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Intellectual Technologies in the Management of Oil Fields

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Abstract—This work is aimed at developing new approaches and at improvement of control of oil-producing wells and an oilfield as a whole based on artificial intelligence methods. A three-tier system of intelligent oilfield control that ensures optimization of oil production and the operation of equipment is proposed; the essential features of the applied artificial intelligence tools that are required for implementation at all levels are described. The concept and the proposals that are made in the work can be a starting point for future research and for building real intelligent wells and intelligent oilfields.

Keywords: intelligent oilfield, oil, production, artificial intelligence

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INTRODUCTION

At large-scale multi-well oilfields, multiple events that must be properly handled for making consolidated operational decisions at an expert level occur every minute. The quality of these decisions depends, among other factors, on the relevance of the incoming information and on its processing speed. Economically effective production of oil within an intelligent oilfield (IO) requires comprehensive automation of all major technological steps. The automation includes the implementation of so-called “intelligent wells” (IWs). The following events may be considered as signs of interest in the creation and introduction of IOs: The international scientific and practical conference Intelligent oilfield: world experience and modern technologies (INMESTOR-2012) (May 10–11, 2012) Gubkin Russian State University of oil and gas); The technical conference of SPE: Management of digital oilfield (St. Petersburg, July 3–5, 2013); the scientific debate on Intelligent wells within the framework of the 5th international specialized exposition Oil production. Oil refinement. Chemistry (Samara, October 20, 2011). A number of other recent publications on this topic have been published [1–4].

The following distinctive features of IWs (as defined by V.V. Kulchitsky in his address to the participants of the round-table discussion on the topic of smart wells) can be identified:

(1) the direct link to the outside world using information communication channels to extract knowledge and organize the appropriate behaviour;

(2) openness due to self-adjustment, self-organization, and self-learning;

(3) the ability of an IW to forecast changes in the external environment and in its own behaviour;

(4) the presence of intelligent control systems to compensate for the inaccuracy of knowledge about an object model;

(5) the ability to maintain autonomous operation during the disruption of links or with the loss of controlling actions from higher levels in the hierarchy of IWs [5].

In our opinion, the following features should be added to the list:

(6) a system for the monitoring, control, and diagnostics of the operation of wells and equipment;

(7) advanced visualization means (including cognitive ones) to support decision making;

(8) the presence of a developed mathematical model of a well (oilfield) coupled with the controlling model of the motor of a valve or a downhole pump; simulation tools;

(9) a high degree of autonomy, the ability to maintain or reach goal states (e.g., maximum flow, maximum efficiency, and the maximum oil-recovery factor) in the conditions of the interaction of external factors that disrupt these states or prevent their achievement.

Without loss of generality, we can consider the use of artificial intelligence technologies in problems that are related to data processing, forecasting, and optimization of the production and management of valve motors and pumps within one well. As the analysis of

