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Drilling Problems Forecast System Based on Neural Network

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Summary

Optimization, digitalization and robotization of oil and gas technological processes based on the use of artificial intelligence methods are among the prevailing trends of the 21st century. The drilling industry is a prime example of these phenomena. The vector of oil and gas drilling is shifting towards complex objects. The improvement of well drilling technologies allows drilling in geological conditions where it was previously impossible. The construction of wells leads to disruption of the natural thermodynamic and stress-strain state of rocks. It is necessary to take into account all the processes occurring in the well and the near-wellbore zone during drilling for the timely recognition of the onset of various complications and accidents. The average time to eliminate complications and accidents is 20-25% of the total well construction time. The task of reducing this indicator is highly relevant. To solve this problem, the most modern technologies are involved, including machine learning algorithms. The main difficulties encountered when using these technologies are the requirements for artificial neural networks for the minimum necessary number of complications or their representable set for the correct "training" of these networks. This report describes how this problem was solved using a full-scale drilling simulator. The drilling simulator makes it possible to recreate a digital twin of a real well and simulate an almost unlimited number of complications of various kinds on it. This approach allows you to create a sample of the required size for the most efficient training and testing of neural network algorithms. Three groups of complications (stuck-pipe or sticking, loss circulation, kick or gas-oil-water occurrence) and standard drilling operations were simulated to minimize the number of false alarms. A total of 86 experiments were modeled, which were then processed using neural network algorithms. The study revealed that the model of an artificial neural network for predicting future manifestations of complications in the form of the "kick or gas-oil-water occurrence", due to its complexity, is trained more efficiently when using not only the input values of drilling parameters, but also the output results of some auxiliary machine learning models. The latest models are trained to solve both regression problems of the indicator function with the model setting to track changes in certain parameters, and the problem of identifying abnormal situations during drilling in real time. When this module trains

an artificial neural network model to detect a pre-accident situation of "kick or gas-oil-water occurrence", the following results were obtained for accuracy: accuracy – 0.89, weighted average f1-score – 0.86. The developed system informs the driller about a possible complication with high accuracy, which allows him to avoid it or minimize the consequences.

Introduction

Well construction accounts for over 40% of all investments in oil and gas production. The vector of oil and gas drilling is shifting towards complex objects and deep sea depths. Well construction leads to disruption of the natural thermodynamic and stress-strain state of rocks. Wells are the main part of fixed assets in the developed oil and gas fields. The cost of drilling wells tends to rise, and drilling complications are becoming increasingly undesirable. Reducing the loss of drilling time to eliminate complications and their consequences is one of the possibilities for increasing the productive drilling time, including through the use of automated systems for preventing complications and emergencies during well construction using artificial intelligence and machine learning methods.

In the process of well construction, for reasons related to natural and man-made factors, various complications and accidents arise. Complication should be understood as the difficulty in deepening the well caused by violations in the well structure, the causes of which are various natural and man-made factors. Complications that arise are traditionally considered expected factors. To prevent them, a well-established complex of technological methods are provided. For various reasons, violations of the technological process of well construction often become accidents. Accident - a sudden general or partial damage to equipment, wells, structures, various devices, accompanied by a disruption of the production process, loss of mobility of the pipe string or its breakage with the abandonment of pipe string elements in the well, as well as various objects or tools, which require special work to be removed. It is much easier to eliminate the complication at an early stage of its development. One complication entails another, and such a chain of complications makes it difficult to eliminate them. At the same time, the main types of complications are: sticking of the drill string as a result of talus and collapse of unstable rocks, narrowing of the wellbore by crumbling rocks; absorption of drilling mud, gas-oil-water showings and brine showings. The share of major complications is more than 85% of the total number of recorded complications; at the same time, in the annual balance of non-productive costs, the share of costs for their elimination is from 5 to 25% of the cost of well construction.

The most significant investment of time is spent on dealing with complications associated with the violation of the integrity of the wellbore, which are noted during the entire deepening of the well. The variety of causes of this type of complications and their relationship requires a whole range of measures to prevent them (Aldamzharov, 2017). Most of the reasons act in a differentiated manner, that is, they are the result of not one, but several types of geological complications. The alternating loads experienced by the drill pipe string and its elements during drilling are largely transferred to the near-wellbore space, thereby contributing to the loss of stability of the wellbore, cavity and groove formation, curvature of the well path and destruction of the core.

