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Using Hybrid Digital Models to Analyse Well Interference and Optimise Field Development Management

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Abstract

Effective development of oil fields is impossible without reliable information on the degree of well interference.

The interference between production and injection wells is evaluated using indicators that are commonly known as the interference coefficients or connectivity coefficients. There is a number of statistical, analytical, and predictive methods for hydrodynamic connectivity (interference) assessment.

This paper focuses on a new approach designed to overcome the challenges associated with the rational development of reserves and well interference assessment with building an improved hybrid material balance model.

The purpose of the research was to evaluate various scenarios for well interference assessment, as well as to identify hydrodynamic communication between injection wells and specific producing wells for prompt decision-making to optimise the development system. The paper discusses the results of studies conducted on one field of Western Siberia, having a complex geological structure and highly heterogeneous.

Well interference coefficients were obtained as the result of the studies, which helped understand what average proportion of water injected from a particular injection well effectively impacts the producing wells in question located in the immediate vicinity. The digital hybrid model was used to identify the injection wells that are hydrodynamically connected with producing wells, estimate the degree of their impact on the production performance of the latter, as well as monitor the dynamics of such influence for each well. Based on the analysis performed, some recommendations were elaborated for improving the oil recovery factor in the oil fields and reducing development costs.

INTRODUCTION

Nowadays [1], on the back of the rather slow increment in oil reserves, as well as due to the significant degree of depletion of many large oil fields and high water content, the issue of field development improvement becomes topical.

Since the upstream sector is one of the most knowledge-intensive and high-tech industries, it appears to be a field of application showing demand for an entire range of state-of-the-art information technologies (IT). They are used to create digital 3D models of oil and gas fields in order to assess reserves and the state of development, as well as forecast process parameters for choosing the optimal strategy for the development of hydrocarbon deposits. Due to the rapid development of computer technologies, highperformance computers together with software can be used for collecting, storing, calculating, presenting, and analysing various kinds of data related to the three-dimensional modelling of deposits. The modern computing systems combined with specialised software (PCs) is an essential tool for any oil and gas company. Therefore, the application and further development of IT when modelling the state of field development as well as optimal management of oil well operation modes are crucial and topical objectives of modern oilfield practice [2].

Up until now, a common approach in the field development was to customise well operation parameters for each well individually by setting flow rates and bottom-hole pressures proceeding from various economic assumptions. This approach has a clear drawback, namely, it neglects the phenomenon of well interference.

Obviously, a change in the operating parameters (flow rate and bottom-hole pressure) of one well results in a change in the operating parameters of other wells, i.e. an important feature of the oil production process is the hydrodynamic connectivity (interference) of wells. When using the reservoir pressure maintenance system, as a rule, the interference between producing and injection wells is taken into account. Undoubtedly, a clear understanding of such interference is a key factor for the improvement of the field development efficiency by adjusting the injection [3]. This is because injection affects both the reservoir drive mechanism and the rate of encroachment.

Thus, reasonable operating parameters should be selected for entire well pads rather than for individual wells. However, it is virtually impossible to process a large amount of data manually without resorting to digital tools. For instance, about 500 thousand measurements can be accumulated for an average field having 100—200 wells.

Currently, there are a number of tools for statistical analysis with the use of machine learning algorithms enabling us to accurately take into account all previously accumulated data on wells, i.e. data on injections, operating parameters, production figures, as well as all historical well measurements.

When composing sets of equations based on physical laws to determine well interference, reservoir pressure dynamics, injection and production pattern across formations, and the maps of residual oilsaturated layers, the most frequently used concepts are a material balance equation, the porous media flow law, and the Buckley-Leverett theory. That said, all systems of equations are set up with a number of assumptions.

In the course of the project, the improved hybrid model of the material balance was used to study the geology of the formation area, calculate and map the geological parameters, identify the areal and vertical patterns of productive formations distribution, and analyse the factors causing the changes in the production profiles along with the interference and the presence of a unified hydrodynamic system.

