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NEURAL NETWORK MODELS OF AN OIL RESERVOIR AREA AND WELL INTERFERENCE

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Keywords: reservoir area model, machine learning, neural network modeling, well interference.
Abstract. The article deals with the issues of building an integrated system for coordinated control of a multilevel distributed technological process of oil production. An analysis of approaches to modeling the reservoir section and well interference has been carried out. A neural network constantly operating dynamic model of an oil reservoir area is proposed as a basis for creating a two-level control system for a group of wells, taking into account their mutual influence in real time. The model provides the required accuracy of describing the physical processes in the reservoir with a simultaneous reduction in the model calculation time and can be included in the control system as a software block.

НЕЙРОСЕТЕВЫЕ МОДЕЛИ УЧАСТКА НЕФТЯНОГО ПЛАСТА И ВЗАИМОВЛИЯНИЯ СКВАЖИН

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Ключевые слова: модель участка пласта, машинное обучения, нейросетевое моделирование, взаимовлияние скважин.
Аннотация. В статье рассмотрены вопросы построения интегрированной системы координированного управления многоуровневым распределенным технологическим процессом добычи нефти. Проведен анализ подходов к моделированию участка пласта и взаимовлияния скважин. Предлагается нейросетевая постоянно действующая динамическая модель участка нефтяного пласта как основа для создания двухуровневой системы управления группой скважин с учетом их взаимовлияния в реальном масштабе времени. Модель обеспечивает необходимую точность описания физических процессов в пласте с одновременным уменьшением времени расчета модели и в виде программного блока может быть включена в состав системы управления.

Introduction

The current state of the oil industry of the Russia fuel and energy complex is characterized by the fact that most of the oil production industries are fields in the late stage of operation, characterized by more difficult production conditions and an increase in the cost of production. [1, 2].

Under these conditions, the problems of increasing the efficiency of field development are of particular relevance [3, 4]. One of the promising areas is the development of an intelligent oil production process control system based on the latest digital automation technologies (“intelligent well”, “digital field”), the purpose of which is to intensify oil production from low-productivity reservoirs [5-7].

An analysis of the available sources allows us to conclude that the use of modern informatization achievements is widespread, but not effective enough, both in domestic and foreign oil production [8-10]. Modern technical means of automation and software [11-16] make it possible to automate the collection, transmission, storage and processing of data, visualize key parameters for process control. Separate models of objects and processes of oil production are being developed and improved. Particularly noticeable is the progress in improving the constantly operating geological and hydrodynamic models of deposits [17], which make it possible to plan and predict development on a global scale with continuous optimization. Due to the complexity and uncertainty of geological models, it seems impossible to build a fully automatic control of oil production in the foreseeable period of time [18]. The possibilities of digital technologies are used mainly in the field of organizational management (MES, MRP, ERP) and business processes.

Such a “direct” extensive introduction of digital technology and related software allows:

– to increase the level of automation in the ICS existing everywhere;

– improve the quality of geological and hydrodynamic models as the basis for field development;

– create hierarchical information support systems using modern digital technologies.

But this does not ensure the full use of the potential opportunities of digitalization and intellectualization [19-22]. The tasks connected with operational, in real time, management fall out of consideration.

1. Analysis of the oil reservoir area and well interference existing models

To date, in the class of mathematical models, the most widely used for reservoir management problems are permanently operating geological and technological models. The disadvantages of such models include:

1) resource-intensive iterative algorithms for identifying hydrodynamic models in the case of analyzing a long history of a development object with a large number of wells do not provide high accuracy of the forecast;

2) Interpolation and averaging of the accumulated parameters during model identification reduce the quality of its forecast.

Operational management based on such models is also associated with a number of difficulties:

1) long process of building and identifying hydrodynamic models does not allow them to be directly used for operational control of production modes;

2) models provide insufficient detail of local development processes.

Recently, there has been a significant increase in interest [23] in simplified reservoir models, which can significantly reduce the time required to build a number of possible field development models.

One of the promising approaches is the use of CRM (capacity resistive model) similar models, which are an analytical solution of the material balance equation. Building a model consists in solving an inverse problem with a large number of parameters and restrictions. Currently, there are several different classes of such models.

The work [24] developed CRM mathematical models and software for solving the problem of assessing the mutual influence of wells, optimizing waterflooding, separating production by jointly developed reservoirs, and simulating the operation of a horizontal oil well under conditions of gas cone formation. A qualitative and quantitative comparison of the CRM model and the hydrodynamic model is given.

