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ARTIFICIAL NEURAL NETWORKS AS A TOOL FOR SIMULATING PHYSICAL PROCESSES

D. DOVGULEVICH
Vitebsk State University named after P.M. Masherov, Belarus

In the paper various possibilities of using artificial neural networks as a tool for modeling physical processes are considered. The main advantages and disadvantages of computer modeling using ANNs in comparison with classical approaches to constructing mathematical models are revealed. The main tasks for solving the successful construction of the model are highlighted.

The machine learning techniques using artificial neural networks has been increasingly implemented in theoretical and experimental physics in recent years.

Thanks to the ability of processing large amounts of data, drawing conclusions based on characteristics without direct correlation, and high speed, the machine learning techniques can be possibly used in conjunction with classical methods of modeling physical processes, and can completely replace the latter, as well.

The purpose of this research is to determine the scope of application of artificial neural networks for modeling physical processes and to identify their advantages and disadvantages in comparison with classical methods of building models.

Methods. The research is based on mathematical models of physical processes using artificial neural networks. Generally recognized methods of scientific knowledge were used.

Discussion. A neural network in the context of mathematical modeling is a model that reflects the dependencies between input and output parameters. However, unlike models built using other approaches, in a "trained" artificial neural network, the correlation of input and output data cannot be written explicitly (for example, "the value of A is positively related to B for cases when the value of C is negative, and D tends to zero").

A neural network can produce high quality results if it was properly trained, but in essence ANNs represent a kind of "black box". Therefore, with a neural network approach in modeling, the focus is on the correctness of the model, the accuracy of predictions and application, but not on the underlying physical processes.

However, neural networks can also be used to analyze the essence of the modeled process, helping to find the most significant input variables, which facilitates further construction of the model using traditional approaches [1].

According to the Cibeko theorem (Universal approximation theorem), an artificial neural network of feedforward with one hidden layer can theoretically approximate any continuous function of many variables with any accuracy [2]. Due to this, the models built with the use of ANN make it possible to reproduce complex dependencies occurring in physical processes and dependencies with a large number of variables, the modeling of which is extremely difficult in other ways.

Due to these properties, artificial neural networks make it possible to solve the different information processing tasks when carrying out computer modeling. For example, it is possible to approximate the original mathematical model, which not only allows to expand the range of problems that are possible to solve, but also significantly increases the speed of calculations [3].

Another task covered by using the ANN is the calibration of the model - the selection of missing parameters based on incomplete and potentially inaccurate information. Most frequently, a computer model uses a number of input parameters, and depending on the context of the application, the parameters will change, and some of them may even be unknown at all. To select the parameters using artificial neural networks, Bayesian calibration of computer models can be used [4].

When solving the problem of automation and control of processes, it is often required to model physical processes in real time. In particular, this is relevant for predicting future states of the system. An example is a system for preventing disruptions and extinguishing a plasma charge. For the correct operation of the system, it is necessary to form a breakdown precursor, i.e. to simulate the process with prediction and form the trigger of the discharge extinguishing system.

To achieve the required performance when calculating the model, the numerical solution of differential equations is replaced with a model built using artificial neural networks. Thanks to the preliminary long-term learning process of the neural network, computations are accelerated to an acceptable value [2].

The simulation using artificial neural networks also has a number of disadvantages, such as:

– Most frequently, the process of creating a model based on ANN is empirical and does not allow describing the obtained patterns in a formal language;

– A sufficient number of correctly selected datasets is required for training and testing ANN;

– ANN training can take a long time and in the case of unsuccessfully selected parameters it can come to a dead end;

– ANN behavior may not always be unambiguously predictable, which causes corresponding risks.

While modeling physical processes, the main tasks will be optimal selection of the type and parameters of an artificial neural network and gathering of training and test data samples in order to achieve the optimal ratio of the sufficient accuracy of the model and the time spent on training the ANN. But in the case of obtaining the correct construction of the model, it can significantly surpass the classical methods of modeling not only in speed, but also in the accuracy of describing physical process [5], which makes this approach popular and effective.

Conclusions. The implementation of artificial neural networks for modeling physical processes is a promising trend. ANN can be used both independently and in conjunction with other approaches. The main advantages of using ANN are higher speed (in comparison with other methods) for a large number of tasks, and an increase in the accuracy of approximating the model.

The main disadvantages when using artificial neural networks and deep learning are the need for a sufficient amount of labeled data for training, a long training time and the inability to formulate the obtained patterns in a formal language, which makes it difficult to understand the operation of the model and in some cases makes the modeling process unpredictable.

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