The well interference and formation pressure maintenance system were analysed to obtain data on the degree to which injection impacts the production across individual flooding zones. This data was used to identify flooding areas for the purpose of implementing conformance control measures with the aim to increase the vertical sweep efficiency and reduce the water encroachment in production wells.

Description of the model as part of the GeoExpert digital platform

Nowadays, there are such trends as the development of field proxy modelling and the intense development and application of machine learning in various sectors to promptly identify the effect of injection wells on fluid production. Taking the above-said into account, efforts were put to develop and apply the so-called hybrid model of material balance, which is based on the CRM (CRMP) model equation, yet with some improvements. In particular, this equation was used to develop a summing output layer of an artificial neural network, which takes into account the imposed physical limitations. However, at the same time, some equation coefficients are yielded by the previous layers of the neural network, namely the time coefficient, the productivity index, and the coefficients of influence of injection wells. For this interpretation, the final equation can be represented as follows:

$$\begin{split} q_{jk} &= q_{j(k-1)} \cdot e^{-\Delta t/\tau_j(x)} + \left(1 - e^{-\Delta t/\tau_j(x)}\right) \left(\sum_{i=1}^{N_i} d_{ij} \cdot f_{ij}(x) \cdot I_{ik} - J_j(x) \cdot \tau_j(x) \right) \\ & \cdot \frac{\left(p_{bott.hole,j}^k - p_{bott.hole,j}^{k-1}\right)}{\Delta t} \\ & 0 \leq f_{ij}(x) \leq 1, \\ & \sum_{i=1}^{N_i} f_{ij}(x) \leq 1, j = 1:n \end{split}$$

Where:

x — a set of parameters calculated on the basis of known historical data, such as flow rate, intake rate, well operation parameters, and others;

 $\tau(x)_j$ – a function of a set of input parameters that adjusts for the time delay of the injection influence on producing well j;

 $J_j(x)$ – Productivity of well j, defined as a function of a set of input parameters;

 $f_{ij}(x)$ – the coefficient of influence of injection well i on the production well j, defined as a function of a set of input parameters;

 q_{jk} – forecast flow rate for the period k, for well j;

 $q_{j(k-1)}$ – flow rate for the most recent known period k-1, for well j;

 l_{ik} – intake rate for well i for the period k;

 $p_{botthole,j}^{k}$ – bottom-hole pressure for well j for the period k;

 $p_{bott,hole, j}^{k-1}$ – bottom-hole pressure for well j for the period k-1;

 d_{ii} - The parameter adjusting for the influence of a well.

It is proposed to neglect the possible impact of wells situated beyond a certain threshold distance. The threshold distance is set by an expert when building a model and can also be used to easily disregard connections with some wells.

The general flow chart of the neural network architecture including the proposed output layer is presented in detail in Figure 1.

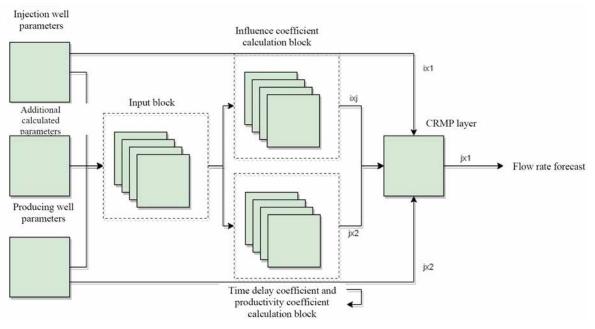


Figure 1—The general flow chart of the neural network architecture

The flow chart shows a set of input parameters of the model, which are processed in the input block fully or partially. The model's input block is a convolutional neural network. At the next stage, we see a division into two parallel blocks with simple fully connected layers of the neural network. In the coefficient calculation block, it is proposed to use the logistic activation function $(f(x) = \frac{1}{1+e^{-x}})$ at the output. In the time delay and well productivity coefficient calculation blocks, SoftPlus $(f(x) = \ln(1+e^x))$ is proposed as an activation function on the output layer. After that, the calculated parameters get to the CRMP layer responsible for the calculation of the flow rate forecast. The functions of the intermediate layers' activation [4] may vary depending on the data provided. The same is true for the number of such layers and their other hyperparameters. When training the model, the mean squared error is used as a loss function and the