Among the accidents, the main place is occupied by the sticking of the drilling tool due to the effect of pressure drop in the zone of permeable rocks and jamming of the drill pipe string, as well as casing strings collapse due to the plastic flow of rocks. According to statistics, stuck-pipe or sticking account 37% of the total number of complications. The time spent on their elimination is almost 50% of the total time to deal with complications.

According to world statistics, up to 40% of kick or gas-oil-water occurrence during drilling in difficult conditions are associated with problems of wellbore stability. Complications associated with the stability of the borehole walls can lead to gas-oil-water occurrence, loss of circulation, collapses, sticking, loss of tools and equipment, as well as the need to re-drill the well. The success of the application of technologies for the elimination of kick or gas-oil-water occurrence is less than 30%.

Loss of drilling fluid is associated with the flow of drilling fluid from the wellbore into the rock formation. Elimination of complications in the form of absorption depends on the method of assessing the causes of absorption and the choice of the most appropriate way to eliminate them. Various types of chemical agents are used to eliminate the loss of drilling fluid: swellable chemical agents, hydrogel fillers, low-density chemical solutions, bridging agents, bridging agents. There are three types of complications of loss of drilling fluid: natural open cracks in the rock; man-made cracks, which were created due to the pressure of the drilling fluid on the rock matrix; natural large caverns formed in the process of rock leaching and possessing structural strength.

Drilling companies are facing complications in the form of "loss circulation" in all oil and gas provinces in Russia and the world. Catastrophic losses during well construction in Eastern Siberia are associated with the Triassic, Carboniferous, Even and Angarsk formations and are associated with the opening of structural cavities, in which many-meter holes are observed during drilling. The probability of opening the zone of partial or catastrophic "loss circulation" is approximately 80%. The use of conventional methods of prevention of losses (drilling with low-density muds, the use of bridging agents, bridging agents, fibrous and flake fillers) has shown to be ineffective. The main types of complications lead to long, costly downtime and significant financial costs for their elimination and elimination.

In recent years, a number of works have been published on the creation of automated systems for preventing complications during well drilling (Eremin et al., 2020). The introduction of automated systems for preventing complications during drilling can significantly increase such an indicator of drilling efficiency as productive drilling time from 30 to 45%. Arnaout et al. (2013) presented an intelligent model for data quality control in real-time operating centers. Macpherson et al. (2013) described current state, initiatives and potential impact of drilling automation systems on the efficiency of well construction. Peng et al. (2014) described a real-time warning system for identifying drilling accidents. Lind and Kabirova (2014) presented the artificial neural networks for drilling troubles prediction. Unrau et al. (2017) described machine learning algorithms applied to detection of well control events. Noshi and Schubert (2018) described data mining algorithms and industry applications from a predictive analytics standpoint using supervised and unsupervised advanced analytics algorithms to identify hidden patterns and help mitigate drilling challenges. Antipova et al. (2019) developed the machine learning model for the drilling accidents prediction based on gradient boosting decision trees. Rodrigues et al. (2020) presented real time drilling problem detection software in deepwater environments.

Below are works devoted to the multicriteria analysis of pipe sticking during drilling and the use of artificial intelligence methods to prevent them. Hempkins et al. (1987) performed the multivariate statistical analysis of stuck drillpipe situations. Weakley (1990) analyzed 600 wells from the Gulf Coast differential and mechanical sticking. Miri et al. (2007) developed artificial neural networks to predict differential pipe sticking in Iranian offshore oil fields. Murillo et al. (2009) presented a study of the application of the concepts of fuzzy logic to the problem of differentially stuck pipe. Jahanbakhshi et al. (2012, 2014) developed a novel support-vector machine approach to predict a differential pipe sticking occurrence in horizontal and sidetracked wells in Iranian offshore oil fields. Naraghi et al. (2013) described the prediction method for drilling pipe sticking by using active learning method. Goebel et al. (2014) invented the method and system for predicting a drill string stuck pipe event. Ferreira et al. (2015) developed automated decision support and expert collaboration system to avoid stuck pipe and improve drilling operations in offshore Brazil subsalt well. Salminen et al. (2017) described a real-time method for stuck-pipe prediction by using automated modeling and data analysis. Zhang et al. (2019) developed a novel method for real time stuck pipe prediction by using a combination of physics-based model and data analytics approach. Alshaikh et al. (2019) described the machine learning method for detecting stuck pipe incidents based on data analytics and models evaluation. Shaker and Reynolds (2020) described kicks and blowouts prediction before and during drilling in the over-pressured sediments.

