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Big Data in Field Development Projects

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Abstract

In recent years, new terms and concepts have appeared that describe the digital transformation currently in progress. The world image, including in the industrial world, has been changed by the concept of intelligent enterprise (IE) - a set of technological innovations, including artificial intelligence (AI), intelligent automation (IA), deep learning technologies, predictive analytics and cognitive computing. The increasing complexity of the oil and gas business and the decreasing optimization potential from traditional approaches require the use of new, innovative digital technologies to remain competitive.

Responding to the market conditions of falling hydrocarbon prices, the oil and gas industry is increasingly mastering Big Data to optimize technological processes and prevent accidents. The emergence of Big Data technologies, predictive analysis and machine learning are changing the general image of many industries, and the oil and gas industry is no exception. New players are quickly emerging throughout the industry, and digitalization will affect the entire value chain throughout in the oil and gas industry. Among the most promising segments for the transition to digital technologies are asset management and infrastructure facilities, field development, geophysical services, pipelines and processing.

Digital technology is the most powerful driver for cost reduction. It is expected that implementing these solutions will, by 2030, reduce the costs of E & P projects by up to 30%. Thus, Russia can leverage these new technologies and retain a share in the world energy market for another 50 years. The oil industry has recently passed the most difficult period in the last 30 years. The fall in oil prices since 2014, the reduction of 350 thousand employees worldwide, and fall in production investment are examples of serious challenges that the industry has faced in recent years. These challenges have resulted in new attempts to optimize business through implementing new technologies to improve the efficiency and profitability of companies.

Introduction

According to the survey conducted by Oil & Gas IQ distributed to representatives of major international oil and gas companies, when answering the question "How can intelligent corporate systems affect your business?" 65% of the respondents voted for cost reduction, 45% for process optimization, 44% for business upgrades, 42% time saving, and 35% winning in competition. With the introduction of sensors that actively collect data on pressure, temperature and flow, and data acquisition systems, the volume of accumulated data

began to grow exponentially. The arrays of historical data on drilling and completion, hydraulic fracturing, geological and hydrodynamic models are growing exponentially from year to year. Taking into account the technological progress of the past three decades, mankind has created the same amount of information and knowledge as was created in the previous 5000 years. However, only 5% of this information is systematized and analyzed. As such, the immediate challenge is to effectively work with this vast amount of information.

During 2017, BP acquired Beyond Limits, a start-up that works with artificial intelligence and cognitive computing, which adapts NASA's upstream technology to the deep-space exploration sector. Chevron is actively developing graphics processors for visualizing seismic data and creating three-dimensional models of deposits. The main goal of this is to identify the most suitable places for drilling. Shell is developing machine-learning algorithms for seismic exploration to automatically detect and classify geological structures in onshore and offshore oil and gas fields. Since 2012, Gazpromneft PJSC has been implementing more than 30 different projects covering all main areas of activity: geological exploration, geology, drilling, development, production, and field development.

Big Data projects traditionally mean digitization of accumulated data in corporations. For example, the Australian company Woodside stated that 64 years of the company's activities were digitized, and the intelligent assistant finds the necessary data in seconds upon request. In essence, this is an electronic data library which undoubtedly improves the efficiency of working with data, but is an example of only the initial level of digitalization. It is important to note that, to a lesser extent, digitalization projects cover the fields of applied field development objectives and optimization of horizontal well operation intervals or hydraulic fracturing stages.

A New Approach to Hydrodynamic Modeling

Contemporary modeling tools allow users to consider the uneven distribution of the horizontal well. However, conventional methods of horizontal well logging with the help of coiled tubing and PLT technologies cannot provide detailed, timely information on the operation of well intervals or hydraulic fracturing stages. Conventional well logging methods are also relatively expensive, dangerous and resource-intensive. But most importantly, they provide bottom hole data only for a very short time frame when the PLT complex of the horizontal section is lowered into the well. This does not allow for tracking the influence of many factors on the well operation. Progress in well digitalization is largely limited due to the lack of data obtained from the bottom of horizontal wells.

