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(54) Title: PREDICTING WELLBORE FLOW PERFORMANCE

(57) Abstract: The method allows to predict the wellbore flow performance characteristics inside the well and at the well bottom in particular using computing system consisting of machine learning system, memory storage, and user interface. The predictions are provided for the input parameters specified through the user interface based on the analysis performed by the machine learning system on data stored in the memory storage. The data includes the actual data collected from the real field operations and the results of numerical simulations. Knowing and controlling the wellbore flow performance characteristics is important for the optimization of the well startup (also referred to as flowback or cleanup) operations.



PREDICTING WELLBORE FLOW PERFORMANCE

Field of the invention

The present invention is related to the field of data analytics in the petroleum industry. More specifically, the present techniques are directed to systems and methods for predicting wellbore flow performance characteristics using machine learning techniques. The method allows to predict the wellbore flow performance characteristics at the bottom of well where these characteristics are usually unknown. Among the predicted characteristics are the wellbore flow physical parameters such as the bottomhole pressure, bottomhole rate, and bottomhole temperature. Knowing and controlling these characteristics is important in the operation of well startup (also referred to as flowback or cleanup) to prevent exceeding critical values of bottomhole pressure, bottomhole rate, and bottomhole temperature that might lead to the negative effects. In the case of hydraulically fractured well these negative effects are associated with the loss of conductivity of the previously created hydraulic fractures due to the proppant flowback or formation failure or other unfavorable processes.

Background of the invention

The invention includes method and system for the prediction of the transient wellbore flow performance characteristics. Among the wellbore flow performance

characteristics of interest in practical applications are the pressure, flow rate, temperature, and volume fractions at particular locations inside the well. Knowing these characteristics is important in application to the fracture flowback or cleanup problem, where the highly transient multiphase wellbore flows are observed. In the flowback problem, the prediction of the downhole parameters is crucial for starting the well in a safe operation envelope and design surface operations (e.g. selecting the choke size) to maximize the well long-term productivity

It is common that the wellbore flow performance characteristics are evaluated using the specialized software where the governing equations of mathematical physics are used to describe the fluid mechanics (for more details see, for example V. DE HENAU AND G. D. RAITHBY, A Study of Terrain-Induced Slugging in Two-Phase Flow Pipelines, *Int. J. Multiphase Flow*, 21 (1995), pp. 365–379). In the present invention, an alternative method and system for determining the wellbore flow performance characteristics based on machine learning techniques are proposed.

Summary of the Invention

Disclosed is a method for predicting wellbore flow performance characteristics of a well penetrating an underground hydrocarbon bearing formation which includes machine learning techniques implemented into the computer system and applied to process historical data collected from various sources.

The method includes storing in a knowledge database in a memory storage a first well data obtained from a plurality of operating wells and comprising historical well static parameters, well dynamic parameters measured at the surface and historical wellbore flow performance characteristics measured during start up and

production by one or more pieces of field equipment installed at the surface or inside the wells.

The method also includes storing in the knowledge database in the memory storage a second well data comprising simulation input well static parameters, simulation parameters used as the boundary conditions at the well outlet and calculated wellbore flow performance characteristics obtained by numerical simulation for a plurality of cases.

Then the method includes performing, by a machine learning system, an analysis of said first well data, wherein said analysis produces first relationships between said historical well static parameters, said well dynamic parameters measured at the surface and said historical wellbore flow performance characteristics measured inside the wells, and performing, by the machine learning system, an analysis of said second well data, wherein said analysis produces second relationships between said simulation input well static parameters, the simulation parameters used as the boundary conditions at the simulated well outlet, and said calculated wellbore flow performance characteristics.

The method also includes inputting, into the machine learning system, new well static parameters characterizing a new well penetrating an underground hydrocarbon bearing formation and new dynamic well parameters measured at surface and predicting, by the machine learning system, the wellbore flow performance characteristics of said new well based on the produced first and second relationships. Then, the method includes evaluating if the predicted wellbore flow performance characteristics satisfy requirements of a safe operation envelope during the new well startup and production, and based on evaluation, adjust, if needed, surface equipment control parameters to satisfy the requirements of the safe operation envelope.

A computing system for predicting wellbore flow performance characteristics of a well penetrating an underground hydrocarbon bearing formation comprises a memory storage for storing a knowledge database comprising a first well data obtained from a plurality of operating wells and comprising historical well static parameters, well dynamic parameters measured at the surface and historical wellbore flow performance characteristics measured by one or more pieces of field equipment installed at the surface or inside the well during start up and production, and a second well data comprising simulation input well static parameters and calculated wellbore flow performance characteristics obtained by numerical simulation for a plurality of cases.

The system also comprises a user interface adapted to receive user inputs for new well static parameters characterizing a well penetrating the formation and an underground hydrocarbon bearing formation, and a machine learning system.

The machine learning system comprises at least one processor coupled to the memory storage and having functionality to execute instructions for performing an analysis of said first well data, wherein said analysis produces first relationships between said historical well static parameters, said well dynamic parameters measured at the surface and said historical wellbore flow performance characteristics measured inside the wells, performing an analysis of said second well data, wherein said analysis produces second relationships between said simulation input well static parameters, simulation parameters used as the boundary conditions at the simulated well outlet, and said calculated wellbore flow performance characteristics, receiving new static well parameters characterizing a new well penetrating an underground hydrocarbon bearing formation, predicting wellbore flow performance characteristics of the new well.