In the last two years, research and development work on the creation of automated systems for preventing complications such as "loss circulation" has intensified. Moazzeni et al. (2010) described Virtual Intelligence method to predict the Lost Circulation in One of Iranian Oilfields. Jahanbakhshi et al. (2014) presented artificial neural network-based for prediction and geomechanical analysis of lost circulation in naturally fractured reservoirs. Al-Hameedi et al. (2018) described Machine Learning approach to Predict Lost Circulation in the Rumaila Field, Iraq. Alkinani et al. (2019) described Prediction method of Lost Circulation Prior to Drilling for Induced Fractures Formations Using Artificial Neural Networks. Hou et al. (2019) presented Automatic Gas Influxes Detection system in Offshore Drilling Based on Machine Learning Technology. Geng et al. (2019) described the seismic-based risk system to predict the lost circulation using machine learning. Abbas et al. (2019) described implementing artificial neural networks and support vector machines to predict lost circulation. Sabah et al. (2019) described application of decision tree, artificial neural networks, and adaptive neuro-fuzzy inference system to predict lost circulation. Abbas et al. (2020) presented two different techniques of artificial intelligence (radial basis function and support vector machine) to predict the lost circulation zones in real time. Hou et al. (2020) described one of the first attempts to predict lost circulation using data-analytics and artificial intelligence while well drilling in South China Sea.

The following articles construct systems for detecting kick troubles based on statistical tools and machine learning technologies. Wylie and Visram (1990) evaluated the probabilities of kick occurrence for land wells in Alberta, Canada. Adams et al. (1993) described kick volumes for the development and exploratory wells of BP. Tallin et al. (2000) estimated probability occurrence of kicks and their magnitude for exploratory wells in Sultanate of Oman. Dedenuola et al. (2003) developed a comprehensive stochastic kick model using data from Shell wells at the Niger Delta. Mason and Chandrasekhar (2005) developed probabilistic models for kick volume, and intensity using data from various wells around the world. Yin et al. (2019) described intelligent early kick detection system in ultra-deepwater High-Temperature High-Pressure (HPHT) wells based on Big data technology. Yang et al. (2019) presented advanced real-time gas kick detection using machine learning technology.

Timely forecasting and prevention of complications is an extremely important and urgent task that requires the use of modern engineering methods and approaches. To achieve the set goals, it is necessary to solve the following key tasks:

1. Development of a classification of complications and pre-emergency situations during the construction of oil and gas wells for the use of machine learning technologies and artificial neural networks.
2. Simulation of the selected complications on a drilling simulator for the purpose of training the neural network.
3. Analysis of the results of the neural network algorithms for predicting complications and pre-emergency situations.

Classification of complications

World experience shows that practically the construction of all wells is accompanied by complications of various types and nature. Complications in the drilling of oil and gas wells include disruptions in the continuity of the technological process of well construction in compliance with the technical design and the rules for accident-free drilling operations, caused by the mining and geological conditions of the rocks being penetrated. The main types of complications are: absorption of drilling flushing and grouting solutions, kick or gas-oil-water occurrence, talus and collapse of unstable rocks, brine showdown. The key complications during the construction of wells in permafrost are: thawing (destruction) of frozen well walls; the occurrence of rock falls; poor quality cementing of wells in the permafrost strata; collapse of casing pipes (Podgornov and Efimenko, 2017). The main factors affecting the manifestations of complications during well construction are given below.

Geological factors: thermobaric conditions in the well (increased reservoir temperature, reservoirs with abnormally high reservoir pressure and anomalously low reservoir pressure, complicated intervals), tectonic disturbances, reservoir properties and the degree of its heterogeneity, the position of productive layers in relation to the bottom and reservoir waters.