Instead of one-time downhole operations, in this approach the well is equipped with high-tech material released into the formation fluid. Next, the fluid is analyzed on the surface using special equipment and software using artificial intelligence. The data are processed automatically and transmitted without interruption to the electronic systems of the customers. Therefore, the service implements the concept of five Vs associated with Big Data projects: Volume – huge arrays of production logging data, ten times more than standard analog logging data; Velocity – efficiency and continuity in obtaining data in a high automation mode and minimum QHSE risks associated with the human factor; Variety – versatility of information on multiphase inflows, the inflow profile response to a large number of variable factors; Variability – selectivity and, finally, Value – the value of data.

The value of the data lies advantage of allowing the data to be tracked through the uneven operation of horizontal well intervals. Uneven operation of the well has a negative effect on the oil recovery factor, leaving unexploited zones of formation drainage. When using analog working methods, these zones appear as white spots in the hydrodynamic model, where a uniform inflow along the horizontal well length is assumed. Obtaining a digitized data array and processing it on an ongoing basis in the hydrodynamic model, the oil producing company can easily overestimate residual reserves online and solve more specific issues related to the well control system performance.

Horizontal Well Production Logging Methods Using Markers for Obtaining Bottom Hole Data

The marking of horizontal wells is performed using marker-reporters consisting of quantum dots stabilized by a polymer shell. Quantum dots are nanocrystals 1-2 nanometers in size obtained by colloidal synthesis and coated with a layer of adsorbed surface-active molecules. Quantum dots obtained by the method of colloidal synthesis are based on cadmium chalcogenides and fluoresce in different zones of the electromagnetic spectrum, depending on their size. Marker-reporters created from quantum dots have the unique ability to absorb energy in a wide range of spectrum and emit a narrow spectrum of light waves, which can be recorded using flow cytometry. Compared to organic fluorophore dyes, which are also used for tracing purposes in the oil industry, quantum dots are more chemically stable and have a fluorescence intensity several orders of magnitude higher.

Quantum dots are used in well tracer technology primarily because of the large number of possible combinations in the synthesis of marker-reporters (over 60), called signatures. At the same time, a unique signature of the hydrocarbon and water phases of the formation fluid is used for each stage or interval. The general scheme of well production logging using markers is presented in Figure 1.

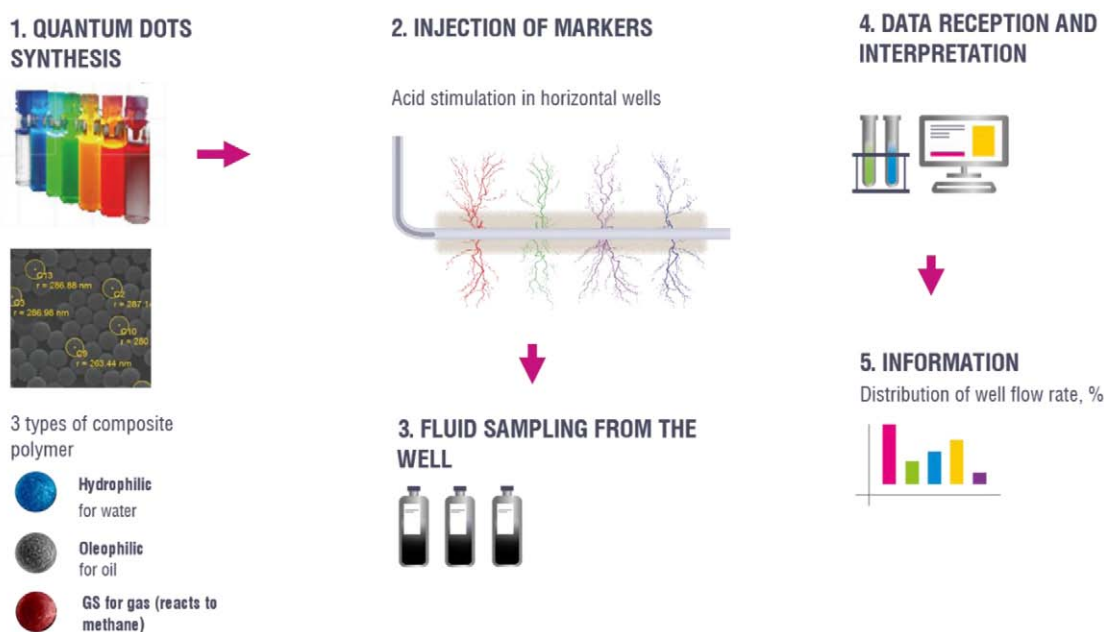


Figure 1—General scheme of well production logging using markers.

