system model.

6 Machine learning model performance indicators

To evaluate the performance of machine learning models in solving binary classification problems, the following indicators are used [2]:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (7)$$

where TP – the number of true positive predictions,
FP – the number of false positive predictions,
FN – the number of false negative predictions.

All three indicators can be obtained from the confusion matrix, which is one of the characteristics of machine learning models and is used in solving classification problems. In the context of the problem under consideration, the precision characterizes the classifier's ability not to classify emergency states as normal. In turn, the recall characterizes the classifier's ability not to classify normal states as emergency. The F_1 (f-score) indicator is interpreted as the harmonic mean value for the precision and recall values. The range of possible changes in the values of precision, recall and F_1 indicators is from 0 to 1. In this case, value 1 corresponds to the best values of the performance indicators of the machine learning model.

Performance indicators (5)-(7) are used when solving binary classification problems, i.e. classification into two categories. A common indicator for assessing the performance of machine learning models is the accuracy, which characterizes the number of true predictions relative to the total number of predictions. For classification problems, the accuracy indicator is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (8)$$

where TN is the number of true negative predictions.

7 Simulation results

Machine learning methods were applied to classify the electrical states of the power system model. Two groups of machine learning models were obtained: for classifying electrical modes into two categories (normal state, emergency state), and also for classifying electrical modes into three categories (normal state, normal state (warning), emergency state). The models are trained based on a sample consisting of parameters of 1182 electrical states. The following machine learning models were selected: decision trees, support vector machine, k-nearest neighbors, ensemble method (bagged trees) and neural network (multilayer perceptron). When training the models, 10-fold cross-validation was used. Characteristics of the performance of the resulting machine learning models for solving the binary classification problem are presented in Table 1. Comparative characteristics of the accuracy of machine learning models when predicting two and three categories of the power system (respectively, when solving the problem of binary classification and classification into three categories) are presented in Table 2.

As can be seen from the tables, all considered machine learning models have fairly high accuracy values. The ensemble method showed the highest accuracy on the training and test data used (accuracy 95.6% in the binary classification problem). As the number of classified categories increases, the prediction accuracy decreases. This may be due to the fact that with an increase in the number of classified categories, the training of the model for each category actually occurs over a smaller number of electrical states. A characteristic feature of the resulting machine learning models is their relatively high computational performance. Power system state classification is performed by the resulting machine learning models in about 50 ms (Intel Core i5, 8 GB RAM).

Table 1. The machine learning model performance to solve the problem of binary classification of power system states.

Machine learning model	Performance indicator, pu		
	Precision	Recall	F-score
Ensemble method	0,9601	0,9629	0,9614
Neural network	0,9514	0,9599	0,9556
Support vector machine	0,9419	0,9736	0,9575
k-nearest neighbors	0,9407	0,9658	0,9531
Decision trees	0,9478	0,9450	0,9464

Table 2. The accuracy of classification of power system states into two and three categories.

Machine learning model	Accuracy, %	
	Binary classification	Classification into three categories
Ensemble method	95,6	91,8
Neural network	94,9	91,2
Support vector machine	95,0	90,3
k-nearest neighbors	94,6	88,7
Decision trees	93,9	85,8

8 Conclusion

The paper discusses the main approaches to assessing the reliability of electric power systems based on the use of machine learning methods. Specific machine learning models have been developed to classify power system states according to the steady-state electrical parameters of power system. The high accuracy and performance of these models are shown. The presented models and the considered approaches can be used as a basis for creating an automatic system for assessing the reliability of electric power systems, namely, a system for identifying in real time potentially dangerous electrical states, the occurrence of which can lead to the development of emergency processes and failures in the power system.

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