Technical and technological factors: wellbore condition (intervals of manifestations and losses, vugs, borehole curvature and kinks, filter cake thickness); the quality of information based on the results of geophysical studies of wells, the design of the casing and the composition of the technological equipment (gap size, length and diameter of the columns, arrangement of technological equipment); drilling mud materials (composition, physical and mechanical properties, corrosion resistance); technological parameters of cementing (volume and type of spacer fluid, upward flow rate, reciprocation and rotation of columns); the level of technical equipment of the cementing process.

Organizational factors: skill level of the members of the drilling crew; the degree of compliance of the drilling process with the technological regulations for well construction.

For the application of models based on neural network algorithms, a method for classifying complications and accidents in drilling was developed. All complications and accidents were divided into three classes, depending on the possibility of using neural network algorithms [3, 4]:

1. Complications and accidents, for the detection of which it is possible to use neural networks;
2. Complications and accidents, the detection of which requires a longer training on the data of a specific section and / or manual input of additional data at a given frequency;
3. Complications and accidents, for the detection of which it is impossible to use neural networks

Possibilities of using neural network algorithms for different types of accidents and complications are presented in Table 1.

Table 1—Application of neural network algorithms for different types of accidents and complications.

Complication / accident	Recorded sign of complication / accident	The nature of the change in the complication / accident sign	The possibility of using a neural network to prevent an accident / complication (1 - possible; 0 - impossible; 0.5 - requires longer training on the data of a particular zone and / or manual input of additional data)
Instable hole	Pump pressure	Sudden increase	1
	Cutting transport	Increase the shape, size and amount of cuttings	0.5
	Impossible to tag bottom	Hookload reduction when lower down	1
	Hookload	Hookload increase during hoist up and reduce during the lower down beyond the allowable intervals	1
Swelling	Hookload	Hookload increase during hoist up and reduce during the lower down beyond the allowable intervals	1
	Impossible to tag bottom	Hookload reduction when lower down	1
	Hoolload	Sudden decrease	1
Key-seating	Tight holes and drags	Hookload increase during hoist up and reduce during the lower down beyond the allowable intervals	1

Complication / accident	Recorded sign of complication / accident	The nature of the change in the complication / accident sign	The possibility of using a neural network to prevent an accident / complication (1 - possible; 0 - impossible; 0.5 - requires longer training on the data of a particular zone and / or manual input of additional data)
Drilling fluid loss	Drilling fluid flow out	Drilling fluid flow outis less than flow in	1
	Mud level in active tanks	Decrease	1
Water, oil and gas influx	Mud flow rate out of the well	Drilling fluid flow out is higher than flow in; including overflow with pumps stopped	1
	Mud level in active tanks	Increase	1
	Gas content	Increase in drilling, increase when circulation is restored	1
	Volume in trip tank	Decrease compared to the estimated volume of drilling fluid, during hoist up operation	1
	Volume in trip tank	Increase compared to the estimated volume when lower down	1
	Pump pressure	Decrease	1
	Rate of penetration	Increase	1
	Rotary torque	Increase	1
	Drilling cuttings size	Increase	0.5
	Drilling fluid outlet temperature	Decrease	1
	d-exponent	Decrease	1
Balling	Shape and size of cuttings	Dense cuttings and pieces of filter cake	0.5
	Flow rate of drilling mud	Drilling mud overflow at the wellhead while POOH	1
	Pump pressure	Increase	1
	Hoo load	Decrease	1
	Rate of Penetration	Decrease	1
Accidents with drill string elements	Hookload	Decrease	0
	Pump pressure	Decrease	0
Drill string and casing sticking	Difference in drill string weight and hook load	decrement while POOH, increment while RIH	1
Sticking with cuttings	Torque	Increase	1
	Axial weight while POOH	Increase	1
	Pump pressure	Increase	1
	The amount of cuttings in shale shakers	Decrease	0
Stuck with instable hole	Torque	Increase	1
	Axial weight while POOH	Increase	1
	Axial weight while RIH	Decrease	1
	Pump pressure	Increase	1
Differential sticking	Difference in drill string weight and hook load	Decrease while POOH, increase while RIH	1

Complication / accident	Recorded sign of complication / accident	The nature of the change in the complication / accident sign	The possibility of using a neural network to prevent an accident / complication (1 - possible; 0 - impossible; 0.5 - requires longer training on the data of a particular zone and / or manual input of additional data)
	Inability to rotate the drill string	Increment to the maximum allowable	1
Stuck with metal debris	Torque	Unexpected and fickle vibrations	0
	Hookload	Unexpected and fickle vibrations	0
	Tools or equipment on the rig site	Absence	0
Bit accidents	Rate of penetration	Drop	0
	Torque	Abrupt change	0

Based on the results of the analysis of accidents and complications during the construction of oil and gas wells, a method for classifying complications and accidents according to the degree of applicability of neural networks is substantiated. It was decided to carry out further studies for the following selected complications: kick or gas-oil-water occurrence; loss circulation; sticking of the drill string due to accumulation of cuttings in the deviated section of the well.