The machine learning system also comprises an input component allowing for the machine learning system to use inputs provided by the user. Then, the computing

system comprises an output component coupled to the database, wherein the output information is produced based on previous operations of the machine learning system.

Brief description of the drawings

Features and advantages of the described implementations can be more readily understood by reference to the following description taken in conjunction with the accompanying drawings.

Fig. 1 shows a flowchart in accordance with one or more embodiments of the disclosure;

Fig. 2 illustrates a computing system in accordance with one or more embodiments;

Fig. 3 shows examples of water and oil source term flow rate functions;

Fig. 4 illustrates an example of the wellhead pressure (WHP) and the bottomhole pressure (BHP) for a selected numerical simulation;

Fig. 5 illustrates an example of oil, water, and gas flow rates at surface for a selected numerical simulation;

Fig. 6 shows comparison of the BHP predicted by the machine learning algorithm against the simulated BHP.

Detailed Description

The invention provides the method for predicting the wellbore flow performance characteristics of transient multi-phase flows using the machine learning techniques. Such multiphase flows are typically formed in oil and gas wells

when reservoir fluids flow from the hydrocarbon bearing formation enter the wellbore through perforations during the well start up and production.

Machine learning area received a fast development in the recent years, and it is extensively used in many applications. It is found to be particularly useful in processing large amounts of data, time series forecasting and analysis, speech recognition and medical data classification.

Among the wellbore flow performance characteristics of interest in practical applications are the pressure, flow rate, temperature, and volume fractions at particular locations inside the well. Knowing these characteristics is important in application to the fracture flowback or cleanup problem, where the highly transient multiphase wellbore flows are observed. In the flowback problem, the prediction of the downhole parameters is crucial for starting the well in a safe operation envelope and design surface operation (e.g. choke size) to maximize the well long-term productivity.

In many new wells the gauges and meters allowing to directly determine the wellbore flow performance characteristics are not installed for economical reasons neither during well start up, nor during the production. Hence, an accurate and systematic analysis of historical data can provide a possibility to make predictions of the wellbore flow performance characteristics for new wells. The modern machine learning techniques are particularly well suited for processing large amounts of data and identifying the key features that make such predictions possible. Such method and system are proposed in this work.

The wellbore flow performance characteristics are transient, especially during the well start up. Hence, these parameters should be predicted as time series. In the present invention the wellbore flow performance characteristics are predicted using a data-driven model based on machine learning algorithm trained on historical field data or results produced by the numerical simulator. The data might contain

information about the wellbore geometry, and of the flow parameters (rate, pressure) measured at the surface and inside of the wellbore, and other available or newly appearing information. In another configuration of the invention, the historical data are represented by a synthetic set of results generated with using the transient numerical simulator of multi-phase wellbore flows. The machine learning techniques can be used to learn historical data imitated by numerical simulations and provide predictions. For example, a linear or polynomial regression, multi-level artificial neural networks, decision trees, or other techniques can be used to construct the data-driven model.

Fig. 1 shows a flowchart in accordance with one or more embodiments.

The disclosed method comprises storing by a computing system storing in a knowledge database in a memory storage a first well data obtained from a plurality of operating wells and comprising historical well static parameters, well dynamic parameters measured at the surface and historical wellbore flow performance characteristics measured during start up and production by one or more pieces of field equipment installed at surface or inside the well, and a second well data comprising simulation input well static parameters, simulation parameters used as the boundary conditions at the well outlet and calculated wellbore flow performance characteristics obtained by numerical simulation for a plurality of cases (Block 1).

In accordance with one embodiment of the invention the historical well static parameters, the simulation input well static parameters comprise at least one of a group consisting of petrophysical properties of the hydrocarbon bearing formations, geological properties, geomechanical properties, fluid properties, configuration of the wells, and other measurable parameters of the wells and formations.

In accordance with another embodiment of the invention the well dynamic parameters measured at surface and the simulation parameters used as the boundary conditions at the well outlet comprise at least one of a group consisting of flowrates

of hydrocarbons, solid particles, peak surface rates of hydrocarbons and particles, pressure, temperature, volume fractions, duration of well cleanup or flowback.

In accordance with another embodiment of the invention the measured historical wellbore flow performance characteristics and the calculated wellbore flow performance characteristics comprise at least one of a group consisting of flowrates of hydrocarbons, peak surface rates, pressure, temperature, volume fractions, rates distribution in the wells and hydrocarbon bearing formations, duration of well cleanup or flowback.

In Block 2, an analysis of said first well data, wherein said analysis produces first relationships between said historical well static parameters, said well dynamic parameters measured at the surface and said historical wellbore flow performance characteristics measured inside the wellbore, and performing, by the machine learning system, an analysis of said second well data, wherein said analysis produces second relationships between said simulation input well static parameters, the simulation parameters used as the boundary conditions at the well outlet and said calculated wellbore flow performance characteristics.