$$Loss = \frac{1}{m} \sum_{j=1}^{m} \| \hat{q}_{j} - q_{j} \|^{2}$$

problem of loss minimisation is solved:

In this case, automated selection of the most optimal model parameters and methods of data preprocessing was used during the model training, inter alia, for the calculation of additional inputs to the neural network in order to improve the loss minimisation function used.

In the future, this model is supposed to be used in combination with an automated training option as part of the service, which is part of the GeoExpert digital platform. This will enable the quick development of models for various data with minimal effort and, in turn, facilitate prompt decisionmaking on the further operation of the wells.

After training the model, a table of the coefficients of the injection wells' influence on each producing well for a selected period of time can be obtained. The data yielded are also used to optimise the injection pattern, select optimal well operation parameters, and choose conformance control measures for the sake of the rational reserves development.

Using hybrid digital models on wells of an oil field in Western Siberia

To test the current version of the hybrid digital model, the degree of well interference was evaluated at the site of an oil field situated in Western Siberia. The field in question is characterised by an impressive number of production and injection wells, as well as a long period of flooding. Due to the high water encroachment in the production wells, the main focus is put on optimising the operation of both production wells and injection wells forming the reservoir pressure maintenance system in order to reduce low-efficiency injection and maximise oil production. The approach used has given a picture of what injection wells are hydrodynamically connected with producing wells and helped estimate the degree of their influence on the production performance of the latter.

The hybrid digital model was used in the case of four multi-well pads with different development systems. The study of well interference coefficients was conducted on 85 wells in total, including 38 producing wells and 47 injection wells.

Input data for the model included the following parameters: historical data on well operation for a period exceeding 3 years, operation parameters, the current fluid flow rate, the current water cut of reservoir products, maps of the fields with a logarithmic scale to identify the distance between wells and the list of well interventions, as well as the intake rate of injection wells. The model also takes into account the coefficient of well remoteness, which can be used to artificially neglect the effect of a remote well in the calculation or adjust the maximum possible influence of the well. This coefficient is set before optimising the model.

It is a common fact that field development management and control are performed with the use of flow simulations. Its main purpose is to substantiate well interventions in the medium and long-term periods of development, as well as to optimise the development systems of the mature fields using modern flooding optimisation technologies and tertiary methods of oil recovery stimulation. The flow simulation process has a significant disadvantage as it requires a large amount of resources to create, optimise and update reservoir flow models, while machine learning offers a high speed of data processing and calculations.

The obtained simulation results were verified by means of comparison with the actual field data and well operation parameters. Field data for each pair of wells (production—injection) was additionally analysed by experts. It should be noted that the identification of hydrodynamic connectivity by this method takes a lot of effort and is not 100% reliable. However, this method is applicable to identify qualitative responses in single wells and issue recommendations for changing operating parameters. A comprehensive analysis of the performance of the entire well pad using this method would be quite a challenge.

Figure 2 shows a field map tile with the boundaries of one of the well pads under study. It also reflects the well interference matrix for two periods of study: for the entire history of wells operation from the very start (Fig. 2, a) and particularly for 2021 (Fig. 2, b).

