Application of neural network technologies in power engineering

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Abstract. In this work, key areas of artificial neural networks using in the energy sector are highlighted. The application of neural network technologies to assess the current technical condition of energy equipment, systems and tools for various purposes is implemented on classification algorithms, allowing to establish the degree of closeness of the current technical state to the "normal" state through the use of key technological (diagnostic) parameters. The prediction of operating modes (normal, emergency, etc.), the occurrence of defects, failures and accidents is carried out by establishing functional dependencies using historical data on the operation of power equipment. The data accumulated for different periods are used to predict the consumption of various types of energy and loads during these periods. On the basis of neural network algorithms, operational intelligent control of the operating modes of energy facilities is implemented, and systems for dispatch control, decision support, repair management, etc. are developed.

1. Introduction
Over the past two decades, with the use of various information and automated systems in the energy sector, a significant amount of statistical data has been accumulated that characterizes various aspects of equipment operation: the values of various technological parameters; information on defects registered and failures that have occurred; additional heterogeneous information. These data can be used to obtain new knowledge about energy facilities, create management systems and decision support, as well as cyber-physical models in the framework of the concept of the new industrial revolution (Industry 4.0) [1].

To solve these problems, artificial neural networks (ANN) technology has shown high efficiency. The application of artificial intelligence methods can significantly improve the efficiency of processing large amounts of data. These methods are implemented in most modern environments for engineering calculations and research, and also by high-level programming languages.

2. Main directions of ANN application in power engineering
ANN can actually be considered as universal mathematical apparatus for establishing functional relationship between set of values of some input parameter (s) and output (output). The popularity of neural network technologies and a significant increasing of publications on this topic are primarily due to two aspects: the emergence of high-performance computing (software implementation of calculations using ANN requires larger computational resources than other methods); the need for research and knowledge of the laws of the processes (the object under study is considered as a black box with measured inputs and outputs).
The spectrum of energy problems solving using ANN is wide [2]: energy consumption forecasting [3]; electric load prediction [4]; demand forecasting [5]; technical condition diagnostics [6]; localization of equipment malfunctions [7]; reliability assessment [8]; operational mode management [9]; asset management [10], etc.

The tasks of monitoring and forecasting technical condition of power equipment are inextricably linked. And this is due primarily to need of maintaining functioning equipment in proper technical condition. Solving the problem of monitoring equipment allows the identification and assessment of the current (actual) technical condition of this equipment, which ensures the implementation of a perspective concept of the organization of power equipment condition-based repair. Comparing the assessment of the technical condition at different moments, we can conclude about its change, for example, deterioration. This, in turn, makes it possible to predict changes in the technical state of power equipment over time during its exploitation.

In addition, there is an acute problem associated with obsolescence and physical deterioration of equipment, which is one of the key hazards of failures and accidents at power facilities. The increase of the risk of accidents is a consequence of the unsatisfactory technical condition, so it is extremely important not only to identify the current one, but also to predict the future state of the operated power equipment.

The presence of the forecast for a certain period of time allows for timely planning of measures to bring the equipment into proper technical condition, including financial and human resources, as well as materials, machines, etc. Therefore, the development and implementation of technical condition monitoring systems and the prediction of the reliability of power equipment is an extremely important area of increasing the efficiency, reliability and reliability of its operation [11].

Consider the features of the application of various types and architecture of ANN for solving problems of monitoring and diagnostics of the technical condition of power equipment. In the most general sense, ANNs can be divided into direct action networks (for example, single-layer and multi-layer perceptrons, networks with radial basis functions (RBF), probabilistic networks) and recurrent networks (for example, Hopfield networks, Kohonen networks / maps).

3. ANN architectures

A single-layer perceptron is a simple-to-implement and most frequently used ANN architecture. Each neuron receives signals \( x_j \) \((x_0 = 1)\) on connections that have weights, \( w_{ij} \). The values of weights \( w_{ij} \) in the learning process are selected in such a way as to minimize the Euclidean metric, \( E \), which is a measure of proximity between the actual output of a single-layer perceptron, \( y_i \), and the required output value, \( d_i \). For training used \( p \) vectors \( \langle x, d \rangle \). As a function of neuron activation, \( f(\ ) \), as a rule, a sigmoid function, is used, and training (selection of weights) is performed by the gradient descent method. Using such ANN, it is possible to solve classification problems, for example, if each input is a specific defect of a unit of power equipment that takes one of two values, and the output generates a signal corresponding to one of the states, for example, «healthy» (output 1) and «not workable» (output 2).

In a multilayer perceptron, hidden layers are added (one in the simplest case). The signal also propagates in the forward direction (therefore, obtaining the signal value after each neuron is similar to that described earlier for the simplest perceptron), and the error signal propagates in the opposite direction (from the output to the input). When using sigmoid neuron activation functions, weights are adjusted according to the \( \delta \)-rule. In this case, the weights \( w(k+1) \) are adjusted for the amendment \( \Delta w \), depending on the learning coefficient \( \eta \) and the negative error gradient.