In Block 3, new well static parameters characterizing an underground hydrocarbon bearing formation and a new well penetrating the formation, and new dynamic well parameters measured at surface are submitted by a user into the computing system via an interface. In accordance with one embodiment of the disclosure the new well static parameters characterizing the underground hydrocarbon bearing formation and the new well penetrating the formation may comprise at least one of a group consisting of petrophysical properties of the hydrocarbon bearing formations, geological properties, geomechanical properties, fluid properties, configuration of the wells, and other measurable parameters of the wells and formations. The new dynamic well parameters measured comprise at least one of a group consisting of flowrates of hydrocarbons, solid particles, peak surface

rates of hydrocarbons and particles, pressure, temperature, volume fractions, duration of well cleanup or flowback.

In Block 4, the comparison of the new well static parameters and the new dynamic parameters measured at surface of the new well with the historical static well parameters and the dynamic parameters measured at surface and the simulation input well static parameters and the simulation parameters used as the boundary conditions at the well outlet is performed by the machine learning techniques.

In Block 5, the wellbore flow performance characteristics of said new well are predicted by the machine learning system based on the produced first and second relationships.

The predicted wellbore flow performance characteristics comprise at least one of a group consisting of pressure, temperature, phase rates, volume fractions along the well and at the well bottom, a duration of the well cleanup or flowback, cumulative values of surface rates and peak values of the surface rates of hydrocarbons, wellhead pressure.

The workflow may also include evaluating if the predicted wellbore flow performance characteristics satisfy requirements of a safe operation envelope during the new well startup and production (Block 6), and based on evaluation, adjusting if needed, surface equipment control parameters to satisfy the requirements of the safe operation envelope (Block 7).

The computing system may be of virtually any type regardless of the platform being used. For example, the computing system may be one or more mobile devices (e.g., laptop computer, smartphone, smartwatch, personal digital assistant, tablet computer, or other mobile device), desktop computers, servers, blades in a server chassis, or any other type of computing device or devices that includes at least the minimum processing power, memory, and input and output device(s) to perform one or more embodiments of the invention.

Figure 2 shows an example of the computing system in accordance with some embodiments. The computing system may include a machine learning system 8 comprising a processor to perform the data analytics and generation of predictions, a memory storage 9 and a user interface 10. Machine learning is the subfield of computer science that gives computers the ability to learn without being explicitly programmed (https://en.wikipedia.org/wiki/Machine_learning).

The computing system comprises the memory storage 9 (e.g., random access memory (RAM), cache memory, flash memory, etc.), one or more storage device(s) (e.g., a hard disk, an optical drive such as a compact disk (CD) drive or digital versatile disk (DVD) drive, a flash memory stick, etc.), and numerous other elements and functionalities.

Software instructions in the form of computer readable program code to perform one or more embodiments may be stored, in whole or in part, temporarily or permanently, on a non-transitory computer readable medium such as a CD, DVD, storage device, a diskette, a tape, flash memory, physical memory, or any other computer readable storage medium. Specifically, the software instructions may correspond to computer readable program code that when executed by a processor(s), is configured to perform one or more embodiments of the method.

The computing system also comprises a user interface 10. The conventional user interface provides a means for one or more users to provide information to the system and retrieve information therefrom. Illustratively, the interface can be Windows-based graphical user interface (GUI) including a keyboard, a mouse and a display.

The example below demonstrates how to predict the selected wellbore flow performance characteristic, namely, the bottomhole pressure ($BHP(t)$) time series from known $WHP(t)$, oil surface rate $Q_o(t)$, water surface rate $Q_w(t)$, and gas surface rate $Q_g(t)$ time series. The analysis can be extended to other wellbore flow

performance characteristics (e.g., flow rate, temperature, and volume fractions, and others). All the functions are given in points 0h, 0.1h, 0.2h, ..., 50h (total 50 hours and 501 points).

To illustrate the method and system, consider a transient multiphase wellbore flow problem. The data set is generated using a transient multiphase wellbore flow simulator. The following parameters are varied to run 2000 simulations:

- Wellbore geometry of diameter 0.057 m consists of vertical segment of length 2845 m connected with the horizontal segment of length 1310 m.
- There are 6 sources distributed along the horizontal segment wellbore. The measured depths (from surface) of the locations of sources have the following values: 3000 m, 3200 m, 3400 m, 3600 m, 3800 m, 4000 m.
- For each source the water rate values $q_w(t)$ and the oil rate values $q_o(t)$ are given as random functions in terms of both starting time and amplitude (see Figure 3). As can be seen from the figure, in this synthetic example the bell-shaped distribution is chosen to specify the dynamics of the inflow rate of water. The dynamics of the oil inflow rate is similar to the one for water at the start until the oil inflow rate reaches maximum and stays at this value. In practical applications, the flow rate dynamics of these source terms is determined by the productivity of fractures and reservoir.
- The gas source inflow rate $q_g(t)$ is fixed to zero. However, oil contains dissolved gas that releases out of solution inside the wellbore so that the resulting surface gas rate $Q_g(t)$ is non-zero.
- The wellhead pressure ($WHP(t)$) is a random function. The generation of $WHP(t)$ functions is constructed to be representative of the variability of this function during the field well start up operations where the value of $WHP(t)$ is controlled by the surface choke opening that can range from narrow openings to

fully open and downstream choke pressure that can also fluctuate and drift as a function of the separator pressure or the pressure in other facility installed downstream of the choke.

