Neural network monitoring and predictive control of the reliability and safety of gas distribution networks using deep learning algorithms

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Abstract. The work deals with the development of an algorithmic, mathematical complex based on neural networks of deep learning to assess and predict the reliability and safety of gas distribution equipment based on diagnostic data. The article describes the features of creating a predictive control system within the framework of the CI-TREMS complex. The work describes the algorithms and presents an example of the implementation of the system on one of the nodes of the gas distribution network.

1. Introduction
The relevance of the problem of forecasting undesirable events at gas supply facilities is confirmed by system-related accidents at facilities [1–4], especially at residential facilities, where annually the number of victims is measured in dozens.

Researchers at the Department of Hydrocarbon Resources Transport developed a complex of collaborative intellectual technological reliability and efficiency management of oil and gas systems (CI-TREMS) - a fundamentally new technology of intelligent instrumental neural network engineering control, forecasting and prevention of emergency situations, incidents, accidents, optimization and ensuring the effectiveness of technical solutions in the management of processes of industrial enterprises. [4,5,9-12]

The process of creating analytical and predictive models and methods of the system is associated with the following steps:

1) analysis of the flow scheme of the facility, parameters and characteristics, determination of production features of the project and control of parameters and modes;
2) creation of a diagnostic architecture that allows evaluating the technical state, reliability and safety of the facility and the reliability of technological processes;
3) substantiation of the methodological support of the predictive control system;
4) software implementation of models and creation of a software package;
5) testing and updating the system at a specific production facility.

The CI-TREMS system is modular and multi-tasking, flexible and adaptive, based on the theory of neural network programming, the theory of reliability, cybernetics, system analysis, statistics and probability, and others.

The main objectives of the system are forecasting and preventing emergency situations.

For this, researchers at IUT have developed methodological support using the apparatus of the probability theory and statistics, graph models, neural network technologies and machine learning to evaluate the indicators of technical state, reliability and risk analysis of gas supply system facilities.
2. Problem
One of the important and relevant tasks of the operation of the industrial fuel and energy complex is the
creation of a monitoring system for gas networks.

When implementing a production facility management system for real-time monitoring, prevention
of incidents and accidents at gas supply facilities and increasing the efficiency of decision-making by
personnel, it becomes possible to increase the safety of the system.

Operational experience allows us to identify the main causes of accidents at gas distribution networks
and stations: deterioration of equipment; poor quality of maintenance and repair; pipe metal corrosion;
defects of construction; external influences. Gas distribution networks themselves are a multi-level
complex technical system. At each level, a complex of analytical studies of a technological and
mathematical nature is required, as well as the creation of a diagnostic tool kit.

![Figure 1](image1.png)

**Figure 1.** Explosion of the gas distribution network of a residential building [1,2]

![Figure 2](image2.png)

**Figure 2.** Destruction of gas pipelines of various levels

3. Materials and methods
The system-related problem of ensuring the reliability and safety of transport and storage of
hydrocarbons in real-time is very time-consuming and multifaceted, requires the use of various methods
and models.

Let us consider an example of a predictive system based on deep learning neural networks.
The advantages of using a deep learning neural network include the following:
- ability to handle significant amounts of data;
- ability to learn automatically according to the operational information provided;
- automatic detection of statistically significant factors and their combinations and elimination

The main reasons for reducing the reliability of GDS is the presence of various operational defects,
they are varied and operational services conduct extensive work to prevent and eliminate them. The
most common defects detected are gas leaks (Figure 3) at the nodes. This defect manifests itself as a
result of leaks in threaded and flange joints and worn out mating surfaces of insignificant factors.
Leakage-related defects pose a direct threat to human life and health, and increase the risk of accidents and incidents at hazardous production facilities. One of the main causes of emergencies, as well as the decommissioning of individual sections or entire piping systems, is corrosion. Identified foci of corrosion in the technological cuts of the insulation also provide information on the status of the technological pipelines of the gas distribution system.

![Defect examples](image)