MLP with the back-propagation error algorithm as a training method is used to diagnose the gas path of a power unit and to identify faults [12]. Like other ANN of this architecture, there is one important disadvantage, namely, that the quality of classification and definition of faults largely depends on the quality of the available training set.

The use of ANN for monitoring and diagnosing the technical condition of thermal power plant equipment is described in [13]. Neural network models are implemented for each component, namely,
for a turbine with a steam generator and for a waste-heat boiler, these models ensured the timeliness of fault assessment to optimize equipment maintenance.

Artificial neural networks are used to monitor nuclear reactor systems [14] and represent a classification model for generalized categories of system behavior. Another example of the ANN using for monitoring the state of atomic reactors is work [15]. It also solves the problem of classifying events to prevent the occurrence of accidents that occur in an object, due to the timely identification of processes that characterize the approach of the object to an emergency. These intermediate events are identified by a forward propagated ANN, trained on the basis of an error back propagation algorithm. Work [16], in which a three-layer ANN is implemented, is also devoted to solving the problem of recognizing accidents at nuclear power facilities. Another ANN application for a nuclear power plant is the work [17], which shows an approach to diagnosing accidents based on a training set containing normal and potentially dangerous (pre-emergency) situations.

The neural network algorithm can be used to build mathematical models of power equipment (for example, gas turbines [18]), when based on the measured data the required dependence of the output parameters of the object (only those that are required to solve the problem) on the existing set of input parameters is built.

In the RBF networks, special activation functions of neurons of the hidden layer are used, the main property of which is a monotonous increase (decrease) with distance from the center (center point). The basis of the theoretical basis of this type of ANN is the Cover theorem on the separability of patterns and the theory of exact approximation of Powell functions. As a rule, the Gauss function \( h(x) \) with adjustable parameters is used for these purposes: \( c \) — the center of the function window and \( r \) - the width of the function window. The key advantages of this type of ANN include: no need for a large number of hidden layers, as a rule, one hidden layer is quite enough; the output layer consists of one (rarely several) layers with a linear activation function. Networks of this type speed up and simplify data processing. For example, a RBF network with one output neuron can be used to predict the probability of failure. At the same time, defects fixed for a specific unit of power equipment are supplied to the input. The process of obtaining the RBF network architecture is reduced to the selection of \( c \) and \( r \), taking into account the type of radial-basis function, as well as the calculation of the weights of synaptic connections.

In the energy sector, RBF nets are used to diagnose bearing failures based on the analysis of vibration signals [18]. In this work, the RBF network is implemented as a classifier that divides all bearings into two classes according to their technical condition. Diagnostics of battery malfunctions are also performed using a RBF network (together with wavelet analysis) and particle swarm optimization [19]. The considered type of ANN is also used to diagnose malfunctions of expensive long-running power equipment, for example, turbines [20]. The proposed approach allows to identify the type of failure and implement the timely detection and elimination of faults that have a negative impact on the turbine operation.

The probabilistic artificial neural network is mainly used to solve the classification problem (of a probabilistic nature) and divides the classes with hyperspheres (the output layer is linear [21]), unlike the MLP, in which the classes are separated by hyperplanes. In such networks, the first layer of neurons contains radial basis functions, and the second layer - the competition layer, calculates the probability that the vector of input parameters belongs to a particular class. The result of the network is the choice of class with the highest probability. This type of ANN is used to diagnose faults in wind turbines based on the measurement of generator current signals [22]. This approach is used to diagnose the technical condition of a wind turbines in real time, as well as gas turbines [23].

The work of [24] is devoted to the solution of problems of monitoring and diagnostics of malfunctions at power plants, in which influence diagrams are used to select a probabilistic neural network architecture. This network is trained in such a way as to estimate the probability distribution of negative events (failures). It allows to assess the probabilities of the causes of failures and rank the reasons in descending order of calculated probability values.

One of the most commonly used recurrent neural network architectures is the Hopfield network. In this type of ANN (is a realization of the associative memory), the output signals \( y_i(k-1) \) are the
input signals $x(k)$ of the network. The output signal of the $i$-th neuron is determined by the function of its activation $f(\cdot)$, the input signal and synaptic weights $w_{ij}$. Selection (calculation) of $w_{ij}$ is carried out in the learning process. The Hopfield network allows you to restore the sample it has memorized from some sample (not ideal) arriving at its input, or to identify the input signal as inappropriate to any of the samples (stored in the memory stored by the network). At the same time, an important aspect is the memory capacity of the network or the number of samples $m$, that the network is capable of memorizing. In this case, the ratio $m \leq 0.15n$ can be used.

In fact, the network allows you to quickly determine the current status of a unit of power equipment. This happens as follows. The current vector of input parameters (defects or diagnostic signs) of a piece of equipment is fed to the network input, and the network forms the sample closest to it (typical state). For example, if the output is a sample of a pre-emergency condition, this means that the equipment is operated in a mode that is dangerous and will lead to a pre-emergency situation and failure (accident) in the future.