The paper [25] considers the issues of improving CRM models in terms of the possibility of operational forecasting of development indicators in the conditions of an elastic water-pressure regime, as well as in the event of a significant change in well operation modes. It is shown that the well interference coefficients, which are the tuning parameters of classical CRM, are sensitive to changes in well operation modes. This limits the effectiveness of CRM in tasks where a significant change in well operation modes is possible, for example, the problem of optimizing the reservoir pressure maintenance system (RPM).

The article [26] is devoted to the question of the correctness of comparing the well interference coefficients based on streamlines with the interference coefficients based on the CRM analytical model.

Using synthetic hydrodynamic models as an example, it has been demonstrated that an injection well affects not only the wells with which it is connected via streamlines, but also other wells through changes in reservoir pressure. As a result, in the case of non-stationary injection, the use of only those connections between wells that correspond to streamlines leads to a decrease in the quality of CRM model tuning.

In [27] two CRM-models are proposed that describe well interference. The models are obtained by combining the material balance equation and the inflow equation. The first model considers the pore volume of the reservoir common to all wells. In the second model, all wells have individual pore volumes between which flows occur.

Synthetic examples show that the first model can be used for an infinite reservoir, and the second model gives better results for a limited reservoir. Development data are understood as: fluid flow rate, injected water flow rate, bottom hole pressure. CRM-models are models obtained by the joint application of the material balance equation (the equation of the continuity of the flow in the reservoir) and the equation of inflow to the well. The advantage of all CRM models is the refusal to use reservoir pressure in calculations, which changes during the development process, and its definitions in field practice are rare and often non-systematic.

In the article [28] the results of the assessment of the predictive ability of the analytical material balance model CRM were obtained in the framework of a retrospective test at the site of a real field. In addition to the single-phase representation, classical for the CRM model, special attention is paid to the predictive qualities of the two-phase formulations of the model. Based on the test results, it is shown that the CRM model in a two-phase setting allows predicting oil production at a high level of accuracy with detailing to waterflooding elements.

The work [23] proposes original numerical methods for determining the coefficients of CRM-models for problems with one production well and with many production wells. For a problem with one production well, conditions are indicated under which the problem has a unique solution, and it will be found by the proposed algorithm. For a problem with many production wells, the results of numerical experiments demonstrated the high quality of the solutions obtained and the advantage in productivity in comparison with other numerical methods.

When the field enters the fourth stage of development, when the share of water in the produced production reaches more than 70% and the structure of residual reserves becomes complex, the most economically feasible ways to increase oil recovery are hydrodynamic methods, which consist in changing the kinematics of flows that have developed over decades by redistributing water injection. In such a formulation of the problem, in order to select the optimal injection distribution, it is necessary to calculate several thousand different options, and make decisions within a month, a week, or even a day. This is an unsolvable task from the point of view of classical geological and hydrodynamic models, the calculations do not keep up with the hydrodynamic picture of the field that has changed during their implementation. It is for this purpose that in the world practice more and more researchers are moving to proxy modeling as a tool for prompt decision-making for deposits at the last stage of development. With the growing interest in proxy models, the issue of evaluating their quality becomes more and more relevant. The authors [29] substantiated the quality criterion, which is the predictive ability.

In [30], based on the results of the adaptation, the CRMP method was chosen for further application on real data and the possibility of medium-term forecasting of development parameters. The results obtained allow us to draw a number of conclusions and identify areas for future research to improve the performance of the algorithm and the use of proxy models:

1. Proxy models can serve as an alternative to geological and hydrodynamic model due to the speed and simplified physics of calculations for the operational management of field development.

2. A proxy model has been obtained that can generate various scenarios of development parameters (liquid/oil production, reservoir pressure) taking into account the current assessment of the interaction between injection and production wells. To carry out the forecast, bottom hole pressures of production wells and injection levels of injection wells are fed into the model.

3. For the adaptation and correct operation of the algorithm, it is not necessary to use a long history of well operation; for a more correct forecast, a period is sufficient in which there are no significant changes in the productivity factor, there were no long-term shutdowns of wells, and no well interventions were carried out.

4. The main limiting factor for the accuracy of the received forecasts is the quality of the initial data, the history of changes in bottomhole pressures and the accuracy of liquid and oil measurements have the greatest influence.