**Figure 3.** Defect examples: a) leaking flange joint; b) nonstandard element; c) foci of pipeline corrosion

| No. of factor | Name of factor (presence of fact, process)                                                                 | Instrumental diagnostic method; normative document                      |
|--------------|----------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|
| 1.           | Corrosion defects                                                                                        | Diagnosis [16]                                                         |
| 2.           | Stress-strain state level                                                                               | Diagnosis [16]                                                         |
| 3.           | Aging of the metal of the pipe, leading to a decrease in strength properties and embrittlement of the metal | Diagnosis [16,17,18]                                                   |
| 4.           | Weld defects                                                                                            | Diagnosis [16,19]                                                      |
| 5.           | Loss of tightness (including gas leakage)                                                               | Diagnosis [16], monitoring                                             |
| 6.           | Electrochemical protection mode and service life                                                         | Diagnosis [16], monitoring                                             |
| 7.           | Poor condition of the insulation coating                                                                | Diagnosis [16]                                                         |
| 8.           | Electrical contact with the supporting structures                                                       | Diagnosis [16]                                                         |
| 9.           | Use of non-standard elements                                                                             | Diagnosis [16]                                                         |
| 10.          | No contact between pipes and supports                                                                    | Diagnosis [16]                                                         |
| 11.          | Thinning elements (tee)                                                                                  | Diagnosis, ultrasound monitoring [16]                                  |
| 12.          | Thinning elements (branch)                                                                               | Diagnosis, ultrasound monitoring [16]                                  |
| 13.          | Thinning elements (coil)                                                                                 | Diagnosis, ultrasound monitoring [16]                                  |
| 14.          | Mechanical damage                                                                                        | Diagnosis [16]                                                         |
| 15.          | Change of geometrical sizes                                                                              | Diagnosis [16], visual and measuring control                           |
| 16.          | Vibration                                                                                               | Diagnosis [20], visual and measuring control                           |
An analysis of production experience and regulatory documentation made it possible to determine a list of groups of factors that determine the reliability of gas distribution stations.

As an example, a 16-factor model of a neural network for implementation in the Python environment is taken as sufficient and necessary for a high-quality diagnosis of the node. Data processing is carried out by three neural networks: the first determines the fact of the incident, the second - the fact of the accident, the third allows you to assess the condition of the object by five levels of danger.

The network consists of an input layer of neurons, the number of which is equal to the number of factors potentially affecting the GDS operation.

![Diagram of a neural network](image)

**Figure 4.** Principle of operation of a neural network
Figure 5. Basic algorithm for the software implementation of a deep neural network

Figure 6. Neural network learning algorithm
As an example, based on the analysis of statistics on breakdowns and accidents, it is enough to single out several levels - from X - normal operation to 1 - accident, or binary - 2 levels of possible states (accident and incident), since they are associated with interruptions in GDS operation. It is assumed that GDS operation is controlled by at least 16 groups of factors (hereinafter in the program code - Factor 1, Factor 2 ... Factor 16). Their number is not crucial and can be easily adjusted. The database can be. Each combination (vector) of the input factors can be associated with several hazard levels: If there are 5 states, then the output layer will have 5 neurons (activated by the softmax function). We will create two three-layer models (one for breakdowns and one for accidents) based on model data. The number of neurons in the first layer is equal to the number of factors (16). The number of neurons of the second layer is taken from 32 to 64 to take into account possible pair and triple interactions of factors. A prerequisite is the import of TensorFlow and the Keras module.

To monitor the learning process, the model displays the minimum information on the learning progress to the console, but often receiving more detailed information in graphical form would be preferable.

To do this, the fit model training method provides a series of information that can be analyzed. We will create the corresponding function and in the future, we will use it on trained models. The function displays the results of training the model in terms of accuracy and error (the first and second window of the graph, respectively) in the form of a graph. According to the presented error graphs, it is possible to determine the optimal number of epochs or the volume of tasks. In our case, the optimal indicator was 5-8 epochs of learning.

A model is created and layers are added to it (input - 16 neurons, hidden - 64 and 16, output - 2). The input and hidden layers are activated by the relu function, the output layer by softmax. Next, the model is compiled. Since Keras provides several optimizers, the most effective one was chosen - stochastic gradient (default parameters, in accordance with the recommendation). The model is trained over seven epochs with a task volume of 32. According to the results, an object for monitoring is presented - history1, which is visualized. An example of visualization graphs for estimating prediction error is presented below.

Figure 7. Program operation algorithm and data streams

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Model accuracy

Accuracy

0.80
0.79
0.78
0.77
0.78

Epoch

1 2 3 4 5 6

Model loss

Loss

0.218
0.217
0.216
0.215
0.214

Epoch

1 2 3 4 5 6

**Figure 8.** Model learning indicators

It can be seen that the accuracy of the trained binary model is very high and amounts to about 90%, which is a good indicator. Models are tested similarly for more states and epochs.

![Technological scheme of GDS](image)

**Figure 9.** Program interface (by nodes)

4. Conclusion

The scientific novelty lies in the development of algorithms and provisions of the state assessment method based on a neural network with deep learning. The use of gas supply in the control system of a production facility for operational control, prevention of incidents and accidents on the basis of continuous analysis of the technical state will improve the safety and reliability of the systems. The use of stochastic models to create neural networks can improve the efficiency of predicting.

The practical value lies in the use of gas supply facilities in the control system of the production facility for operational control, prevention of incidents and accidents based on continuous analysis of the technical state. The presented software package was tested at the production facilities of PJSC Gazprom during the assessment and forecasting of the state and risk analysis of gas supply system facilities.
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