The typical $WHP(t)$ being the simulator input boundary condition and $BHP(t)$ function being the result of calculation are shown in Figure 4 for a selected simulation out of 2000 total simulations. Figure 5 shows the surface flowrates $Q_o(t)$, $Q_w(t)$ and $Q_g(t)$ being the results of the same simulation. The machine learning algorithm based on artificial network having training and predictive capabilities was constructed. At the first step, this algorithm was trained on the dataset comprising 2000 numerical simulations described above. At the second step, the algorithm was tested to predict the unknown bottomhole pressure for the new simulation that was not a part of the described dataset. To do this, the $WHP(t)$, $Q_o(t)$, $Q_w(t)$ and $Q_g(t)$ of this new simulation were used as the input for the trained neural network. The neural network produced the wellbore flow performance characteristic of interest in this example, namely, the bottomhole pressure. The comparison of the neural network prediction with the result of new numerical simulation is shown in Figure 6. The normalized root mean square error (NRMSE) of prediction with respect to the numerical simulation result is below 5%. The predicted bottomhole pressure is evaluated against safe operation envelope and adjustments in the wellhead downstream choke pressure control or choke schedule are implemented.

Claims

1. A computer-implemented method for predicting wellbore flow performance characteristics of a well penetrating an underground hydrocarbon bearing formation, the method comprising:

- storing in a knowledge database in a memory storage a first well data obtained from a plurality of operating wells and comprising historical well static parameters, well dynamic parameters measured at the surface and historical wellbore flow performance characteristics measured during start up and production by one or more pieces of field equipment installed at surface or inside the well,
- storing in the knowledge database in the memory storage a second well data comprising simulation input well static parameters, simulation parameters used as boundary conditions at a well outlet and calculated wellbore flow performance characteristics obtained by numerical simulation for a plurality of cases,
- performing, by a machine learning system, an analysis of said first well data, wherein said analysis produces first relationships between said historical well static parameters, said well dynamic parameters measured at the surface and said historical wellbore flow performance characteristics measured inside the wellbore,
- performing, by the machine learning system, an analysis of said second well data, wherein said analysis produces second relationships between said simulation input well static parameters, the simulation parameters used as the boundary conditions at the well outlet, and said calculated wellbore flow performance characteristics;
- inputting, into the machine learning system, new well static parameters characterizing a new well penetrating an underground hydrocarbon bearing formation and new dynamic well parameters measured at surface,
- predicting, by the machine learning system, the wellbore flow performance characteristics of said new well based on the produced first and second relationships,

- evaluating if the predicted wellbore flow performance characteristics satisfy requirements of a safe operation envelope during the new well startup and production, and
- based on evaluation, adjust, if needed, surface equipment control parameters to satisfy the requirements of the safe operation envelope.

2. The method of claim 1 wherein the historical well static parameters, the simulation input well static parameters and the new well static parameters comprise at least one of a group consisting of petrophysical properties of the hydrocarbon bearing formations, geological properties, geomechanical properties, fluid properties, configuration of the wells, and other measurable parameters of the wells and formations.

3. The method of claim 1 wherein the measured historical wellbore flow performance characteristics and the calculated wellbore flow performance characteristics comprise at least one of a group consisting of flowrates of hydrocarbons, peak surface rates, pressure, temperature, volume fractions, rates distribution in the wells and hydrocarbon bearing formations, duration of well cleanup or flowback.

4. The method of claim 1 wherein the predicted wellbore flow performance characteristics of the new well comprise pressure, temperature, phase rates, and volume fractions along the well and at the well bottom.

5. The method of claim 1 wherein the predicted wellbore flow performance characteristics of said new well comprise a duration of the well cleanup or flowback.

6. The method of claim 1 wherein the predicted wellbore flow performance characteristics of said new well comprise cumulative values of surface rates and peak values of the surface rates of hydrocarbons, wellhead pressure.

7. A computing system for predicting the wellbore flow performance characteristics of a well penetrating an underground hydrocarbon bearing formation, the system comprising:

- a memory storage for storing a knowledge database comprising a first well data obtained from a plurality of operating wells and comprising historical well static parameters, well dynamic parameters measured at the surface and historical wellbore flow performance characteristics measured during start up and production by one or more pieces of field equipment installed at surface or inside the well, and a second well data comprising simulation input well static parameters, simulation parameters used as boundary conditions at a well outlet and calculated wellbore flow performance characteristics obtained by numerical simulation for a plurality of cases,
- a user interface adapted to receive user inputs for new well static parameters characterizing a well penetrating the formation and an underground hydrocarbon bearing formation and new dynamic well parameters measured at the surface, and
- a machine learning system comprising at least one processor coupled to the memory storage and having functionality to execute instructions for:
 - performing an analysis of said first well data, wherein said analysis produces first relationships between said historical well static parameters, said well dynamic parameters measured at the surface and said historical measured wellbore flow performance characteristics measured inside the wellbore,
 - performing an analysis of said second well data, wherein said analysis produces second relationships between said simulation input well static parameters, the simulation parameters used as the boundary conditions at the well outlet, and said calculated wellbore flow performance characteristics;

- receiving new static well parameters characterizing a new well penetrating an underground hydrocarbon bearing formation and new dynamic well parameters measured at the surface,
 - predicting wellbore flow performance characteristics of the new well,
 - an input component allowing for the machine learning system to use inputs provided by the user and
- an output component coupled to the database, wherein the output information is produced based on previous operations of the machine learning system.