The first step in the digitization of technology is the use of special software with machine-learning algorithms to ensure improved accuracy and productivity of the bottom hole data interpretation. The flow cytometry equipment treats a marker as a point in the 15-dimensional coordinate space. Therefore, it is extremely difficult to manually analyze the data using cytofluorometry from the software supplied. The particular difficulty lies in the presence of a large number of signals and the large number of marker-reporter codes in the analyzed sample. Moreover, errors resulting from the "human factor" are certainly possible.

An innovative data processing approach is used for accurate and prompt determination of markers in formation fluid samples. It is based on artificial intelligence, or machine-learning, using the algorithm "Random Forest" (Gurianov, Gazizov, Medvedev, Ovchinnikov, Buzin, 2019). The principle of the operation can be simplified as follows: initially, the neural network is trained on "referee" samples of marker-reporters, from which the so-called "decision tree" is built. At each depth, parameters are sorted according to a certain parameter, e.g. if the particle fluoresces with green light or not. The depth of the tree can be varied. Such

trees differing in structure are created in a large variety. As a result, passing through such a tree, the marker of the desired code falls into a strictly defined "basket." Algorithms then can understand which basket each specific code should fall into. Then a mixture of a large number of markers is examined on the created tree and sorted, i.e. the algorithm considers the number and type of markers in the mixture. Each tree makes its decision, or, relatively speaking, "votes" on the composition of the mixture. Using well formation fluid with marked material for learning allows users to achieve a high accuracy in data interpretation.

Machine-learning algorithms allow for the processing of a large data array with a given accuracy in a short time frame and eliminate the "human factor." Unlike conventional methods of horizontal well production logging that require downhole operations, the analysis of formation fluid samples allows for increasing the volume of data tenfold. Moreover, instead of a one-time picture of well operation, the oil producing company receives information continuously for several years. According to various sources, only a small percentage, 5-10%, of the horizontal well stock has been analyzed. In this case, one of the best results is the achievement of 25% exploration of the total well stock at the Salym field. Thus, there is scant and irregular receipt of production logging data, which does not enable a systematic approach to the control of the developed area. The systemic approach in development plays a major role in obtaining the maximum net discounted income and is caused by the variability of the formation properties, its boundaries, fluid saturation, physical and chemical properties of oil. The peculiarities of the changes in the formation parameters between the wells are largely uncertain and can only be specified using a systematic approach. Without a systematic approach, observable facts – results of various kinds of measurements and logging operations remain just a set of disparate information and, at best, can only serve as the basis for geological and technical measures at single wells.

Examples of Hydrodynamic Modeling Based on Production Logging Using Markers

Wells that utilize markers allow users to obtain data on a monthly basis for several years, representing a data set to be linked with hydrodynamic modeling data. Large data arrays on the horizontal well operation were used to adapt sector filtration models with further selection of measures and calculating efficiency. Several typical scenarios demonstrating the benefits of the new approach are presented below.

Let us consider the first scenario where, based on the calculation results, the horizontal well is operating with 5 working intervals stimulated by multi-stage hydraulic fracturing. It is surrounded by four vertical injection wells with hydraulic fracture I1, I2, I3 and I4. When implementing Option 2, the oil producing company did not conduct production logging operations and did not identify that only 2 out of 5 ports were in operation. For Option 2, well production logging with markers was carried out within months, and the oil producing company took geological and engineering measures to activate the connection to the well toe, and all 5 hydraulic fracturing stages made a certain contribution to the total well flow rate. As a result, with the implementation of Option 1, which is common in the fields of Western Siberia, the oil producing company received 11,200 tons of oil within 2 years (Figure 2).

