Improving the information veracity of the complex of multiparametric control of the relaxometer based on a neural network

2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE) | 979-8-3503-9952-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/REEPE57272.2023.10086740

Galina A. Ovseenko[1], Rustem S. Kashaev[2], Oleg V. Kozelkov[3]
[1, 2, 3] Kazan State Power Engineering University
[1, 2, 3] Kazan, Russian Federation
[1]galinka.ovseenko@mail.ru, [2]kashaev2007@yandex.ru, [3]ok.1972@list.ru

Tamara K. Filimonova[4], Tatyana S. Evdokimova[5], Aliya M. Mardanova[6]
[4, 5, 6] Kazan State Power Engineering University
[1, 2, 3] Kazan, Russian Federation
[4]filimonova.tamara@bk.ru, [5]evdokimovats97@gmail.ru, [6]mardanova.am@kgeu.ru

***Abstract*— The article deals with studies of measurements of physico-chemical characteristics by a proton magnetic resonance relaxometer by methods of veracity control and operation control. The choice of the neural network structure is justified, the algorithm of training the neural network in the Statistica 10 mathematical package is described according to the following parameters: spin-spin relaxation times, proton population and amplitude of spin-echo signals, which carry out a multiparametric analysis of fluid characteristics in digital intelligent deposits. This article solves the problem of increasing the information veracity of the complex of multiparametric control of the proton magnetic resonance relaxometer as part of the device-software package by developing and applying methods, algorithms and software based on them to evaluate the operating modes of the nodes of the complex of multiparametric control based on the use of artificial neural network technology.**

Keywords*— *neural network, relaxometry, proton, control, parameters

I. Introduction

The application of modern methods of production process management is one of the priority areas for improving the operational efficiency of an oil company, which is achieved by optimizing investment investments, implementing loss management systems and increasing the oil recovery coefficient.

The existing concept of an intelligent field implies the creation of additional profitability of an oil and gas asset by organizing a cycle of data collection, modeling, and decision-making. Actualizes the introduction of an "intelligent field" with control and management of oil production and raw material preparation with express control, automated multiparametric hardware and software complex characteristics of well fluid, oil and water, as well as the environment.

The aim of the work is to increase the veracity of automated multiparametric hardware and software complex measurements by digital methods through neural networks, the main advantage of which is the possibility of training, during which, excluding "misses" and "noises", the relationships between the parameters are determined and a conclusion is made about their veracity [1].

Veracity in physical measurements is one of the main characteristics of the measurement process. It shows the degree of veracity of the measurement result, characterized by the probability that the true value of the measured value is within the specified limits. It is necessary to understand the veracity of measurement results as the veracity of models used in measurements, and the degree of veracity of measurements means their accuracy [2]. The veracity of the measurement control results is characterized by the probabilities of control errors of the 1st and 2nd kind.

In the process of making a decision by the means of control, an error of the 1st kind indicates that the correct hypothesis about the correspondence of the veracity of the measurement was rejected by the means of control, an error of the 2nd kind indicates that an incorrect hypothesis about the unveracity of the measurement will be accepted [3].

The veracity of measurements can be assessed by comparing the readings of duplicate measuring systems. This method has the right to exist, however, if we consider the duplication of the entire measuring instrument, taking into account the cost of components, then the use of the method becomes economically impractical.

Engineering methods can also be used to assess the veracity of measurement data, and data validation and correction are carried out by the measurement systems themselves. Errors in the system, for example, incorrect data collection, their loss during transmission, are tracked at the upper information level according to a set of veracity criteria: comparing the readings per day with the sum of hourly measurements, by the presence of gaps in the read information at the measurement interval, by alarms from the complex, by going beyond the specified measurement limits.

This article introduces the concept of unveracity of measurements of physicochemical characteristics of oil dispersed systems (ODS) - borehole fluid, oil and wastewater by proton magnetic resonance parameters: spin–spin relaxation times T_{2Ai}, T_{2Bi}, T_{2Ci}, proton populations P_{2Ai}, P_{2Bi}, P_{2Ci}, and the amplitudes of the spin-echo signals A_{Ai}, A_{Bi}, A_{Ci}, as the output of the total measurement error δ_i beyond the permissible limits.

One or more properties of ODS can be taken as a δ_i– flow rate, humidity, density, viscosity, dispersed distribution of water and oil droplets.