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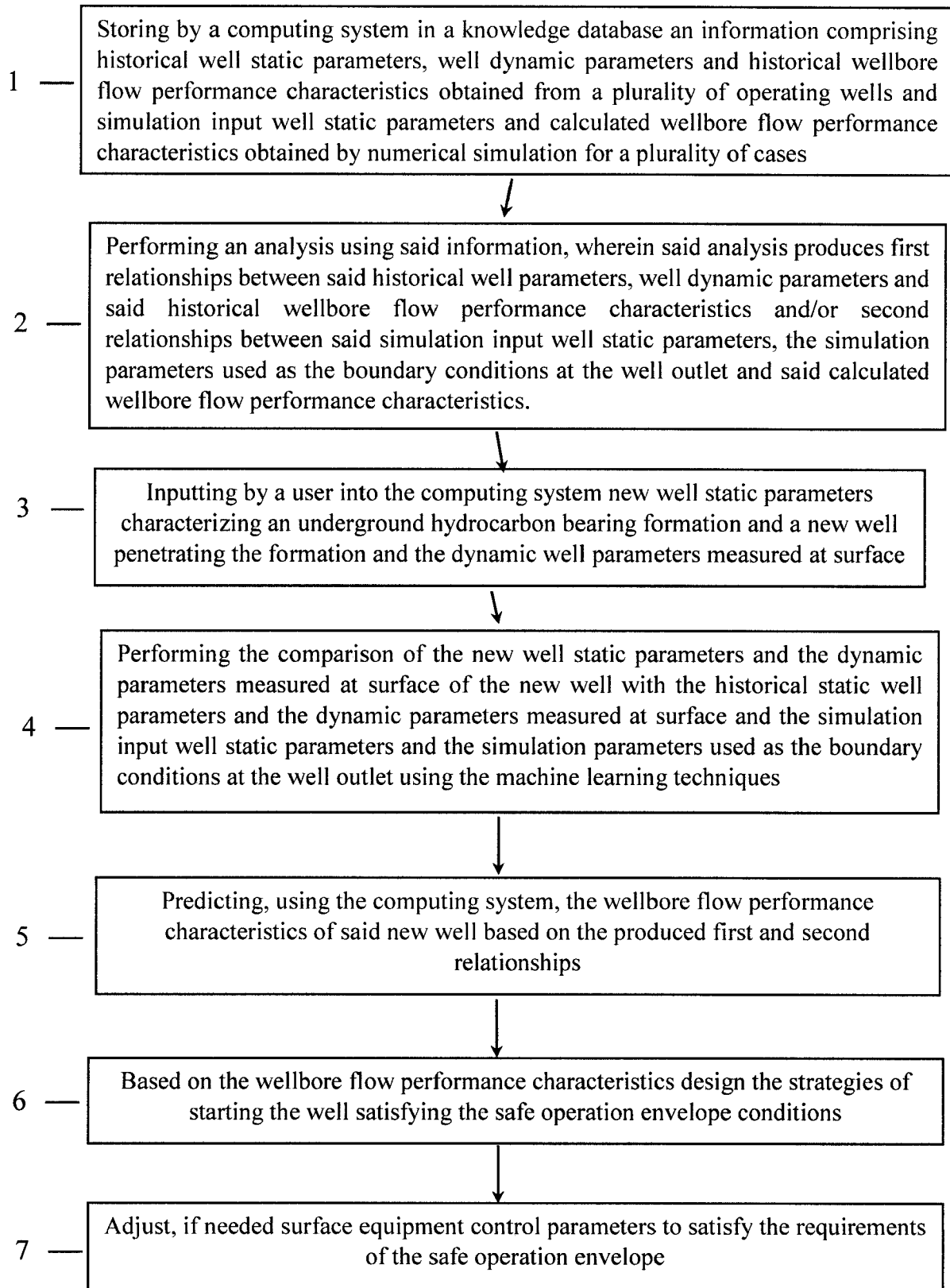