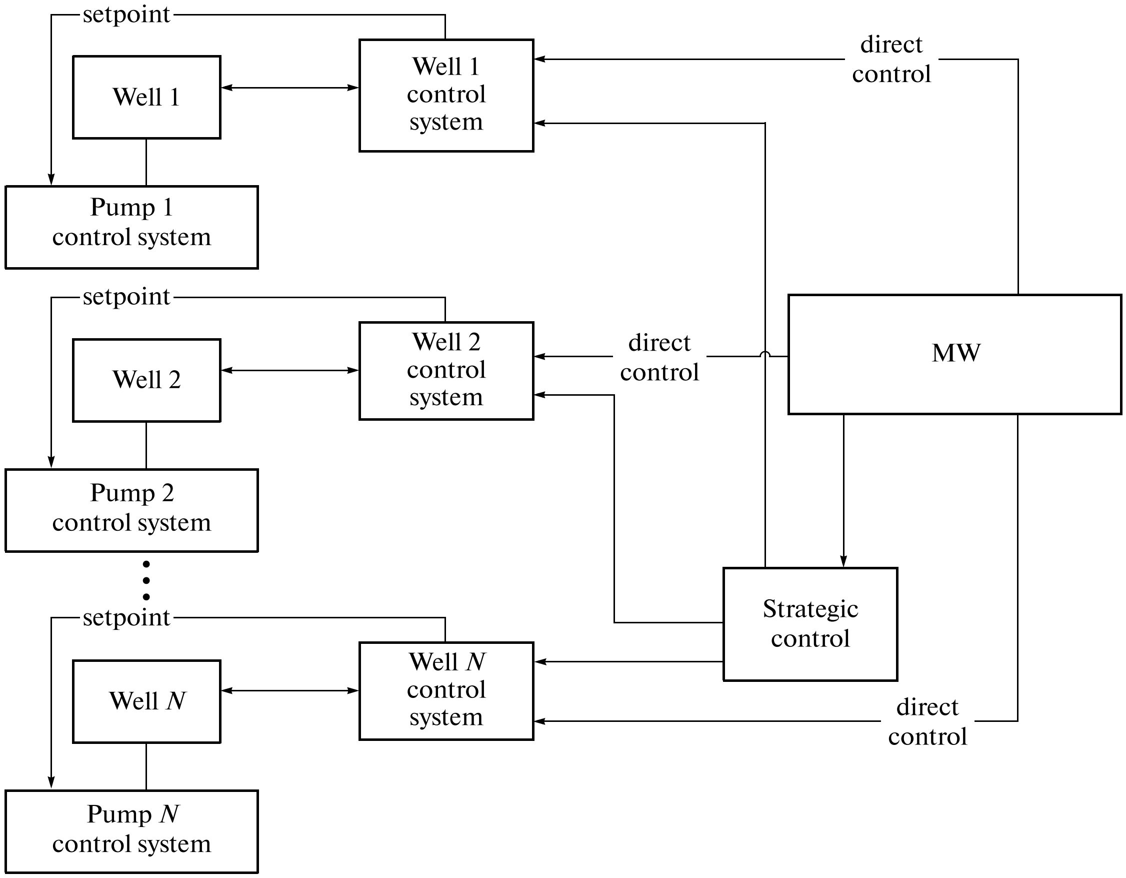

Fig. 1. The general scheme of smart oilfield control.

world-class scientific publications shows [4, 6–21], a scientifically sound concept of artificial-intelligence methods in both the management of individual wells and fields as a whole does not yet exist. This fact may be explained by separation from the latest achievements in the theory of building intelligent dynamic-control systems and a lack of communication between the developers of such systems with leading scientists in the field of artificial intelligence.

It is advisable to use the following technologies as the basis of well automation: domestic expert-system technologies, intelligent information-processing techniques based on neural networks and genetic algorithms, Bayesian networks, software tools for building intelligent application systems, and the accumulated and formalized expert knowledge in the field of automatic control of downhole pumps and motors [22–26]. It is advisable to proceed from the principle of "discreet-time" control to "continuous" monitoring, diagnostics, and control of well equipment using high-performance computing facilities for processing data. We should proceed from the concept of local process optimization within the framework of an intelligent well to the task of building an intelligent oilfield within the concept of networked control, which allows one to perform global optimization using data about different processes. The technology may be based on management workstations (MWs) of pump stations that operate as integral parts of data-processing network that are used to manage an oilfield.

THE INTELLECTUAL COMPONENT OF THE OILFIELD

The dynamic component of an intelligent oilfield within the unified scientific–technological space is implemented on the basis of the technologies for the acquisition, storage, and processing of knowledge using software tools. The component can use the intelligent-agent technology, neural networks, genetic algorithms, pattern analysis, and other modern achievements of artificial intelligence. The intelligent component should implement the data-acquisition means, data-analysis means, a database, and a knowledge base. The modules of the intelligent component should be adaptive and able to optimize its functions; trainable and able to adopt additional information and accumulate useful knowledge in order to accomplish tasks within the framework of a module's functions more accurately; communicative and capable of interaction with other modules and thus, if necessary, able to perform actions outside the scope of its own functions in the course of operation.