In most cases, the unveracity of measurements in the proton-magnetic resonance relaxometer unit of the instrument-software complex in the multiparametric method of proton magnetic resonance relaxometry is associated with unintentional or intentional influencing effects on the measurement processes, such as the influence of radiation at a frequency close to magnetic resonance, temperature, drift of microcircuit parameters, subjectivity of the choice of separation points of the envelope of spin signal–secho on exponential components, damage to equipment [4-8].

II. USIND METHODS JF VERACITY AND FUNCTIONING CONTROL

Control of the accuracy of measurements by the proton-magnetic resonance relaxometer as part of the automated multiparametric hardware and software complex is carried out using the method of monitoring the functioning of the measuring system using client-server technology [1].

The client part is located at the location of the instrument and software complex. The server part of the system is located on a personal computer, where the software for monitoring the functioning of the complex is installed.

The most important technical feature of the complex is that the system is provided with group control algorithms, i.e. the ability to measure all (at least three) proton-magnetic resonance parameters and physico-chemical characteristics (PCC). This property is a key condition for the application of methods of group control of the functioning of a complex of multiparametric accounting of influences affecting the measurements of the PMR relaxometer.

The method of operation of the system for monitoring the functioning of the complex of measurements by proton-magnetic resonance-parameters using a neural network is as follows.

A command is sent to the information network to remember the current experimental measurement vectors of PMR parameters:

$$N_{ij}=[T_{2Ai}, T_{2Bi}, T_{2Ci}, P_{2Ai}, P_{2Bi}, P_{2Ci}, A_{Ai}, A_{Bi}, A_{Ci}], \quad (1)$$

where $j= A, B, C$ – molecular phases corresponding to PMR parameters. Multiparameter measurement vector data N_{ij} processed according to the formulas for dividing the envelope of spin-echo signals into components:

$$A_i = \sum A_{0j}\exp\,(-t/T_{2j}),\ \text{где}\ j = A, B, C, \quad (2)$$

$$ln(A_i/A_0) = -t/T_{2i} + lnA_i. \quad (3)$$

Differences in experimental values N_{ij} calculated by equations (2, 3) proton-magnetic resonance parameters with model theoretical values N_{ijT} form the current vector N_{it}:

$$N_{it}=[|A_{2AЭ}-A_{2AT}|,|A_{2AЭ}-A_{2A}T|,|A_{2AЭ}- A_{2AT}||T_{2AЭ} - T_{2AT}|,|T_{2BЭ}-T_{2B}|,|T_{2CЭ} - T_{2CT}|,|P_{2AЭ} - P_{2AT}|,|P_{2AЭ} - P_{2AT}\ |,|P_{2AЭ} - P_{2AT}|,|]. \quad (4)$$

The vector N_{it} is processed by the artificial neural network to determine compliance with the mode of operation of the relaxometer proton-magnetic resonance and output a conclusion about the operation of the relaxometer in the form of a vector N_{out}=["Norm", "Wrong" and "Uncertainty"] [1-5].

The results of the control are displayed on the operator's monitor, and are also stored in the database for further decisions. Monitoring of the state of the automated multiparametric hardware and software complex operation mode is performed by comparing the measured parameters of proton-magnetic resonance relaxation N_{ij} with theoretical values N_{ijT} parameters obtained by approximating the envelope of the spin-echo signal curves for each proton phase. The deviation of the parameters is represented as:

$$\alpha N= (N_{ij} - N_{ijT}) \cdot 100\% \quad (5)$$

It is obvious that the correct functioning of the PMR relaxometer corresponds to the value α N close to zero, and also when| α N |⩽ 3 σ , where σ – standard deviation [8].

III. MATHEMATICFL MODEL

A mathematical model for the normal standard deviation σnorm it was decided to search in the form of a universal power dependence described in [5]. Kramer's method, obtained:

$$\sigma_{norm}= 0,65N^{-0,12}{}_{norm}. \quad (6)$$

To solve the problem of verifying the current multiparameter measurement, the Statistica 10 mathematical package was used, which allows the formation of artificial neural networks of different configurations. Each neural network was trained on the same tasks. To analyze the distribution of vectors of neural network input data, we will select the most informative proton-magnetic resonance parameters.

Modeling of the optimal structure of a neural network is accompanied by the emergence of questions related to determining the number of neurons m in the network, the number of hidden layers n, using the neuron activation function using the neuron activation function f, as well as the network learning algorithm.

In our case, the number of neural network inputs is determined by nine signs represented by real numbers. The task of the neural network is to determine at the output of it the necessary class of the state of the operating mode of the complex in the form of one of three possible nominal variants determined by the vector of output data:

$$Pout= [Pout1, Pout2, Pout3]^T, \quad (7)$$

where:

- *Pout1* = operating mode "Norm";
- *Pout2* = operating mode "Wrong";
- *Pout3* = the mode of operation is "Uncertainty".