The article [31] proposes the concept of operational waterflooding management, which involves solving an optimization problem in a system of production and injection wells, including a mathematical model of the control object (proxy model), a decision-making system, and a special administration format. The authors propose a formalized approach to the operational management of waterflooding, which involves the introduction of integrated planning. The technique was tested on the fields of Western Siberia and Kazakhstan and confirmed the calculated efficiency - an increase in oil production by 10-25%.

The paper [32] considers an approach to solving problems of ensuring the rational development of reserves and assessing the mutual influence of wells with the construction of a predictive model, which includes the integration of the results of dynamic marker monitoring of the profile and inflow composition of horizontal wells, the Spearman rank correlation method and hybrid digital models based on computer learning. The system of long-term dynamic marker monitoring of horizontal wells allows obtaining a data flow for managing and optimizing field development to assess the mutual influence of not only injection and production wells, but also the impact of injection wells on specific ports of marked production wells using historical work data, as well as well location maps.

The paper [33] proposes a system for determining well interference coefficients, including a database module, a data sampling unit, a data preparation module, a coefficient calculation module, a reporting module, and a report display unit. The proposed system makes it possible to study the phenomena of interference and mutual influence of wells in order to optimize production indicators for oil production.

The paper [34] reviews the existing methods for estimating the mutual influence of wells, including a new method based on partitioning the computational domain into Voronoi polygons, taking into account the material balance between the polygons. The number of polygons corresponds to the number of wells, the outer boundaries of the polygons can be both impermeable and permeable, with the ability to set the flow. It is shown that the application of different methods to the same oil object can give an ambiguous assessment. Based on this, it is concluded that there are no universal methods for assessing the mutual influence of wells, and the most reliable results for practical use can be obtained if a computationally efficient and at the same time physically meaningful approach is used.

In [35] a critical analysis of the proxy modeling method INSIM-FT (Interwell Numerical Simulation Front Tracking models) was carried out. The results of testing on synthetic models and on the site of a real field are presented. The analysis showed that based on the results of solving the inverse problem of hydrodynamics in the proxy model, it is impossible to draw conclusions about the real parameters of the reservoir, and even a satisfactory history matching is not a guarantee of good predictive ability. Criteria for the application of the method are formulated.

As in the widely used CRM models, INSIM-FT is based on the material balance equation, but, unlike CRM, the INSIM-FT algorithm theoretically allows you to reproduce not only the liquid rate, but also the oil rate, using physically meaningful methods. However, when solving the inverse problem of hydrodynamics, the physical meaning of the variation parameters is lost. At the end of the adaptation, the relative permeability curves, the permeability and saturation fields can differ significantly from the real ones, there is a deformation under the result. A whole set of restrictions on the corridors of parameter variation is needed, based on experimental and field studies. An analysis of development trends shows that proxy models based on physical principles are becoming overly complicated and are increasingly approaching hydrodynamic simulators. It is possible that CRM and INSIM are dead-end directions of development, and it is worth paying attention not to the reproduction of physical fields, but to a direct study of the response of production to injection, or to combine the direct and inverse problem by creating a simulator without a grid domain and finite difference methods.

In the article [28] the results of the assessment of the predictive ability of the analytical material balance model CRM were obtained in the framework of a retrospective test at the site of a real field. In addition to the single-phase representation, classical for the CRM model, special attention is paid to the predictive qualities of the two-phase formulations of the model. Based on the test results, it is shown that the CRM model in a two-phase setting allows predicting oil production at a high level of accuracy with detailing to waterflooding elements.

The work [36] proposes a new operational and sufficiently accurate approach to the use of the fixed current tube theory for the analysis and design of the development of an oil reservoir area containing a small number of injection and production wells. The simulation is performed in two stages. At the first stage, a two-dimensional stationary problem of filtration in a horizontal plane is solved - a field of filtration flows is constructed, current tubes are formed. At the second stage, geological and technical measures are modeled by solving a two-dimensional problem of two-phase filtration in a vertical section along the stream tube. The decomposition of a three-dimensional problem into a series of two-dimensional ones makes it possible to use high-resolution computational grids at both stages of modeling. Some results of application of the described approach are demonstrated. To evaluate the effectiveness of various options for flooding systems, quantitative characteristics are proposed that reflect the interaction of injection and production wells, the degree of involvement of oil reserves in development, as well as the coverage of oil reserves by displacement.

