EVALUATION PROCEDURE OF TECHNICAL CONDITION OF DEEP DRILLING EQUIPMENT WITH USE OF NEURAL NETWORKS[1]

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This paper is dedicated to the deep drilling equipment technical condition evaluation problems. A new method is based on one of directions of an artificial intellect, biological foundations of the natural intelligence and allows to project systems, capable of training and self-organizing without a master on the basis of the images acting on a neural network that enables to adapt a network for a solving problem.

INTRODUCTION

Recently wider application is discovered with the methods of synergetics, giving a possibility to describe processes in complicated systems of various natures with the help of some universal models. Researches of last years show that appearances in spheres with a complicated unregulated structure frequently discover scale invariance (fractality) of spatial-time properties. On this basis some common engineering systems modeling and diagnosing methods can be produced.

For example, it is known that time series plot diagrams of samplings, read at normal work of complicated plants, frequently have fractal structure (like coastal lines). Therefore, academician A.H. Mirzadzhanzade has suggested using fractal performances of time series plot diagrams of samplings (dimension of Hausdorff, Hurst index, correlation dimension) as diagnostic criteria, defining a control plants' status.

By analyzing time series plot diagrams of samplings, the technological well drilling parameters, it is possible to see their fractal structure that most likely is a consequence of the spatial-time phenomena accompanying this process. We offer a specific example of the technological situation accompanying the process of a well drilling in which fractal performances application allows receiving practically important information based on normal operation, i.e. without carrying out of active experiment.

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PROPOSED METHOD

Today practically all drilling rigs incorporate automated mud logging stations (AMLS) of drilling technological geological and geophysical (a density, a porosity, fluid conductivity of well, hole drift angle, etc.) parameters monitoring. The ground and downhole autonomous measuring system cite data, after preliminary processing and digitization are entered in the specialized computer through the coordination unit, where on the set algorithms data processing and inference are made.

For more information on a deep equipment condition it is necessary to connect the unit consisting of the low-frequency digital filter, ADC and computer interface device to monitoring system already available on AMLS. The unit connection allows producing the necessary analysis on the algorithms developed by us and various estimation criteria of the equipment condition application programs.

The methodical manual is developed and introduced at the drill works of Western Siberia, Far North and JOC "Bashneft" for practical implementation of such equipment condition monitoring system. A disadvantage of the suggested equipment condition monitoring system is that under the given conditions on AMLS there is no possibility to simultaneously conduct the analysis by all criteria. First, the operator determines value of one criterion, and then it is necessary to make adjustment of the system to another, etc.

We offer the monitoring system which uses some generalized index as output parameter. One of directions of an artificial intellect lays in its basis, viz. construction of the networks consisting of neural elements. This direction is based on the biological foundations of natural intelligence and allows to project systems, capable of training and self-organizing without a master on the basis of the images acting on a network that enables to adapt a network for a solving problem. The neural Kohonen networks widely used in optimization and control pattern recognition tasks, relate to such networks.

The demo program in ‘C’ (gcc 2.95.2 compiler) is presented as an example of the neural network operation. It is intended for solution of the equipment condition recognition task on the digitized technological drilling parameters recording data.

The set of constants and matrixes is used at the network implementation for its common parameters determination (such mode of neural network programming refers to "matrix" or "classical"). The initial values are appropriated to weights of a network at the beginning of its training. It is necessary to take into account that filling of weights proceeds from requirements of a protuberant combination method.

The first step of training is the initialization of the check-array in which the data are stored, allowing defining when it is necessary to stop training process. The number of a neuron which "has won" for a class with number equal to a column index in array is stored in the first line of array. The number of advantages is in the second line. If it will exceed **L** for all classes so training stops. The normalization of entering values is made during the training.

The following step is the determination of each neuron weighed sum.

Next neurons outputs and the neuron-"winner" are determined. Then the neuron-"winner" weights are corrected. Training initial rate value and magnitude, which affect its rate of change, are manually selected.

The last step is the successively recognized images quantity determination. Training will be carried out until every image will be successively recognized ***L*** times.