A neural network model has been selected to classify the states of the operating modes of the metering units of the complex of multiparametric control of the characteristics of borehole fluid, oil and water.

Due to the fact that the number of features at the input to the neural network and the value of the expected result at the output are known to us, the network architecture is a classic static one [8] for which a learning algorithm with a "teacher" is used.

A neural network of direct propagation without feedback is used because of the simplicity of its implementation and the possibility of obtaining a guaranteed result after passing data through layers. From the point of view of architecture, according to the generalized classification of the neural network, we will have a homogeneous network.

IV. RESULTS

A suitable structure of an artificial neural network will be experimentally determined to solve the problem of monitoring the functioning of a relaxometer and an instrument-software complex.

The choice of the neural network structure will be based on the fact that real data obtained from the complex during its operation is considered. Data vectors containing information about the operating modes: "Normal", "Incorrect" and

"Uncertainty" are fed into different models of artificial neural networks with different numbers of hidden layer neurons.

The neural network model that is best suited will be determined based on:

1) The highest value of classification veracity by the network for all subsamples: training, control, test;
2) Construction of a scattering diagram of target and input variables;
3) Matrix error analysis.

The mathematical package Statistical 10 is used, the data of the states of the modes of operation of the accounting blocks of the complex will be analyzed, for which the statistics of the modes obtained in the laboratory in the amount of n = 1866 are considered.

Using the scheme of statistics t=989 modes "Norm", which was chosen earlier when developing the criterion of veracity of accounting for the instrument-software complex obtained from operation and statistics of the n complex. Several cases corresponding to the operating mode of the instrument-software complex "Norm" were considered. Further, modeling of situations in which the operating mode of the instrument-software complex was evaluated as a "Malfunction" was carried out [1].

Within this framework, single changes in the normal operation of the relaxometer, various variations of incorrect data processing, and the combination of the factors under consideration are considered.

The incorrect scheme of the relaxometer operation and data processing with an error output (SKO) beyond the limits are also considered 3σ, in which the veracity of monitoring the characteristics of the downhole fluid and oil is not ensured, the state of the operating mode of the relaxometer of the complex is assessed as "Uncertainty".

Data from archives were used to create multiparametric input vectors. It is necessary to form a training set for a neural network with the maximum inclusion of possible errors, since this increases the veracity of verification.

Let's compare two possible application strategies – a multilayer perceptron (MLP) with an N-P-M structure, where N is the number of input neurons, P is the number of hidden layer neurons, M is the number of output neurons and the radial basis function [10].

For both architectures, it is necessary to build at least 10 single-layer structures with different numbers of neurons in the hidden layer.

The intermediate results of building neural networks are shown in Table 1 and in "Fig 1" below, which indicate the architecture of the model and the veracity of the network classification. By the veracity of the classification, we will understand the percentage of correct control of the functioning of the multiparametric accounting complex for a multilayer perceptron (MLP).

The analysis of the table and graph shows that the most suitable architecture for building a neural network to solve the problem of controlling the functioning of the complex is a multilayer perceptron and the two best structures are shown in Table 2, which showed winning learning results on all subsamples.

For control, the structure of MLP 9-6-3 is less complex in architecture and therefore is preferable for verifying the operating modes of the complex.

For the considered artificial neural network, the best result was shown by the iterative learning algorithm BFGS and the activation function of neurons of the hidden layer – identical.

When making a choice in favor of using the most appropriate method, it is necessary to compare methods based on the classical theory of mathematical statistics and an artificial neural network. The advantages of one control method over another should be based on the use of the same statistical data, as in the case of training an artificial neural network with a 9-6-3 MLP structure [13].

The proof of the normal distribution of a statistical sample of data implies that the statistical elements must belong to one class, in our case, the class of the operating mode of the multiparametric control complex "NORM". In turn, the training of an artificial neural network assumes that data belonging to different classes should be fed to its inputs.

This means that in order to obtain a correct conclusion about the operating mode of the instrument-software complex, in addition to the available statistics obtained from systems in operation, it is necessary to use data from the states of the "Malfunction" and "Uncertainty" modes for network training, which can be obtained in laboratory conditions.