The work [37] proposes a methodology for predicting the effectiveness of geological and technical measures, which allows to combine the main methods at different stages of evaluating the effectiveness and predict the increase in fluid and oil flow rates, additional production, changes in the dynamics of reservoir pressure and the rate of watering of well production. The developed methodological approach includes a combination of several methods for predicting the increase in the flow rate of liquid, oil and additional production. The combination of the statistical and mathematical methods of forecasting can significantly increase the predictive reliability of the effects of geological and technical measures. As part of the study, a script was developed that allows you to automatically calculate the effects of radial drilling, which significantly reduces time costs and allows you to quickly evaluate the effectiveness of the event. Combining statistical and hydrodynamic modeling makes it possible to reduce uncertainties and shortcomings of existing methods by combining methods at different stages of the forecast.

2. Local oil reservoir models based on machine learning technologies

Current trends [38] in the development of domestic and modern scientific thought in the field of hydrocarbon production are increasingly gravitating towards production control processes by regulating the operation modes of injection wells. At the current stage of development of production control technologies, the tasks of automating and robotizing the processes of controlling the operation modes of injection wells in the concept of neural network optimization are coming to the fore, which is one of the main directions in the development of the field in the context of a digital field.

As a result of studies [39], it was shown that with a minimum set of input data in the absence of data on the geological structure of the reservoir, neural network methods allow solving problems of assessing the degree of interaction (interference) of wells (coefficients, or functions of mutual influence of wells of the “debit-debit”, “debit- acceptance”).

Given the availability of data on the geological structure and hydrodynamic characteristics of the formation, neural network methods are able to solve the problems of quantifying the degree of interaction of wells operating in the modes of a given flow rate or bottomhole pressure (coefficients or functions of mutual influence of wells such as pressure - flow rate, pressure - injectivity), as well as n-dimensional interpolation and mapping.

The results of comparison [39] of neural network methods for solving the above problems with standard methods for solving them, used in oilfield geology, showed their complete viability and competitiveness. Moreover, the methodology for calculating the technological efficiency of geological and technical operations, taking into account the interference of wells, is currently absent in the practice of oil producing enterprises. It is especially noted that these methods are noise-resistant and capable of operating under conditions of highly “noisy” input information.

In the study [40], a methodology was developed that allows to quantify the mutual influence of wells, including taking into account the delayed effect, within the same development object. A vector autoregression model was considered, the parameters of which were found using Bayesian estimation. The application of the developed methodology for constructing a vector autoregression model with parameter estimation based on the Bayesian approach made it possible to take into account the mutual influence of well flow rates, taking into account the delayed effect.

The work [41] proposes a neural network structure for adapting the computational grid obtained on the basis of a reduced mathematical model of an oil reservoir section. For data preprocessing for the adaptation method, it is supposed to use the apparatus of mathematical statistics. The next step in the development of the structure is the integration of the properties of adaptation and forecast in a single model that can replace the hydrodynamic model of the field.

The paper [42] considers the problem of predicting the operating modes of production wells under conditions of non-stationary waterflooding using neural network modeling. In the learning process, neural networks allow you to establish meaningful relationships between production and injection parameters in a group of wells. This information is further used to predict well operation modes. The use of neural networks makes it possible to reduce the time for calculating the predicted mode, relative to the time spent on numerical modeling, which makes it possible to apply this approach in the problems of operational control and production optimization. The paper considers the possibilities of predicting the operating modes of production wells using a recurrent neural network LSTM, using the example of a field with a waterflooding system. The accuracy of predicting the operating modes of production and injection wells using a trained LSTM neural network in the problem of oil production with a reservoir pressure maintenance system has been studied. The achieved prediction accuracy allows using the trained neural network to predict the real parameters of well operation. High calculation speed and forecasting accuracy make it possible to integrate a neural network into a field management system and apply it in optimization of well operation modes.

The article [43] provides an overview of possible waterflood management solutions. The practical implementation of the “Neural Network Production Management Technology” includes the following steps: evaluation, selection, predictive analytics. The result is a digital technological regime of wells that corresponds to the set goal and the solution of the optimization problem in artificial intelligence algorithms using the Atlas - Waterflood Management software and hardware complex.

The technique proposed by the specialists of “Tyumen Institute of Oil and Gas” is a proxy model of the field, built on the basis of neural networks and primary field data [44]. The team of authors proposed and tested a method for controlling the operation modes of injection wells at the site of a real field. The effectiveness of neural network technologies for managing waterflooding processes has been proven.