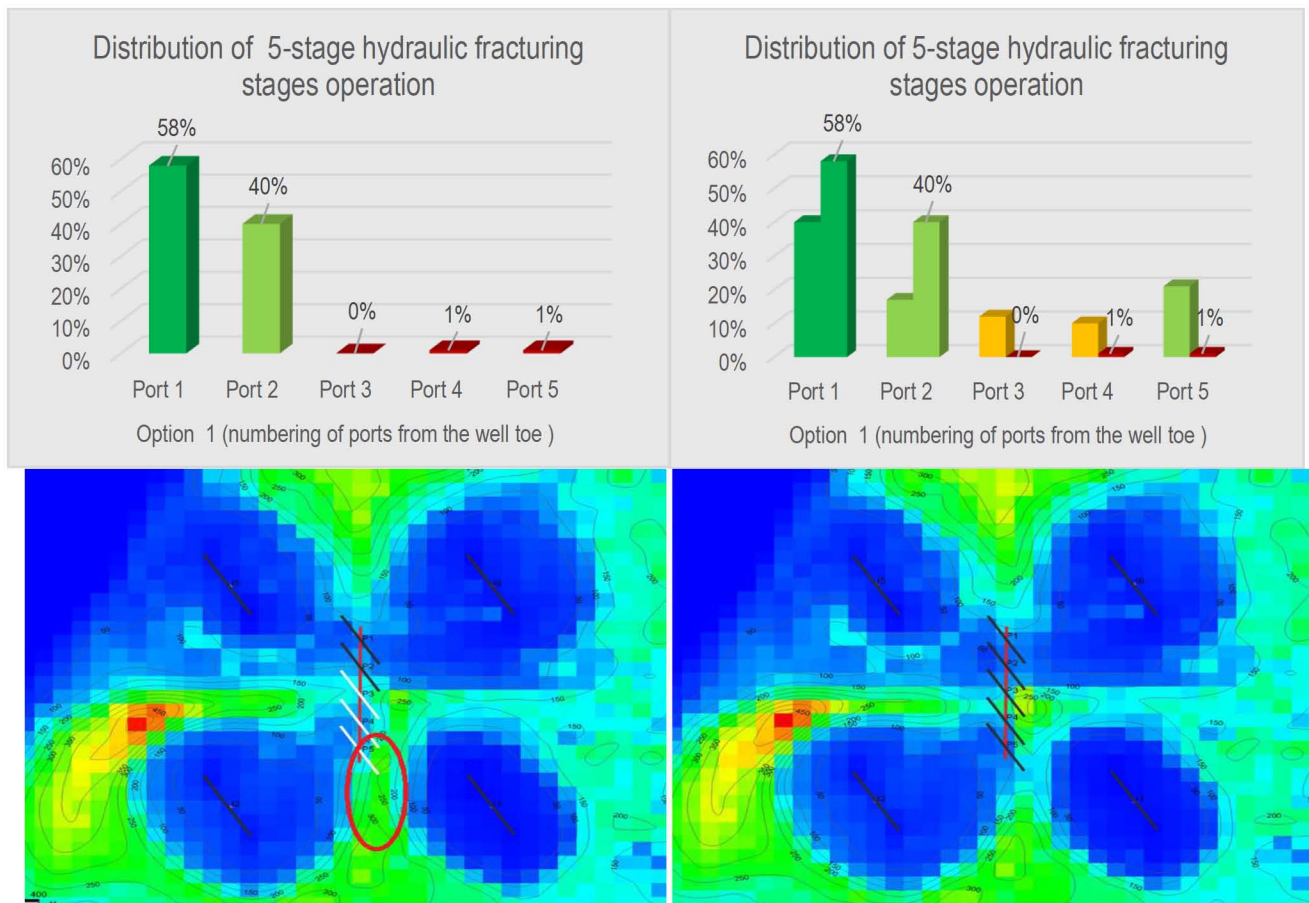


Figure 2—Two options of horizontal well operation with a 5-stage hydraulic fracturing

The second scenario stipulates the water breakthrough identification in the middle of the horizontal well with 5 hydraulic fracturing stages. Here, the well is surrounded by four vertical injection wells with hydraulic fracturing. According to production logging using markers, a water flow rate of 65% was recorded in Port 3. The percentage distribution of the contribution of the water and oil phases of the liquid is calculated separately. Production logging using markers allows for prompt identification of the flooded port and taking measures for repair works or closing the port in the presence of a controlled completion. When operational decisions are made on conduction repair works or closure of the port, redistribution of filtration flows occurs, leading to an additional production of 7,200 tons of oil within 2 years.

Visualization of the calculation of the water breakthrough elimination efficiency from Port 3 of the horizontal well with a 5-stage hydraulic fracturing is presented in Figure 3.