TABLE I. TABLE NEURAL NETWORK TRAINING RESULTS

Network ID	Architecture	Learning Performance	Test training performance	Learning algorithm	Error functions	Function activation of neurons of the hidden layer
6	RBF 9-3-3	0.54063	1.0	RBFT	Sum of squares	Gaussian
7	MLP 9-6-3	0.87354	1.0	BFGS	Sum of squares	Identical
8	RBF 9-2-3	0.58808	0.0	RBFT	Sum of squares	Gaussian
9	MLP 9-8-3	0.66731	0.0	BFGS	Sum of squares	Identical
10	RBF 9-2-3	0.25928	0.0	RBFT	Sum of squares	Gaussian

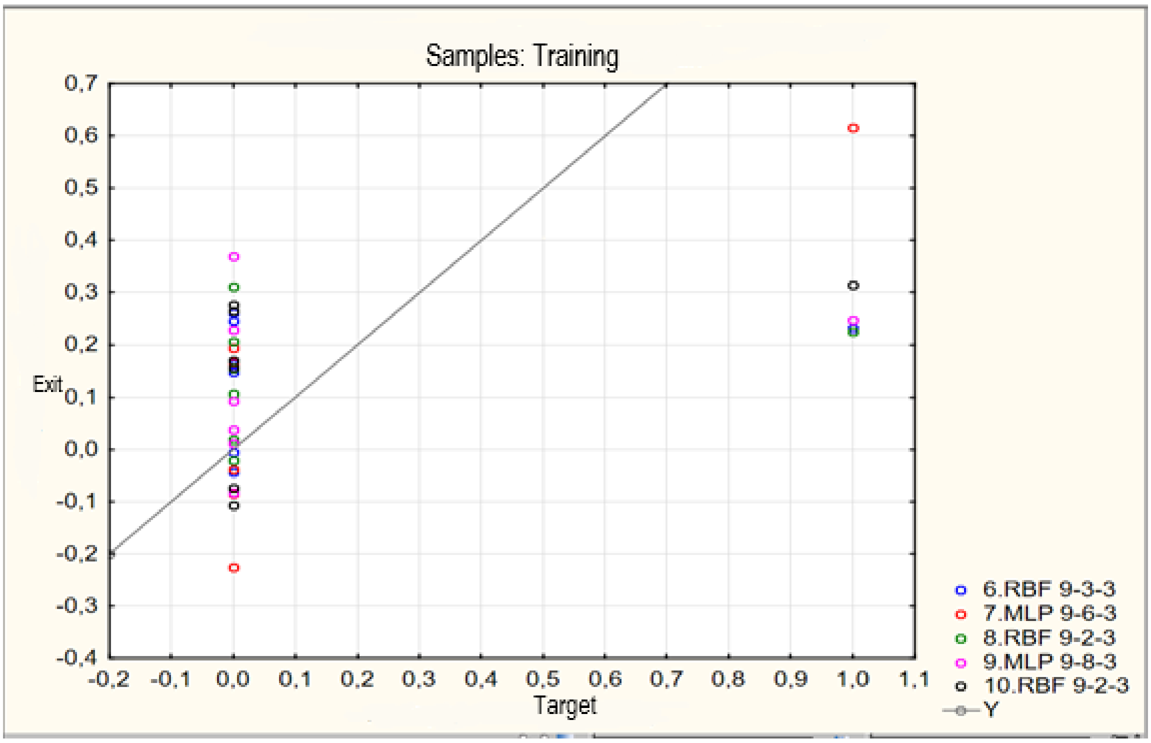

Fig. 1. Neural network training with MLP and RBF architecture

TABLE II. TABLE THE MOST SUITADLE MLP STRUCTURES

Network ID	Architecture	Learning Performance	Test training performance	Learning algorithm	Error functions	Function activation of neurons of the hidden layer
7	MLP 9-6-3	0.87354	1.0	BFGS	Sum of squares	Identical
9	MLP 9-8-3	0.66731	0.0	BFGS	Sum of squares	Identical

V. CONCLUSION

The possibilities of using multiparametric data read from the sensor of the proton-magnetic resonance relaxometer in determining the operating modes of the relaxometer and their use as input signs for verifying the operating modes "NORMAL", "MALFUNCTION" and "UNDEFINED" are considered. A method for monitoring the functioning of a multiparametric control complex based on the theory of artificial neural networks is proposed. The type of the selected artificial neural network, its architecture, the number of neurons at the entrance, in the inner layer and at the exit from the network, the methods of network training, the use of the activation function identical, in order to obtain a reliable classification by the network are substantiated. The results of verification of trained neural networks are compared to solve the problem of determining the modes of operation of the metering units of the complex of multiparametric metering of distributed energy consumption, it is shown that a neural network with the multilayer perceptron type gives a higher result compared to the radial basis functions (RBF).

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