The models of the oil reservoir and well interaction considered above make it possible to reproduce the main parameters of development, however, the features of the models do not allow them to be used for the purposes of operational management and short-term forecasting.

Table 1 discusses some approaches to modeling the development of oil reservoirs, their advantages and disadvantages.

Thus, the main requirements that an oil reservoir model designed for the purposes of operational management should meet:

1) The model must correctly reproduce unsteady well operation modes.

2) Two-phase fluid movement must be taken into account.

3) The model should reproduce the work of both production and injection wells.

4) The model must correctly handle the situation when there is an imbalance between the injected and injected fluid volumes.

5) Reservoir pressure - a value that changes during the development process and depends on the volumes of fluid injected and extracted from the reservoir.

6) Based on the model, it is possible to perform short-term forecasting of field development parameters.

The initial data for creating the model are the accumulated indicators of oil and water production, as well as data on bottomhole pressures.

Thus, the main approaches to modeling the oil production process are considered, the possibility of using the considered models for the purposes of operational management is analyzed. It is shown that the existing models of the oil reservoir section cannot be used for operational management. The requirements for the model of an oil reservoir section are formulated.

Table 1. Integral models of displacement characteristics

Oil Reservoir Description Method	Method advantages	Method disadvantages
Analog and physical models	1) Do not require the use of computer technology. 2) They have a visual representation of the ongoing physical processes.	1) The complexity of creating a model and the complexity of conducting experiments.
Grid hydrodynamic models	1) Detailed description of the pressure distribution in the oil reservoir. 2) The scale of the model is practically unlimited (whole fields can be modeled).	1) High requirements for the characteristics of the VT. 2) Long model calculation time. 3) Large labor costs in the process of creating a model.
Neural network models	1) High speed of calculations.	1) Unpredictability of simulation results. 2) The labor-intensive process of choosing the structure and training of the neural network.
Transfer Function Models	1) High speed of calculations.	1) The inability to take into account a large number of input parameters. 2) The complexity of rebuilding the model.

3. Architecture of digital solutions for well operation control

The paper [45] presents the architecture of digital solutions for managing well operation modes in the problems of efficient development of mature oil fields. Specialists of TING LLC in collaboration with engineers and geologists of oil producing companies have developed a technology based on the synergy of experience and artificial intelligence, created an industrial software product in which, based on field measurements, a set of tasks is solved for the operational management of well operation modes and optimization of oil production.

In the article [46], the authors provide evidence of the effectiveness of the integration of digital technologies for managing the flooding processes and planning the technological modes of operation of production and injection wells, and also indicate the vector of action, which is associated with the prospects for the development of “production control” technology.

The comprehensive integrated model of the Vatyeganskoye field includes [47] digital twins of more than 3,000 wells across 12 development targets. The digital intelligent tool is based on IPM Petroleum Experts software products (PVTP, MBAL, PROSPER, GAP) and covers the entire production chain of oil production from the reservoir to the entrance to the central oil treatment facility. The integrated model consists of linked models of the reservoir, wells, and models of gathering systems and reservoir pressure maintenance. It is designed to optimize the entire system as a whole, taking into account the mutual influence of its components. The stability of the model is achieved by adapting it to a retrospective time period, which increases the accuracy of forecast and scenario calculations. The model is used by the Customer on-line during the daily work of field specialists.

In [48] the author proposes to implement in the oil production process control system the developed application that solves the problems of modeling the oil production process and optimal control of well operation modes in a single software package.

4. Management of the oil field development process based on the model of the oil reservoir area and the well interference model

In order to quantitatively assess the impact of measures to increase oil recovery of a well, a group of wells and predict the values of development parameters for a certain time interval and a number of other tasks, it is necessary to develop a local model of an oil reservoir area with a group of wells opening the reservoir in the form of certain dependencies, equations and determine the specific values of a number of incoming into these equations of unknown parameters, i.e. it is necessary to identify the parameters of the reservoir section model. The simulation-based oil production management process is shown in Figure 1.

Historical data on the development of an oil reservoir area (data on bottomhole pressures, water cut and well flow rates) are the initial data, on the basis of which the parameters of the oil reservoir area model are identified. In the course of identification, those parameters that have the greatest influence on the process of fluid movement in the reservoir change. Further, on the basis of the model, the optimal flow rates of the fluid are calculated in accordance with the control criteria laid down with the control system. The obtained values of optimal flow rates are transmitted via communication lines to actuators that change the operating mode of the downhole pump in accordance with the recalculation of the magnitude of the control action (required flow rate) into the performance of the downhole pump (rotation speed). Then there is an accumulation of new data on the operation of downhole equipment, which then enter the block for identifying model parameters and supplement the existing historical development data. The control process is continuous, and sets of new control actions on the reservoir are generated each time after receiving data on the current well operation modes.