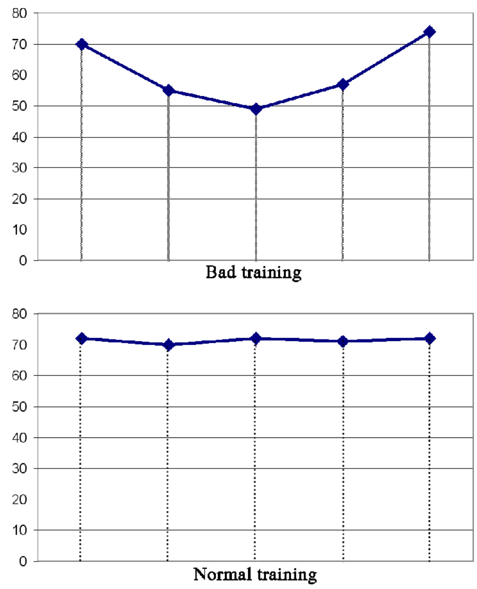

Figure 1. The Kohonen network training quality estimation by the histograms form of the correct classifications amount

After the training completion the network is ready to work. The recognition process is similar to training in many respects. For the operation beginning it is necessary to give a classified vector to inputs. After that it is necessary to find neuron-winner's number – it is a recognition result. Algorithmically the network efficiency check process completely repeats separate train levels.

Sometimes it is useful to observe some network operation parameters during work deducing them on a histogram. Output values of neurons and the amount of correct classifications relate to such parameters for each class. It is possible to define the quality of network operation by the nature of the modification. This is especially important, when the network is used for solving real, production problems which are usually characterized by a long training period.

The indication of successful network training is the wide spread in the magnitudes with dominance of one neuron output for each input vector for a histogram of output neurons values. The spread should increase during the training; however, if it goes too slowly it is necessary to stop training and try to adjust network parameters. Histograms of output values could help to check an already trained network. If at indications of some class feeding to the vectors input one neuron is activated greater than others, the further recognition quality check for the given class can be excluded.

Histograms of the correct classifications amount for each class can also help understand the work training success. If one or several columns are lower than others, their values are often counted as zero. It indicates that the training process goes badly.

These diagrams' appearance helps to estimate the quality of network training at first approximation after its completion. If the spread in the length of the diagram columns isn't great, the network is trained normally. If some columns noticeably are shorter than others, most likely some classes will be badly recognized (Figure 1).

Table 1

The results of network training for a first well

	K_1	K_2	K_3	K_4	K_5
D_1	2.082801	0.290144	5.312719	2.87	61
D_2	2.073179	0.234897	8.834877	0.85	55
D_3	2.642142	0.230787	3.177501	0.43	46
D_4	2.817404	0.171277	3.108624	0.36	24
D_5	3.004035	0.008657	3.029995	0.38	10

Histograms of the correct classifications amount for each class can also help understand the work training success. If one or several columns are lower than others, their values are often counted as zero. It indicates that the training process goes badly.

We shall consider the evaluation of a drilling bit status by technological parameters recordings of drilling (pressure and bit weight) as an example at boreholes №30569 and №30570 Nizhnevartovsk DD-2 with the techniques discussed. In Figure 2 there is a neural network variant of the deep drilling equipment condition estimation.

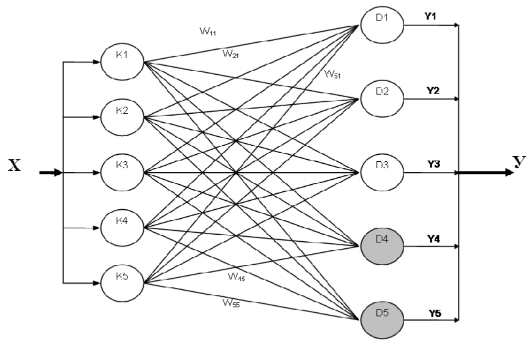

Figure 2. The neural network variant
of the deep drilling equipment

Neural network operation begins with determination of required criteria or classes amounts – K_i. There are five criteria used for offered variant of NN: entropy, Jinny coefficient, a variance, a spectrum and wavelets. The amount of indications on which the recognition or

classification of a bit status D_i will be carried out is determined: D1 – the serviceable drilling bit, equipment wear "C" =10 %, support gap "P" up to 1 mm; D_2 – "C" =10-40 %, "P" up to 2 mm; D_3 – "C" =40-60 %, "P" up to 3 mm; D_4 and D_5 correspond to a preemergency status. The analyzed X-signal feeds on inputs of criteria, for example, liquid pressure oscillations or axial load. Trained neural network allows getting the status number $Y \in D_i$ describing a fact bit status at output.