Using this approach, for example, a quick determination of the current state of generators occurs [8]. In electricity distribution networks, Hopfield networks are also used to assess the current state [25]. The increase in the length of distribution electrical and heat networks leads to an increase in the computational complexity of solving the problems of identifying their technical condition, therefore, the Hopfield networks are increasingly used as high-speed classifiers of the technical condition of equipment specifically for such objects [11].

Kohonen self-organizing networks (maps, if used for visualization) are another important diagnostic tool for energy systems and equipment.

The classical Kohonen network consists of a single layer (Kohonen layer) of the “winner takes all” neurons. Each element of the input vector $x_j = (x_{i1},...,x_{in})$ is connected to each neuron of the Kohonen layer. Neurons are linear weighted adders that form a signal $s_j$ at the output, where $j = 1,m$ is the number of a neuron in the Kohonen layer. The formation of the output signal $y$ of the network produces a block $l$. In this block, the output is the number of the neuron $k$ (the cluster to which the input feature vector belongs), which turned out to be a “winner”, i.e. for which the distance between the input vector $x$ of the network and the vector of weights of this neuron $w_k = (w_{k1},...,w_{kn})$ was the smallest. Usually the Euclidean measure is taken as the distance. Usually the Euclidean measure is taken as the distance: $\|x - w_i\|$. During training, the adjustment of neuron weights is made according to Kohonen’s rule, which has the following form: $w^{(t+1)} = w^{(t)} + \eta^{(t)}[x - w^{(t)}]$, \( \eta^{(t)} \) is a learning rate that decreases with time.

The use of Kohonen self-organizing maps and networks as a universal classifier for failures of electrical transformers is described in [26]. The network is trained to identify all possible malfunctions and can be used as a replacement for an experienced expert in the process of testing electrical transformers.

Kohonen maps (along with auxiliary factor analysis tools) are used to classify situations that arise in electrical power systems. For example, in [27], this approach was used to build SOM models that cluster the current equipment operation modes, highlighting emergency and normal operation modes (with different variations that affect the scale of impacts to bring equipment into proper technical condition and prevent accidents).

Self-organizing networks are used to reduce the number of learning patterns when building simulators for nuclear power plants, in which various, including pre-emergency and emergency, operating modes are simulated using the ANN [28].

Kohonen’s neural networks are used, for example, to extract diagnostic information and form the optimal number of condition categories and to obtain, on their basis, estimated metrics for rational determination of symptoms in the diagnostic systems of nuclear power plants [29]. In addition, Kohonen’s networks have proven themselves in monitoring equipment diagnostics in real time and ensuring timely diagnosis of faults that can lead to an emergency shutdown of equipment and the resulting financial losses.
4. Solutions for energy sector using ANN in MPEI

At the Department of Automated Process Control System MPEI using ANN various scientific and applied problems are solved. For example, anomalies (outliers) are defined in data that goes to various application systems that provide prediction, control, etc. Anomalous are called such parameter values in the sample, which significantly (up or down) differ from the normal (nominal) value. The presence of anomalous values (in the works, outliers are considered) of technological parameters can significantly affect the forecast. Therefore, the identification of anomalies and their subsequent preprocessing as required to eliminate the effect on the forecast is an important task. The results obtained allow us to state that the developed neural network algorithms for solving this problem make it possible to identify all outliers in the data sample with their total number up to 10%, including closely spaced outliers.

Outliers elimination is necessary to predict the values of technological parameters, for example, the power of various generating plants. As part of the work carried out by the research team of the Department of Automated Process Control Systems, a module for predicting the values of technological parameters was implemented [30]. This neural network module is used as part of the power equipment defect identification system. Each defect of a piece of equipment is characterized by a specific set of parameters. Thus, the construction of the functional dependence of the arising defects on the changing parameters will allow to solve the problem of the timely planning of measures to bring the equipment into proper condition. At the input of a mathematical model for identifying defects in process equipment, the predicted values of the parameters arrive, and at its output a set of defects is formed that may occur at a specific point in time [30].

The elimination of defects leads to the fact that the probability of a failure is reduced, and the appearance of a new defect increases its increase. The solution of the problem is made only for obvious defects in the process equipment. The mathematical model built in [31] and the forecasting system that implements it provide for establishing the functional dependence of the probability of failure of a unit of power engineering equipment on defects that were recorded during its operation.

5. Conclusion

The solution of various problems of energy with the use of the mathematical apparatus of the ANN is a promising direction due to the features inherent in these methods. High accuracy and generalizing ability in combination with the possibility of building a diagnostic model only on the basis of the measured inputs and outputs of an object allows us to make an assumption about the acceleration of further penetration of various types and ANN architectures into diagnostic systems, predictive analytics and control system of power equipment in general. The considered approaches in the field of neural network diagnostics of equipment of energy facilities are effective and prove an increase in the reliability and safety of operation of equipment with the availability of sufficient volumes of diagnostic data for training. At the same time, information on the current technical condition without an accurate prediction of the state for a certain time interval or to failure (accident) is not sufficient for making decisions on planning and implementing measures to maintain power equipment in proper technical condition.

6. References

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