Fig.1

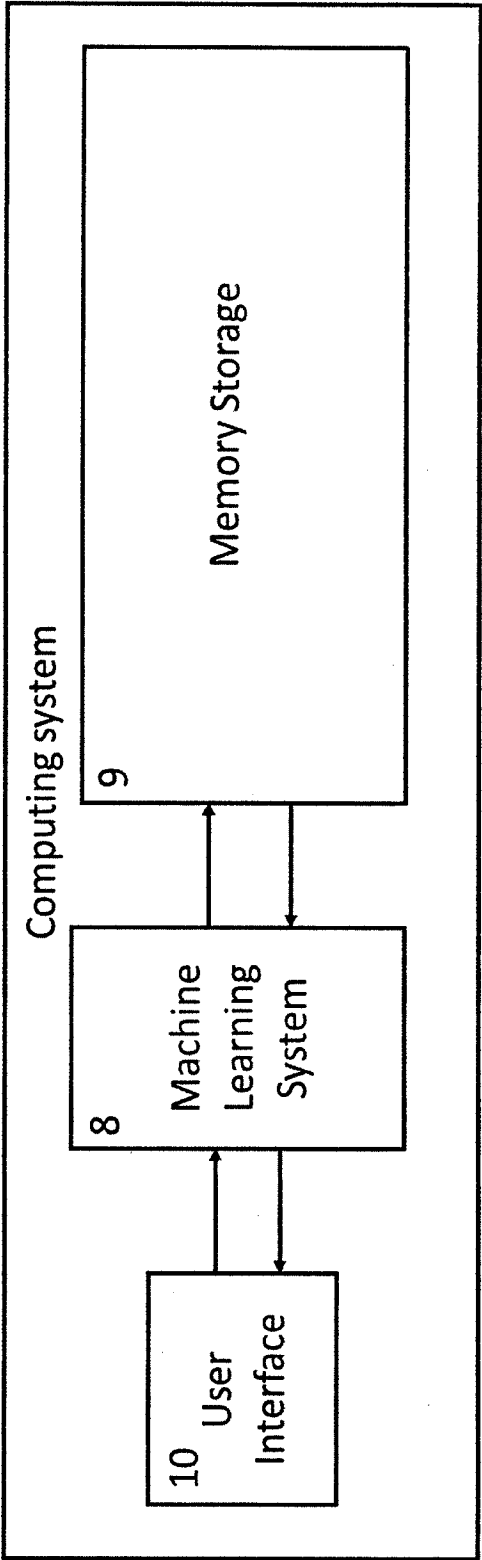


Fig.2

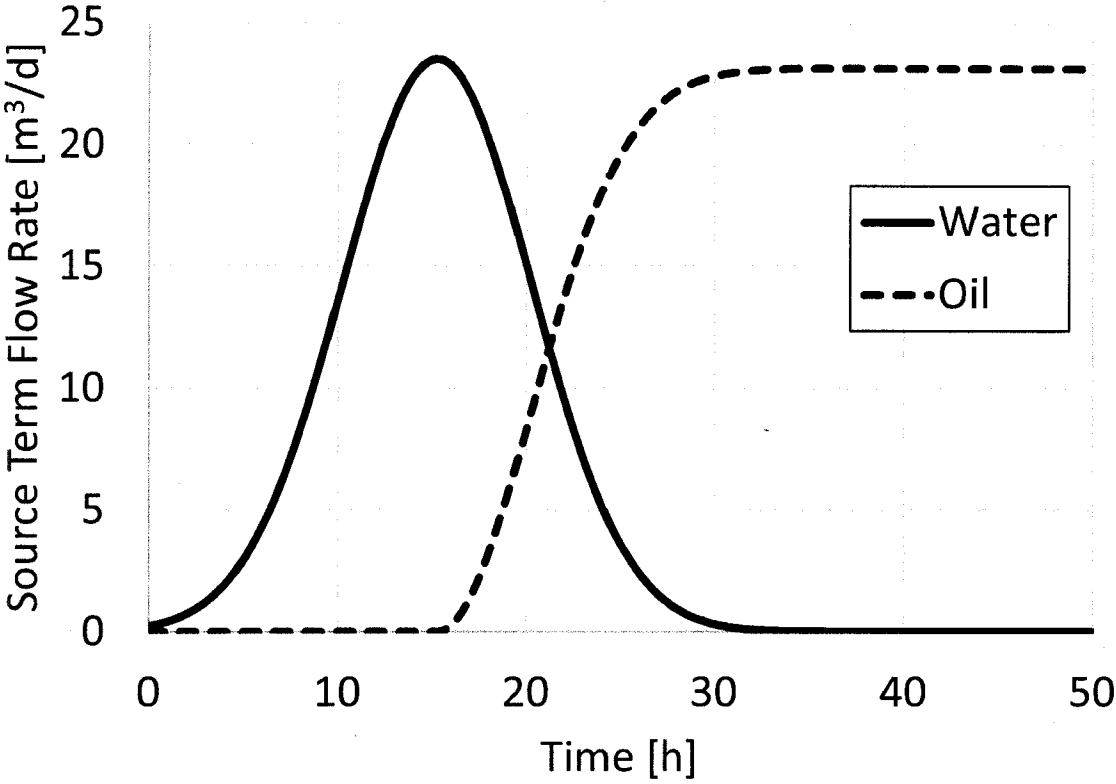


Fig.3

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