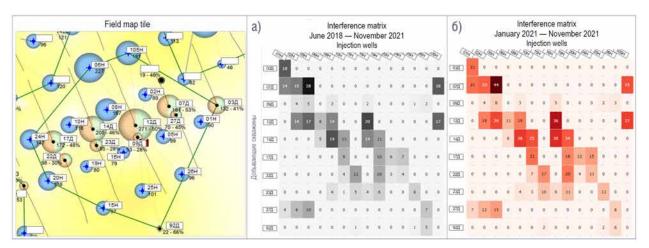


Figure 2—The map tiles of the area under study and the well interference matrix

According to the field map tile, the well pad in question consists of 10 producing and 14 injection wells. The producing well stock is mainly represented by wells with a horizontal completion, while the injection wells are mostly directional wells. Horizontal laterals of the producing wells were drilled with azimuths \sim 150° and \sim 330° along the horizontal stress.

Upon establishing the well interference coefficients (Fig. 2, a and Fig. 2, b), the following conclusions were made:

- The production wells of the "northern row" (Nos. 17D—07D) are exposed to stronger influence by injection wells both percentage-wise and in absolute figures;
- For the production wells of the "southern row" (Nos. 22D—27D), weak flow connectivity between oil production and injection wells was revealed. The reason may be the worse reservoir properties relative to the northern part;
- The relatively high water encroachment of the "northern row" wells may be due to a greater hydrodynamic connection with the wells of the reservoir pressure maintenance;
- The wells of the "northern row" show high production rates, while the "southern row" wells are characterised by relatively low performance.

In case of a large number of wells, it is important to limit the area of influence for some "remote" injection wells in order to avoid the possibility of detecting "false connections". For this purpose, well pads (cells) were allocated on the presented field for independent calculations (for instance, one of the cells is shown in Figure 3). The pad boundaries were set up to have a production well in the center of each cell evenly surrounded by the first row of injection wells of the reservoir pressure maintenance system. Part of the injected water can spread beyond the boundaries of the well pad in question and flow to producing wells located outside these boundaries. Therefore, it should be noted that the purpose of the selected boundary setting method is to identify well interference only for one producing well situated in the center of each the well pad.

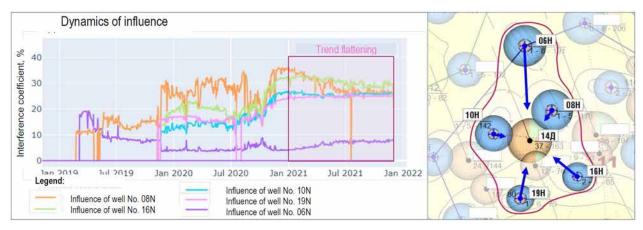


Figure 3—Analysis of well interference within a well pad

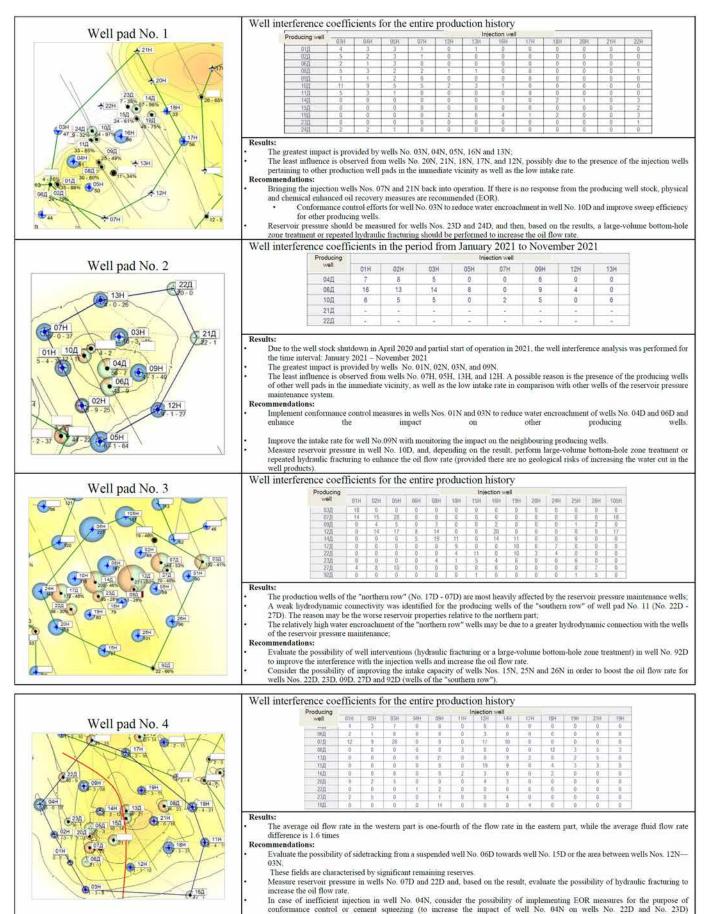
As the figure shows, five injection wells Nos. 06N, 08N, 10N, 16N, and 19N situated in the immediate vicinity were considered as influencing the production well No.14D. Remarkably, well No. 06N is the most remote one from the producing well as it is situated on the periphery of the well pad under study (beyond the boundary, there are producing wells of the neighbouring pad, and therefore we cannot exclude the probability of migration of the injected water beyond the pad).