Planning an experiment on a drilling simulator

One of the difficulties in using neural network algorithms to prevent complications is the need for preliminary training of this algorithm. Tens and hundreds of examples are usually required for training. There are not so many complications in drilling wells, but their elimination takes a lot of time. The limited number of complications occurring in real wells in comparison with the time of standard drilling dictates the need to use full-scale drilling simulators for their simulation.

The small number of complications that actually occur during drilling is not sufficient for proper training of the neural network. The neural network must recognize quite rare events, but the cost of each error can be very high. A drilling simulator was used to fill the gap in the number of emergencies. The full-scale drilling simulator DrillSim-5000 allows you to simulate all types of work that are performed on a drilling rig, including technologies to prevent complications and accidents during well construction. The main feature of the simulator in comparison with a real well is the ability to simulate various complications in an amount sufficient for training a neural network.

Simulators have been used for many years for preliminary preparation for drilling a real well, for training drilling crews, and for developing contingency plans. Paper Blikra et al. (2014) describes how the simulator allowed the engineering team to refine the drilling program prior to operations. The Managed pressure drilling (MPD) system and various contingency options were tested. Drilling contractor, operator and Managed pressure drilling (MPD) contractor agreed on the sequence of work, communication methods and best practices before starting work. Decision trees have been updated. In article Rommetveit et al. (2007) describes how the simulator is used to simulate and analyze real data from the rig. The simulator has the ability to visualize the real drilling process and a decision support system. Tang et al. (2016), Odegard et al. (2013) presented virtual well simulator used to predict complications such as stuck-pipe or sticking, loss circulation, kick or gas-oil-water occurrence, and many others. The functionality of the DrillSim-5000 simulator allows you to make a well model as close as possible to the actually drilled well. To build such models, wells drilled in the Volve field were analyzed. The analysis of the well trajectories showed that out of 10 wells for which detailed data are available, 4 wells have a tangential profile, 3 wells have a j-profile, 2 wells have an s-profile and one well is vertical. The side trunks are also built according to one of the listed profiles. All profile types used on Volve were taken into account when planning the experiment. In the course of work on the project, a model of the well was built for the Volve 15/9-F-10 field during the production casing drilling phase. The main parameters of the well are as follows:

Messured depth / True vertical depth: 2620/2295 meters.
Intermediate column diameter: 508 mm.
Depth of running the intermediate casing along the borehole / vertical: 1389/1351 meters.
Open hole diameter: 444.5 mm.
Drilling fluid density: 1.51 kg / 1.
Drilling fluid type: oil based.
The plastic viscosity of the drilling mud: 10 cP.
Drilling fluid dynamic shear stress: 9.58 Pa.

Parameters common for all types of well profiles are shown in Table 2.

Table 2—Geometric parameters of the well.

1. General parameters of the well	
Parameter	Value
Rotor table altitude, m	9
Depth of previous casing running, m	1389
Liner running depth, m	0
Open hole diameter, mm	444,5
True vertical depth of the point of beginning of curvature, m	325
The messured depth of the well bore, m	2620
2. Parameters of the drilling site for the tangential profile.	
Parameter	Value
Angle of curvature of a section of a set of curvature, °	45
Curvature gain, °/30 m	0,75
Stabilization section length, m	500
True vertical depth, m	2295
3. Parameters of the drilling site for the S-shaped profile.	
Parameter	Value
Angle of curvature of a section of a set of curvature, °	85
Curvature gain, °/30m	0,75
Stabilization section length, m	1300
Curvature angle of the curvature drop section, °	45
Curvature drop rate, °/30m	0,7
True vertical depth, m	2255
4. Drilling section parameters for a horizontal profile	
Parameter	Value
Angle of curvature of a 1st section of a set of curvature, °	45
Intensity of 1st set of curvature, °/30m	0,75
Stabilization section length, m	500
Angle of curvature of a 2nd section of a set of curvature, °	90
Intensity of 2nd set of curvature, °/30м	0,6

True vertical depth, m	2255

In order to generate a training sample for the neural network, a series of experiments was planned. In total, modeling was carried out for three types of complications:

- kick or gas-oil-water influx;
- loss circulation;
- sticking of the drill string due to accumulation of cuttings in the deviated section of the well.