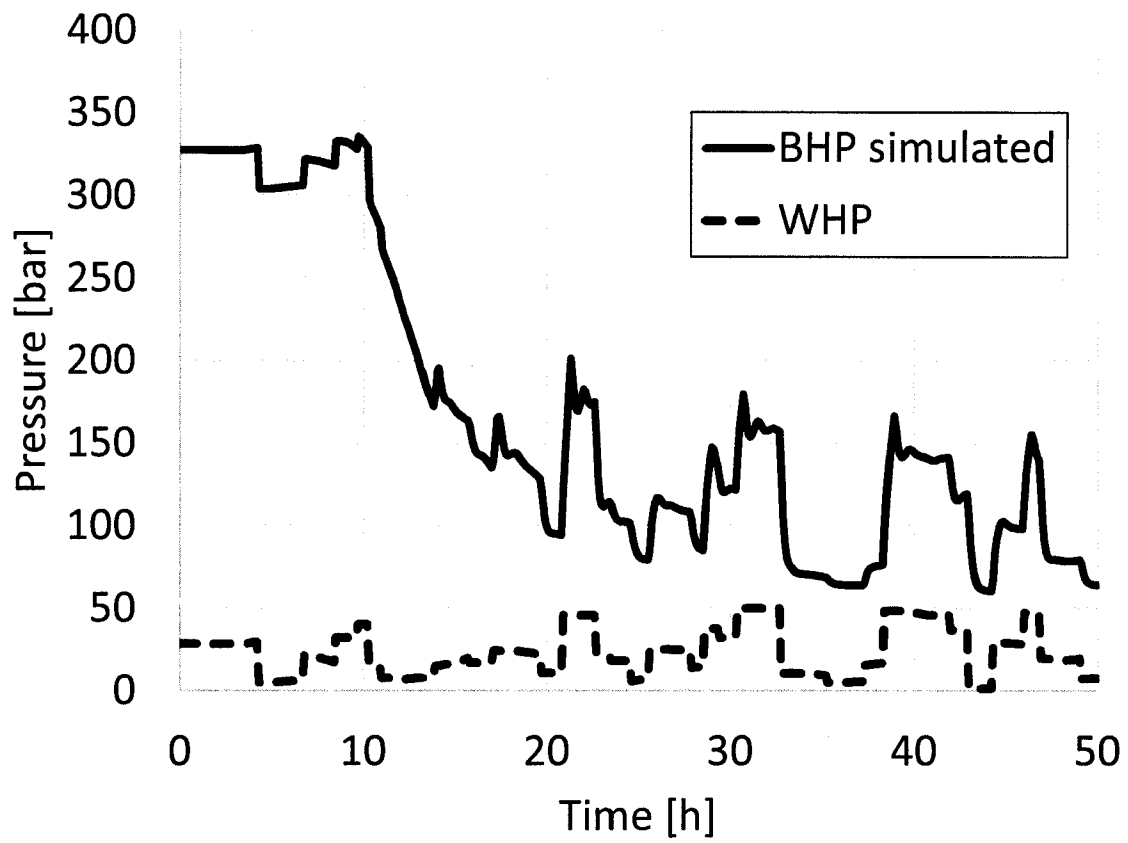


Fig.4

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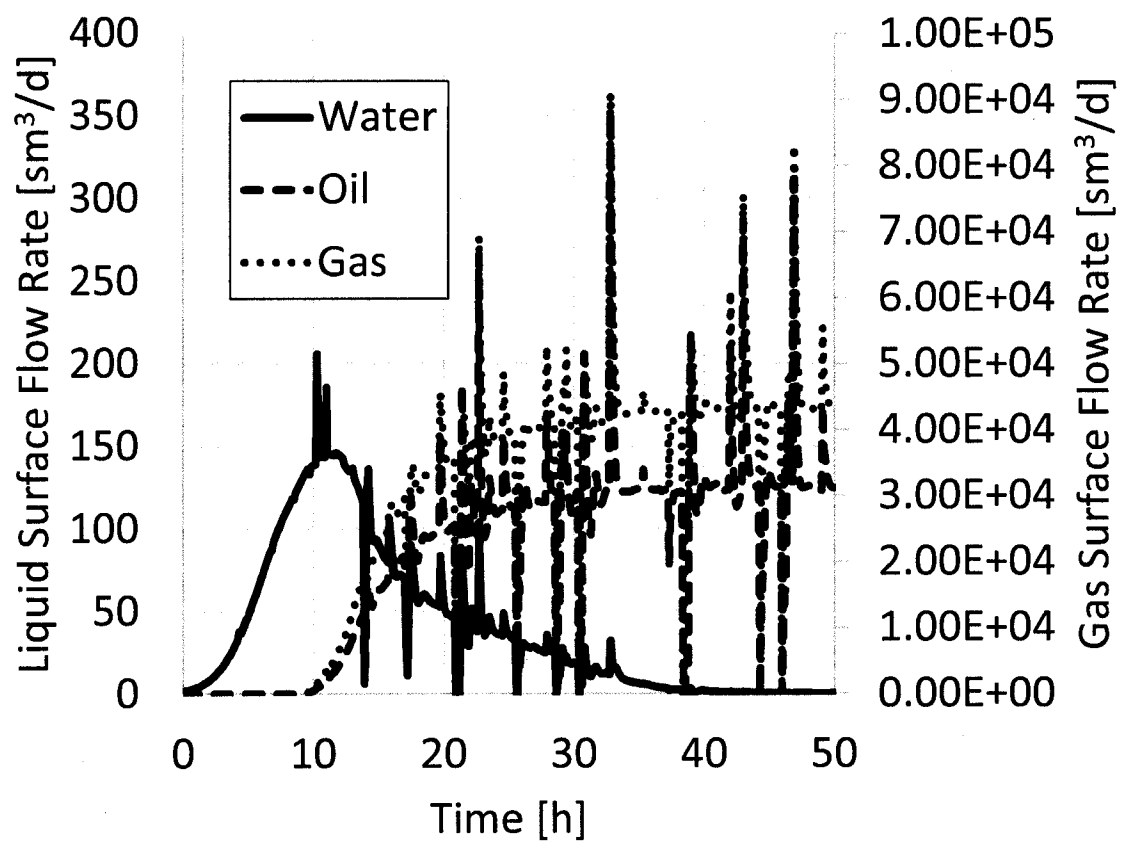