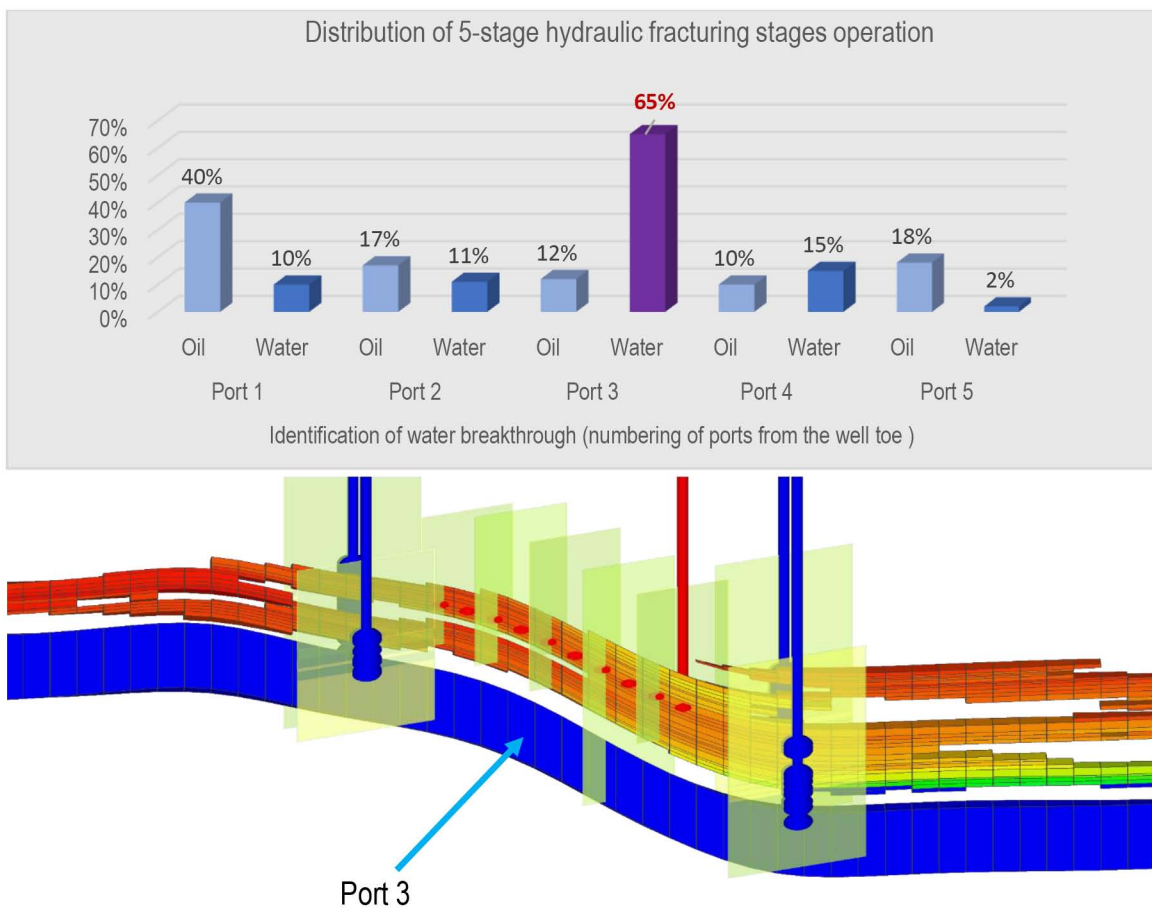


Figure 3—Visualization of the calculation of the water breakthrough elimination efficiency from Port 3 of the horizontal well with a 5-stage hydraulic fracturing.

Let us now consider the third scenario where, based on the calculation results, a horizontal well is operating with 5 working intervals stimulated by multi-stage hydraulic fracturing and surrounded by four vertical injection wells with hydraulic fracturing in I1, I2, I3 and I4. In the case where a high water flow rate is detected using the production logging using markers, pilot changes in the injection wells operation mode are made (4 samplings within 2 months). In determining the injection well influencing the water breakthrough, costs should be stopped or reduced, which leads to an increase in oil production of 2,989 tons over 2 years (Figure 4).