Methodology for modeling complications of the "kick or gas-oil-water influx" type.

Table 3—Matrix of the range of variation of parameters for modeling complications of the type "kick or gas-oil-water occurrence".

№	Parameter	Value 1	Value 2	Value 3
1	P_f	$1{,}05*P_{BHP}$	$1{,}15*P_{BHP}$	–
2	K	50	200	–
3	T_f	$0{,}5*T_{cap}$	$1{,}2*T_{cap}$	–
4	Mud Type	WBM	OBM	–
5	Trajectory type	tangent	S-shape	–

Methodology for modeling complications of the "loss circulation" type.

Table 4—Matrix of the range of variation of parameters for modeling complications of the "loss circulation" type.

№	Parameter	Value 1	Value 2	Value 3
1	P_l	$0{,}97*P_{BHP}$	$0{,}95*P_{BHP}$	$0{,}90*P_{BHP}$
2	T_f	$0{,}5*T_{cap}$	$0{,}9*T_{cap}$	$1{,}2*T_{cap}$

Methodology for modeling complications of the «sticking of the drill string due to accumulation of cuttings in the deviated section of the well» type.

Table 5—Matrix of the range of variation of parameters for modeling complications of the "*sticking of the drill string due to accumulation of cuttings in the deviated section of the well*" type.

№	Parameter	Value 1	Value 2	Value 3
1	T_f	$0{,}5*T_{cap}$	$0{,}9*T_{cap}$	$1{,}2*T_{cap}$
2	V_{cut}	Low	Middle	High
3	Trajectory type	tangent	S-shape	G-shape

Methodology for modeling drilling without complications.

Table 6—Matrix of the range of variation of parameters for modeling drilling without complications.

№	Parameter	Value 1	Value 2	Value 3
1	Mud Type	WBM	OBM	–
2	T_f	$0{,}5*T_{cap}$	$0{,}9*T_{cap}$	$1{,}2*T_{cap}$
3	Trajectory type	tangent	S-shape	G-shape

In total, 86 experiments were carried out to train and test the operation of the neural network.

Method of conducting the experiment. Simulation of each borehole drilling experiment is carried out according to the following method.

- A priori model parameters are set for each experiment in accordance with the experiment planning matrix.
- The well drilling process is started.

  a. Initial conditions: bit downhole, pumps off, rotor off.
  b. Starting the pumps (each time the speed was chosen arbitrarily in the range of 60-100 strokes / min).
  c. Rotor starting (rotation speed 60-140 rpm).
  d. Running the bit downhole, creating a load on the bit (in the range of 4-10 tons), starting the drilling process.
- The drilling process is carried out without complications for 20-40 minutes.
- The type of complication is set (only for "sludge accumulation"). Complications such as "absorption" and "oil and gas seepage" will occur automatically when the specified depth is reached.
- Depending on the type of simulated complication, the procedure is as follows:

  a. Upon receipt of direct signs of complications such as "kick or gas-oil-water occurrence" lifting the bit from the bottom, stopping rotation, circulation, closing blowout equipment, waiting for pressure stabilization.
  b. In the event of a "loss circulation" complication, continue drilling for 5 minutes, then stop the pumps and wait another 5 minutes before terminating the experiment.
  c. If problems arise with a complication such as "slime accumulation", it is necessary to increase the rotor speed and pump speed, trying to reduce the height of the slurry pad, or reduce the load on the bit. Continue drilling for another 30 minutes or until a complication such as " stuck-pipe or sticking " of the drill string and the rotation of the rotor stops.
- In the resulting graph, set a mark for the beginning of the type of complication, and transmit the received information for data analysis using neural network algorithms.