The figure also shows the dynamics of well interference coefficients throughout the entire accumulated historical data. At the beginning of well operation, the influence of two wells Nos. 06N and 08N, not exceeding 20%, is seen. It is worth noting that the influence coefficients in the initial period are purely provisional. Their accuracy is largely affected by the non-steady well operation mode (reaching steady-state production), stops, and short-term downtime periods.

Another important consideration is that the injection wells were launched at different time periods (from February to November 2019), and therefore the most reasonable approach would be to assess the interference starting from the commissioning of the last influencing well. The dynamics show a flattening trend in the well interference curves over the last year of well operation (January 2021– November 2021), which may indicate a stable fluid flow through the reservoir (steady-state production).

Table 1 shows the summarised results of the efforts performed to identify the reservoir flow connectivity in the Kondinsky field's reservoirs. It should be mentioned that different development systems are used at each reservoir, and therefore, results were obtained specifically for each well under study and recommendations were issued to increase the efficiency of field development. Moreover, the technique used enables identifying inefficient injection. According to the results of the hybrid model application, a certain amount of the injected water does not reach the producing wells in the immediate vicinity. It can be assumed that the water flows into the non-target reservoir or beyond the well pad boundaries in directions opposite to the location of the producing wells.

Table 1—The results of the activities performed to identify the hydrodynamic connectivity



RESULTS AND CONCLUSIONS

Quantitative assessment of the mutual interference coefficients helps understand what average proportion of water from a particular injection well falls on the producing wells under study located in the immediate vicinity. The digital hybrid model was used to identify the injection wells that are hydrodynamically connected with producing wells, estimate the degree of their impact on the production performance of the latter, as well as monitor the dynamics of such influence for each well.

Not insignificantly, when using the current version of the hybrid model, a number of factors that could affect the interference coefficient were ignored. Therefore, the coefficients obtained and the recommendations issued require further evaluation. Several assumptions were made in the course of work, namely, some factors were disregarded such as the geometry and length of the horizontal lateral and production data on the wells located at the neighbouring pad though still capable of impacting the wells under study.

Importantly, the method demonstrates the utmost efficiency in case of the integrated application of the results of the hybrid digital model-based analysis and production profiling surveillance in horizontal wells. The latter enables assessment of the interference between not only injection and producing wells, but also between an injection well and an interval. An integrated approach provides an opportunity not only to identify the most encroached intervals/sections of the horizontal lateral but also to establish which of the injection wells in the immediate vicinity provides a stronger impact on the performance of producing wells.

The well interference assessment both for the entire operation history and in specific time intervals, obtained in the course of experiments, is easy to implement and shows fairly high reliability coefficients based on a comparison of simulation and actual data. The approach employed in the study can be replicated at other reservoirs and oil fields.

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