Stop of pumping into well I5

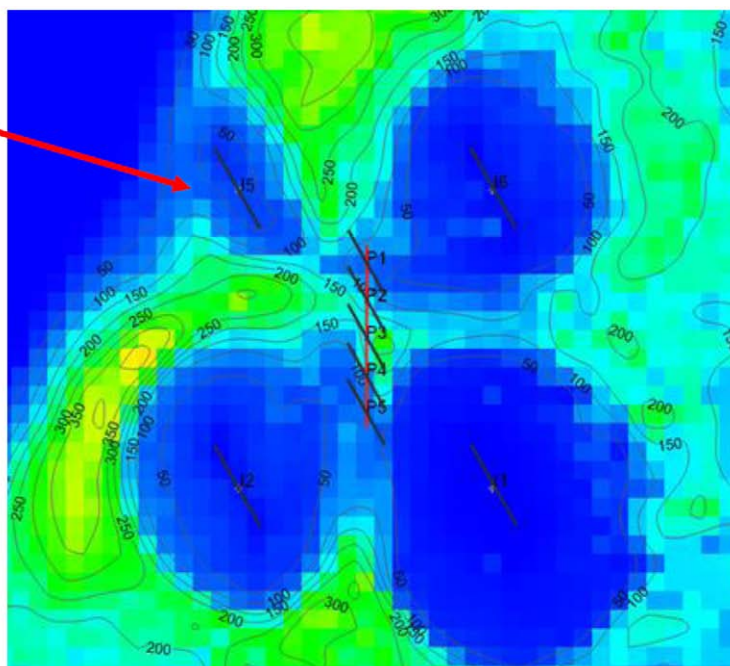
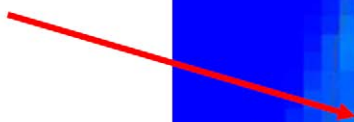


Figure 4—Visualization of Selective Well Control

Field Scale

Undoubtedly, the above scenarios serve only as a demonstration of a qualitatively different approach to the control of production, leading to a much more difficult task due to the increase in the number of injection and production wells indicated in Figure 5.

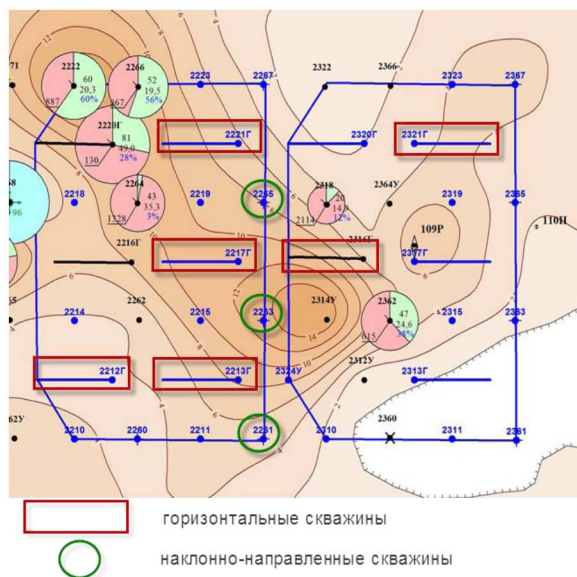


Figure 5—Demonstration of an increase in the number of injection and production wells.

Increasing the well interval data informative capacity and the automation of hydrodynamic modeling using an independently compiled program module dynamically connected to the main program allows for a more adequate assessment of reserves based on the data obtained by production logging using markers. Thus, Figure 5 indicates the explored sector by the hydrodynamic modeling of one of the largest fields in Western Siberia, where a mechanical calculation was applied in the conceptual design cycle. The difference

in the discounted cumulative production ratio between the scenario with 100% hydraulic fracturing ports and the scenario with half non-working ports is very large – greater than 94,000 tons. Such an immense scale of lost profit prompts the application of production logging methods with markers to inactive and flooded ports of multiple hydraulic fractures, even at the drilling and hydraulic fracturing stage, and laying the construction potential for conducting geological and engineering operations for activating non-operational ports, isolating the flooded ports, etc. The industry is keenly aware of examples of a positive profit margin on the developed projects, including the East-Messoyakhskoye field project, which was considered unprofitable when using conventional logging methods when the geological model was not fully confirmed in practice. Evaluation of a huge number of options for adjusting the concept and eventually reaching solutions such as increasing the length of the horizontal well section, increasing the density of the drilling grid allowed for the additional reception of about 60 billion rubles to the net discounted income of the project and aided in the successful development of the field.