The general scheme of an intelligent oilfield control is shown in Fig. 1. The scheme includes the following most important modules:

(1) a real-time monitoring system of elements and processes;

(2) a system for the simulation, recognition, and analysis of the global current situation that supports the works supervisor in emergency situations (ES) and at normal operation;

(3) a real-time system to forecast the development of emergencies in time and their distribution over the interacting sub-systems;

(4) a real-time scheduler to adjust the working plan during emergencies; solution optimization using planning tools and neural networks;

(5) an interface to inform operators about possible ways to make the technological process stable;

(6) a real-time solver to output recommendations to the operational staff about ways to prevent inappropriate influences on the object: (recommendations on counteracting emergency situations; issuing opinions on the possibility (appropriateness) of specific control actions in the given current situation);

(7) a subsystem that displays the current situation;

(8) user interfaces.

Currently, Russian approaches to the intelligent dynamic control problem have been developed. The control method includes: closure rules, computational functions, transition rules, control rules, sub-goals, and control zones. Control rules select a control strategy out of a set of acceptable strategies in accordance with the current goal. In fact, at this stage, the rules are defined by and are identical to the system of intelligent control commands.

The controlled objects have a number of essential characteristic features that are related to the fact that their state parameters are described by differently typed variables: e.g., quantitative, Boolean, or linguistic. At the same time, the states have no comprehensive a priori description. For such systems, the behavioural rules either have no comprehensive analytic description or cannot be described analytically at all. However, the states can be described with a set of expert or empirical knowledge. The controlled object's state vector is formed according to current data. The acceptable alternative methods for the resolution of a situation are outlined taking the a priori information about the situation into account.

An efficient decision is inferred by applying three types of mechanisms. The first type is the rule-based mechanism. For this mechanism, every particular vector that describes the current status of a situation corresponds to an efficient way to resolve the situation. These mechanisms are implemented in the form of "if ... then ... else ..." rules, where the completeness and consistency of the rules is provided by an expert-assisted simulation. The second type of mechanism is based on algorithms of multi-criteria choice. In such a case, the set of alternative resolutions and the set of result evaluation criteria for every resolution are defined. The third type consists of the mechanisms for presenting a successful precedent that is appropriate for the current situation. In such cases, the most relevant mechanism is to use a knowledge matrix and a situation description vector that have linguistic variables as coordinates.

The computational mechanism of the system consists of a set of rules, a database, and some strategy to select rules. Execution of the rules means the execution of corresponding closure procedures, targeting, selection of a control method, and transition. The implementation of intelligent control as a process was described in [27, 28].

THE ORGANIZATION OF AUTOMATED WORKSTATIONS

The current state of oilfield development is increasing the level of requirements for automated workstations that are used for the management of geological and technological services, which leads to the expansion of functional capabilities in terms of intelligent information processing. This encourages the growth of the saturation of a company's units by high-performance computer hardware and advanced software. Much attention is given to connectivity with the global information network, as well as the information-processing system and measuring system.

The hardware of the automated workstation must ensure the efficient implementation of all of the software features. A multiprocessor computing system in the form of a cluster using GPU accelerators can be used as a hardware platform. The issue of equipping wells with sensors and monitoring devices that collect technological information directly on oilfields is of particular importance. The collected data are processed and analyzed in order to support techno-economic decisions regarding different aspects of the production cycle. Further development of these systems will provide real-time remote access to information about processes in wells. This will make it possible to optimally pick the operation mode of the well pad and every separate well according to a production model. We propose to use the structure of the intelligent component of modular automated workstations [21]. Tools that were created on the basis of this approach have been used to build a number of applied systems [13, 14].

SPECIFICATION OF THE SCIENTIFIC AND TECHNICAL CHALLENGES THAT REQUIRE SOLUTION: SUGGESTIONS

The following scientific and technical challenges that require solution within the scope of building an intelligent oilfield should be noted.