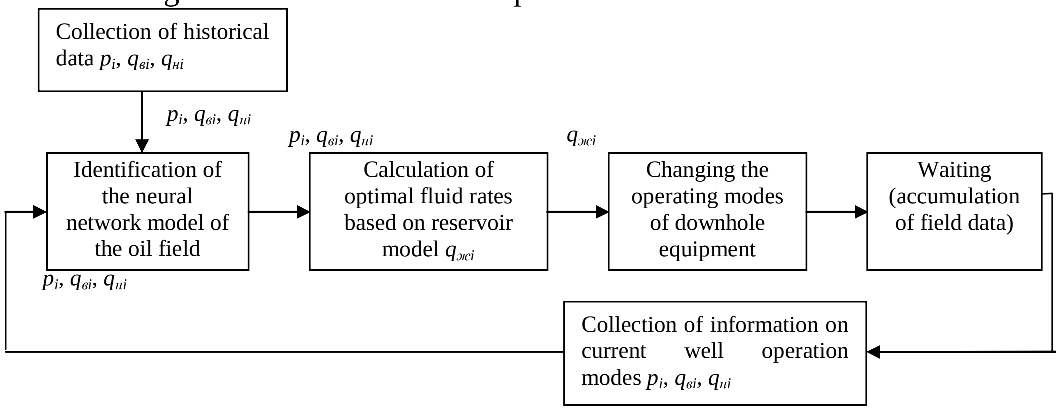

Fig. 1. Scheme for managing the process of developing an oil field based on an oil reservoir model

The proposed solution is to build an integrated system for coordinated control of a multi-level distributed technological process as a whole. For this, a neural network constantly operating dynamic model of an oil reservoir area is being developed as the basis for creating a two-level control system for a group of wells, taking into account their mutual influence in real time. The model provides the required accuracy of describing the physical processes in the reservoir with a simultaneous reduction in the model calculation time and can be included in the control system as a software block.

The algorithm for automatic identification of model parameters as current field data becomes available makes it possible to implement an algorithm for choosing the optimal well flow rate, taking into account technological limitations and economic costs.

Thus, it becomes possible to involve an unobservable object - an oil reservoir - in the process of operational management in the form of a hierarchical system of dynamic models “reservoir-well-pumping equipment”, combining the object and the control system in a single information space, providing measurements, control, diagnostics and management. The applied digital technologies make it possible to optimize the control process through the iterative formation of virtual clusters (groups of producing wells) and pump performance control in order to increase the flow rate of low-watered wells.

It is proposed to apply a new approach to the structuring of the control object based on the selection of elements of the control system:

– section of the oil reservoir, which will make it possible to simplify the modeling with high accuracy of physical processes in the reservoir to take into account the mutual influence of wells as a factor that determines the algorithm for choosing the optimal flow rate of a production well at the group level of the control system;

– well as an object of control and optimization at the local level of the control system;

– pumping equipment, the performance of which is regulated taking into account the efficiency of the joint functioning of the local and group levels of the control system.

Thus, the “reservoir-well-pump” model is being developed, which, in combination with modern automation tools and information technologies, allows creating a single multifunctional information space for the purposes of management, monitoring, diagnostics and forecasting.

The model is dynamic, periodically identifiable, functions as a software unit in the control system and allows eliminating the effect of insufficient field data due to the impossibility of obtaining them by direct measurements.

Conclusion

The scientific significance of the results lies in the integration of systemic principles of construction, operation, development of control systems for the technological process of oil production. The proposed models of objects and processes of oil production provide high adequacy with a decrease in the calculation time and are the basis of a complex technology for modeling and controlling the oil production process in real time.

Of practical value are application software modules that implement the proposed algorithms and modeling technologies, placed on the controllers of wells and groups of wells, with the ability to identify model parameters and select operating modes of installations without operator participation. The efficiency of production modes is also ensured, for example, the uniformity of the advance of the fronts of the displacing agent of the reservoir pressure maintenance system by ensuring rational levels of performance of the equipment of virtual well clusters.

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