Comparison of the calculation of the sector model in the software tNavigator with the expected performance of multi-stage hydraulic fracturing (conventional approach) and based on machine-learning in statistical sampling, taking into account the processing of historical data on drilling, completion, hydraulic fracturing and production logging is presented in Figure 6.

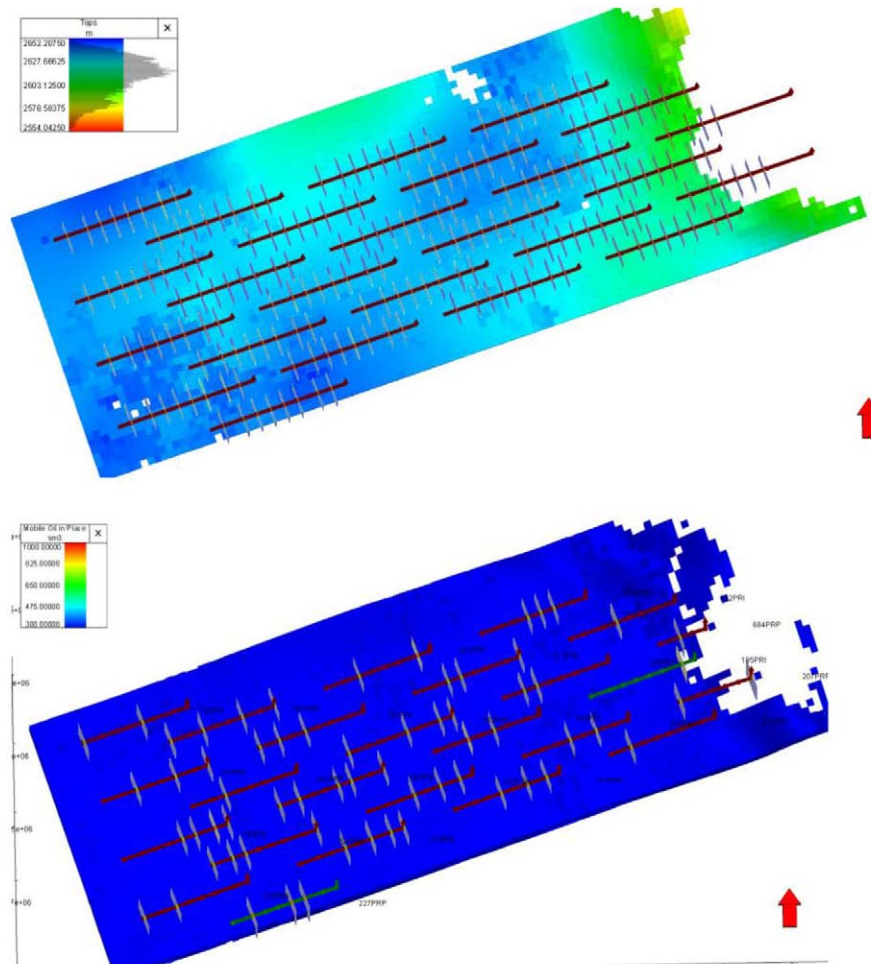


Figure 6—Comparison of the calculation of the sector model in the software tNavigator with the expected performance of multi-stage hydraulic fracturing (conventional approach) and based on machine-learning in statistical sampling, taking into account the processing of historical data on drilling, completion, hydraulic fracturing and production logging

Conclusion

The developed technology allows users to conduct logging operations with an automatic transfer of information to the oil producing company databases. When compared to conventional methods, the data volume is increased tenfold. Instead of a one-time picture of the well operation, the oil producing company receives information continuously for several years. The production process is optimally digitized, including the use of software with machine-learning algorithms that is applied to interpret bottom hole data and cognitive production logging data recognition. The project is successful in terms of digitalization, as it involves the application of innovative well logging technologies:

- Processing and sorting the arrays of bottom hole data using the machine-learning algorithm "Random Forest"
- Ensuring the receipt, storage, transmission and management of large amounts of data with minimal human intervention
- Ensuring interaction with packer elements for hydrodynamic modeling
- Processing and organizing unstructured information using software that utilizes artificial intelligence, specially designed for reservoir fluid production logging for the presence of flow indicators
- Performing automated generation of analytical reports, as well as the introduction of prognostic models for localizing hydrocarbon reserves and maintaining the efficiency of the formation pressure maintenance system.

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