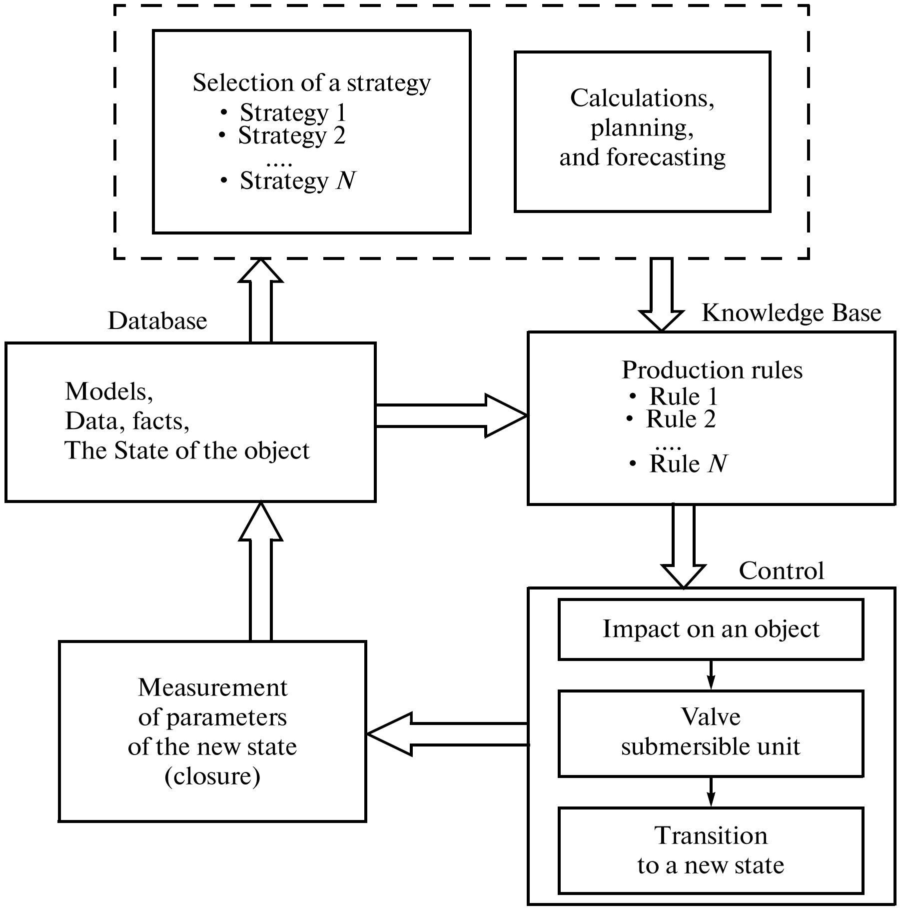

Fig. 2. A schematic diagram of intelligent analysis and control.

The Development of Control Strategies and a Goal-Setting Module

Let the "trajectory" of a dynamic object (a pump station) while it reaches the preset flow be defined as a sequence of calculated phase states. We propose to use a rule-based dynamic system, for which certain control strategies related to the desired global goals can be introduced. The set of strategies includes:

—a point-wise moving strategy; the strategy is acceptable, e.g., to control and stabilize downhole pump operation (a preset rotation frequency);

—a strategy for achieving the maximum (or minimum) value of a target criterion (efficiency, pressure, etc.); the strategy is acceptable to control the operation of separate pumping stations in general based on a known model of the environment (or well);

—other strategies, their number is determined by the number of goals; the strategies are based on the principles of processing the corresponding particular trajectories.

The goal-setting system, as applied to the pump station operation, contains the following actions:

(1) switching the facility on (the Work operation mode);

(2) switching off and disablement of switching on the facility (operation modes: On hold, Emergency, and Blocked) related to malfunction or to deviation of the controlled parameters;

(3) adjusting and maintaining the rotation frequency of the electric motor;

(4) forecasting the state of the environment and generating a plan of controlling actions;

(5) maintaining the maximum efficiency;

(6) maintaining the maximum well flow (or a preset pump suction pressure);

(7) the selection of an operation mode for a well pad and each well according to the production model;

(8) transition to the system of selection and switching rules;

(9) transition to the checkup and diagnosis system.