During the experiment, the operator (driller) directly controls the following parameters: pump speed; rotor speed and WOB as a decrease in the "weight on hook" parameter during drilling. The rest of the parameters are output for the driller. On their basis, he learns about the complications that have occurred.

Using simulation data to train a neural network

For the formation of topology, training and validation of the model for predicting the occurrence of pre-emergency situations of the "kick or gas-oil-water occurrence" type during drilling, an appropriate software module was developed using simulator data. The forecasting problem was solved using several approaches, including the regression method as well as one-class classification. The implemented software module uses methods based on machine learning and an artificial neural network with a topology that includes the use of recurrent neural networks of long short-term memory (LSTM - Long Short-Term Memory).

The procedure for preparing data from the simulator for the formation of training samples from archived data. Based on the results of experiments on modeling the drilling process with the occurrence of trouble situations, 69 simulation records were obtained, including 33 related to drilling with complications such as "kick or gas-oil-water occurrence", 27 with cuttings accumulation at the bottomhole, 9 with "loss circulation". Each entry was marked with a point in time indicating the onset of the complication. This moment was further interpreted as an extreme moment of prediction. The frequency of recording the parameters during the simulation was varied. On average, the time interval between neighboring points was 38 seconds, the minimum time interval was 6 seconds, and the maximum time interval was 2 minutes. These sizes of time intervals resulted in a small number of points available for analysis. In this regard, the stage of adding intermediate points with a time interval of 1 second was included in the data preprocessing process. To obtain the parameter values at these points, the linear interpolation method was used. The preprocessing procedure for the training sample is implemented in the form of a program launch script and a set of functions.

Procedure for adding auxiliary machine learning methods. In the course of the study, it was revealed that the model of an artificial neural network for predicting the impending complication of the type of "kick or gas-oil-water occurrence" due to its complexity learns better, when, in addition to the initial values of drilling parameters, it also receives the result of some auxiliary machine learning models that are trained to solve regression problems indicator functions with model tuning for tracking changes in certain parameters, as well as with the task of highlighting abnormal situations in the readings of the observed parameters during drilling.

Topology formation procedure, training and validation of an artificial neural network. This procedure is designed to form the topology of the artificial neural network model, train it, and also validate it. The procedure allows you to save the weights of the trained model and load them for use in the forecasting process. The neural network topology consists of three layers:

1. The first two layers are a multilayer perceptron (MLP), consisting of fully connected layers, each layer has four neurons with sigmoidal activation function, the multilayer perceptron (MLP) is applied to each tick of the sequence independently of the others;
2. The next recurrent layer consists of four neurons of the Gated Recurrent Unit - GRU;
3. The last output layer is designed to solve the problem of classifying two neurons with the softmax activation function.

When training this module of the artificial neural network model to determine gas-oil-water seepage, the following quality indicators were obtained: accuracy - 0.89; weighted average estimate f1 - 0.86.

The procedure for generating output data and signaling about emergency situations. The "Kick_Predictor" class was used to predict the occurrence of complications such as "kick or gas-oil-water occurrence" by parameters in real time. The constructor of the class receives the configuration, on the basis of which the sequence of preprocessing procedures for the parameters and the used model are formed. For the model, immediately after its assembly, the trained weights are loaded. The output of the procedure is the output of the model for class 1 (corresponds to the expectation of "kick or gas-oil-water occurrence"), which means the degree of confidence in the occurrence of an emergency event and the assessment of the situation in accordance with the specified criterion: if the confidence value for class 1 is greater than the value for class 0, then it is worth submitting an alarm about an impending pre-emergency condition, otherwise do not give a signal.

Conclusions

The project results are as follows:

1. Complications and accidents arising during drilling were according to the degree of applicability of neural network algorithms.

2. The possibility of using a drilling simulator for creating a training sample for a neural network is shown.
3. For predicting and recognizing drilling complications, the most optimal neural network topology was selected, which allows predicting complications with high accuracy and within an appropriate period of time, which will allow the driller to take appropriate actions to prevent complications or minimize their consequences.

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Index:

P_f – formation pressure
P_{BHP} – bottom hole pressure
K – permeability
T_f – drillability of the reservoir rock.
T_{cap} – drillability of the cap rock
P_l – maximum BHP before losses start
Vcut – cutting accumulation velocity

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