The results of network training for a standard well (first drilled borehole №30570 at the cluster 769) are presented in **Table 1**. The greatest values of the criteria corresponding to certain images are established for each bit status (indication). Then the greatest values obtained for each pair «class - neuron» are used for comparison with the values obtained during the subsequent drilling, and thus the evaluation of flowing bit state goes.

The results of a neural network operation for five intervals at the following borehole №30569 drilling same cluster are presented in Figure 3. The network operation analysis has shown that the maximum bit wear has been reached at drilling the fourth and fifth intervals.

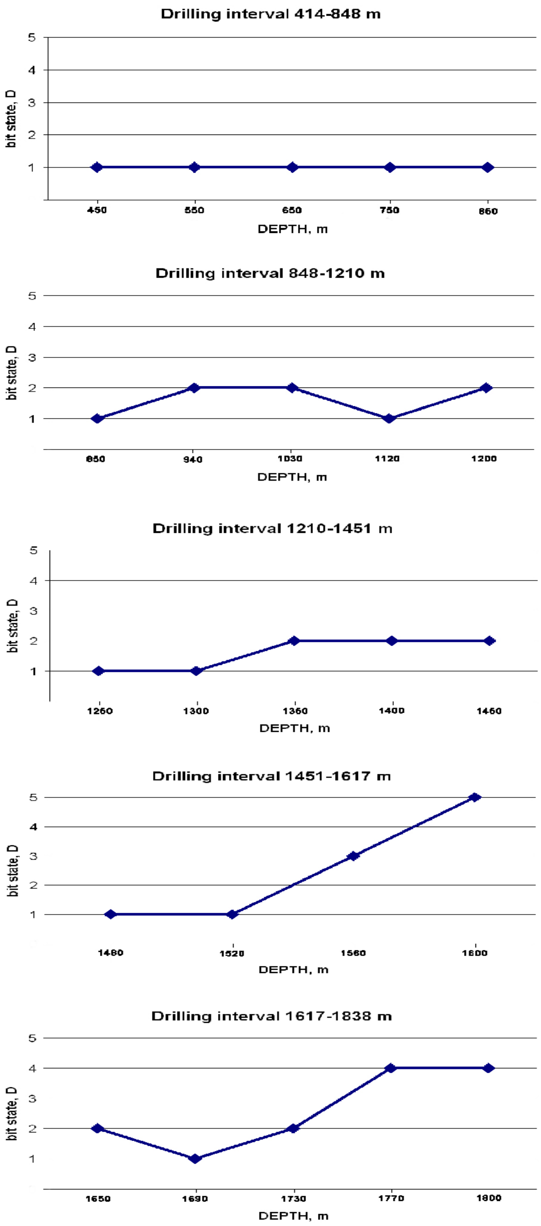

Figure 3. The result of a neural network operation for five intervals

Apparently, at the first slotting generalized index values during the neural network operation were classified not exceeding than one that corresponds to a minimum bit wear – $В_1П_2$. At the second and third drilling intervals generalized index values have not exceeded value "2", and the network recognized a bit status for 9 and 6 times accordingly, and the actual bit wear becomes – $В_2П_3$. At the fourth slotting, on depth of 1600 m, network has recognized the bit status of $В_4П_3$, classifying it as the fifth preemergency status - D_5. And at the fifth interval, on depth of 1800 m, the bit status has been recognized according to classification as the fourth and has not varied up to the end of drilling, and the actual bit status becomes $В_3П_3$.

CONCLUSIONS

The developed deep drilling equipment technical condition evaluation system is based on the images classification acting to the neural network, as output parameter is used the generalized index joining to the network operation some of diagnostic criteria. This networks type can find an application in other areas of oil extraction concerned with pattern recognition, their classification, by optimization and that's input data can be presented in a digital sort.

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