The development of the rules system for intelligent control

The proposed general scheme of the intelligent control of a pump station as a complex dynamic object (Fig. 2) consists of two intelligent control circuits: one of them (internal) controls the rotation (stabilization) of the valve motor of a downhole pump (and its reverse operation). The other (external) circuit performs general pump station control following the control strategy and in accordance with the state of the media in which the pump is submerged. The goal-setting block, which sets the global station control goals and solves strategic tasks of choosing the control mode, is essential.

The planning block forecasts the flow of event and model state parameters for a specified number of steps. An integrated database that contains telemetry data, necessary facts, and current model-state parameters is required for the operation of the model. For knowledge representation, frames, rules and semantic webs that support the representation of an object, its attributes, structure, and behaviour procedures are used.

In our case, the knowledge base contains the production rules that set the conditions that trigger the production of specific controlling signals for the pumping station in accordance with current goals and the formulated plan. The control block changes the position of the system that controls levers. Consequently, the system passes to a new state. In a dynamic environment, the operation of an intelligent system implies a timely reaction to changes in environment parameters and takes the existence of transient processes between states into account. This restricts both the time for performing the analysis and the time to measure current parameters in order to update the database on time (closure) [11, 12].

The implementation of a continuous control mechanism is based on carrying out the following functions:

(1) external queries and setting goals, criteria, and control strategies;

(2) queries to a knowledge base and the corresponding database;

(3) retrieving the current parameters from the knowledge base and database;

(4) a request to generate the plan (sequence of control selection rules);

(5) plan generation (performing calculations of goal functions, forecasting, and planning);

(6) plan development: obtaining the calculated and experimental data, comparison of the current global situation with the calculated one, issuing a query to look up the applicable rules and regulations (the applicable rules are rules that have preconditions that comply with the current state);

(7) the comparison of the current global situation with the calculated one;

(8) the selected production rule is transferred to the system for execution;

(9) synchronization of the internal clock cycles of the system to the real time;

(10) the measurement (closure) and storage of the current state parameters in the database.

The algorithm runs continuously to reach and sustain the global goal state. The control procedure is based on application of the rules, which are the main means to synthesize and to represent plans during operation.

The development of the mathematical simulation block for the valve motor control

To simulate the motor control and stabilization system, we propose to use the structured scheme that was described in [29]. These solutions allow one to comply with the requirements on the valve motor control system: adjustment and self-calibration of the positioning sensors, programmed control, and correction of disturbances of transmission. As a result, the dynamics of the positioning and rotation-speed stability improve. The developed procedures for the adjustment and identification of parameters facilitate the use of additional features of the control block.

The use of a proportional-integral-differential controller as a digital rotation frequency controller leads to the issue of finding the optimal controller settings. We propose to use one of the techniques of AI, viz., to adjust the proportional-integral-differential controller that digitally controls the frequency of the downhole motor using gradient descent and genetic algorithms. It is possible to choose the sum of a series of fuzzy membership functions as an integrated estimate of the transient process. The distinctive feature of the proposed technique is the use of interdependency between the parameters of the proportional-integral-differential controller and estimates of the quality of the transient process in the closed control loop expressed in the form of ratios. This approach is substantiated by the fact that an experienced engineer is able to accurately set the controller parameters based on his own experience and corresponding knowledge [30].

Development of a calculation and forecast module for key indicators

The module calculates the following:

(1) *the pump efficiency taking* the influence of the viscosity, free gas, and operating mode into account;

(2) the pump head relating to water at the optimal operating mode;

(3) the horsepower of the pump and submersible motor;

(4) Interpolation using a parametric cubic spline.