Fig.5

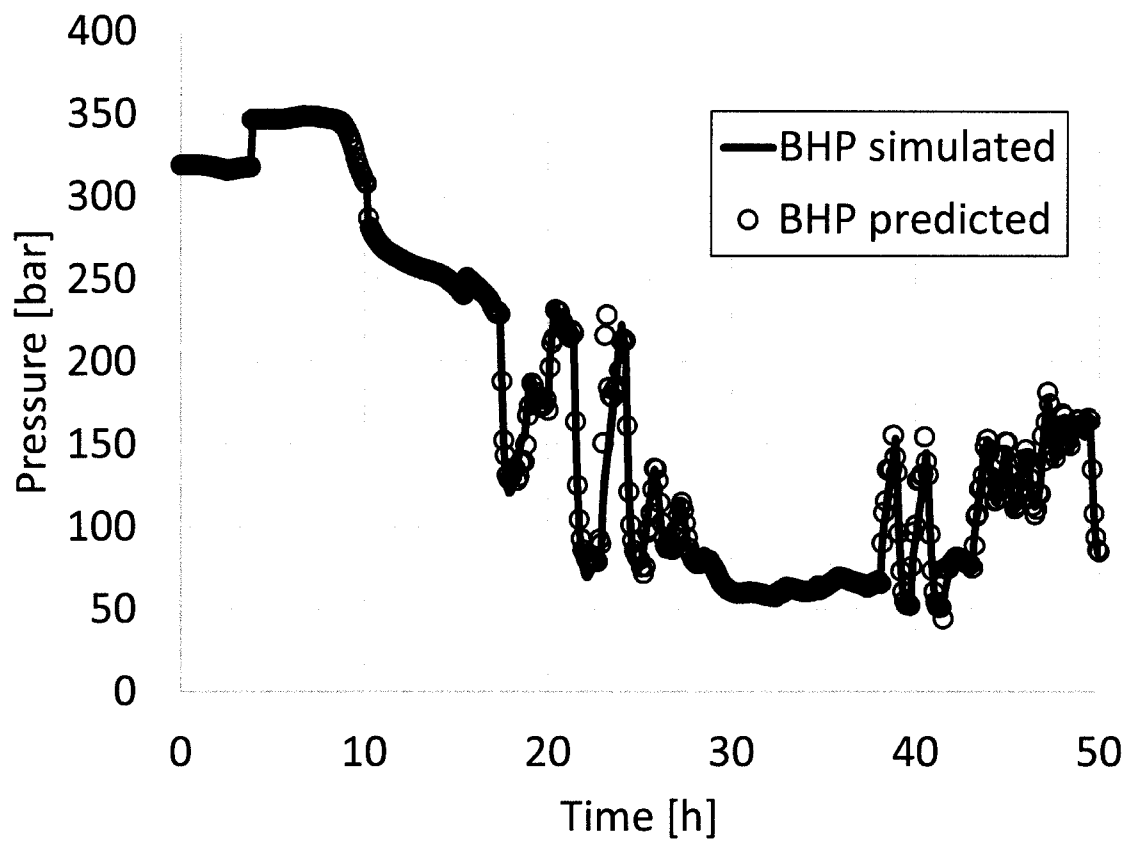


Fig.6

INTERNATIONAL SEARCH REPORT

International application No.

PCT/RU 2017/000433

A. CLASSIFICATION OF SUBJECT MATTER <i>E21B 47/26 (2012.01)</i> <i>G06Q 50/02 (2012.01)</i> According to International Patent Classification (IPC) or to both national classification and IPC		
B. FIELDS SEARCHED Minimum documentation searched (classification system followed by classification symbols) E21B 47/00, 47/26, G06Q 50/00, 50/02 Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched Electronic data base consulted during the international search (name of data base and, where practicable, search terms used) PatSearch (RUPTO internal), RUPTO, EAPATIS, USPTO, Patentscope, PAJ, SIPO, K-PION		
C. DOCUMENTS CONSIDERED TO BE RELEVANT		
Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	LEA J.F. et al. Well Modelling: Optimized Production and Troubleshooting Using Nodal Analysis. Rogtec, 09.10.2014, pp. 72-74, 76, 78-85	1-7
Y	RU 2613374 C2 (INTELLIZERV INTERNATIONAL HOLDING, LTD.) 16.03.2017, abstract, paragraphs [0003], [0073]	1-7
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