The splines allow one to develop software and to model surfaces of a complex form using a unified methodology. Using splines, e.g., Hermite splines, it is possible to store geometric data in digital format with arbitrary precision. This is used in data-transmission and data-recovery systems and makes the hardware solutions substantially simpler.

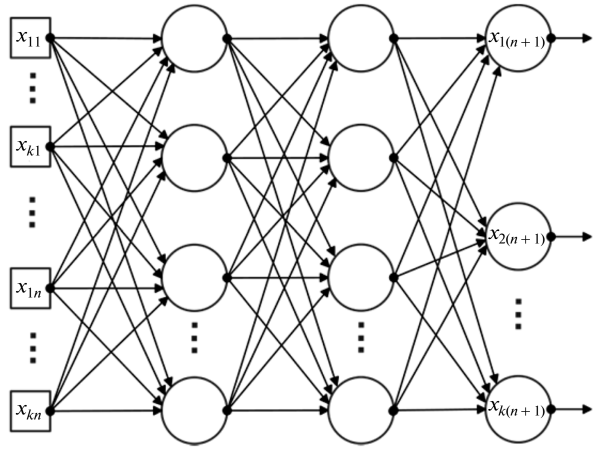

Fig. 3. The architecture of the forecasting neural network.

Development of the forecasting block

This block forecasts the state of technical subsystems using a direct-propagation artificial neural network (ANN) with a sigmoidal activation function. The number of inputs of the first layer is equal to kn and corresponds to k vectors of goal coordinates (in the k-dimensional space covered by the window of width n). The number of neurons in the first and second layers is chosen experimentally. The third layer contains k neurons; the output of each of these is used to forecast the coordinate of the next point (forecast). The training method of ANN is as follows. Let us scan the available time series with a sliding window. Covering n values of the series with a sliding window, we attempt to obtain the $(n + 1)$th values (Fig. 3). For a long-term forecast, the obtained forecast point is added at the end of the available sequence of points.

Development of the monitoring and diagnostics block

The process of detecting deviations and looking for system defects that can be formalized as a task of recognition (classification) of a situation on the basis of measurement and intelligent data analysis is referred to as monitoring and diagnostics. The ongoing monitoring of sensor failures is also based on the correlation analysis of data. We propose to use the probabilistic neural network (PNN) for the identification of abnormal situations. The probabilistic network is trained to evaluate the probability density function; its output is considered to be the expected model value at the given point in the space of inputs. The standard training is not required for the probabilistic network, as all of the network parameters are determined immediately from the training data. In order to minimize the error, the output that has the maximum probability density is selected in the last layer. This technique allows one to obtain a good approximation to the true probability, provided there are a sufficient number of training examples. A fully connected two-layer forward propagation neural network (two-layer perceptron) may be an alternative solution. The well-known Widrow–Hoff learning rule is used to configure the network. It is also possible to build a discriminant function with the group method of data handling (GMDH). The GMDH allows one to restore the dependency between input and output variables using sample observations. In this case, it will be used for the classification of input vectors.

CONCLUSIONS

The field of knowledge that is being developed involves introducing intelligent technologies within the scope of creating a unified scientific and technological oilfield space. These include: methods for the optimization of operation modes for complex technical systems; expert knowledge-based decision-support systems; the unified requirements for interfaces and modules of intelligent systems, and means to represent and to store knowledge, including the architectures of distributed knowledge bases; and mathematical and software support.

Advanced intelligent technologies and tools based on them can be used for the following purposes: modelling goal-attaining processes, identification of the global situation, diagnosing failures, and adjustment of technological processes to achieve the most efficient outcome for an oil field. The implementation of an integrated system for the monitoring, analysis, and control of production in real time could help to eliminate existing technological deficiencies, increase profitability, and extend the life cycle of an oil field. Consequently, we can say that the task of introducing intelligent systems within the scope of creating a unified scientific and technological oil-field space is a relevant one; its implementation is a strategically important scientific and technical challenge. The proposals that were made in this paper can be a starting point for future research in the domain of building intelligent oilfields.

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