



(51) International Patent Classification:

E21B 21/08 (2006.01) *G06N 3/02* (2006.01)
G06G 7/50 (2006.01) *E21B 47/00* (2012.01)
E21B 43/16 (2006.01)

(21) International Application Number:

PCT/US2023/074558

(22) International Filing Date:

19 September 2023 (19.09.2023)

(25) Filing Language:

English

(26) Publication Language:

English

(30) Priority Data:

63/376,140 19 September 2022 (19.09.2022) US

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(81) Designated States (unless otherwise indicated, for every kind of national protection available): AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CV, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IQ, IR, IS, IT, JM, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, MG, MK, MN, MU, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, ST, SV, SY, TH,

(54) Title: FEEDBACK LOOP MODEL FOR INJECTOR-PRODUCER RELATIONSHIP IN HYDROCARBON RESERVOIRS

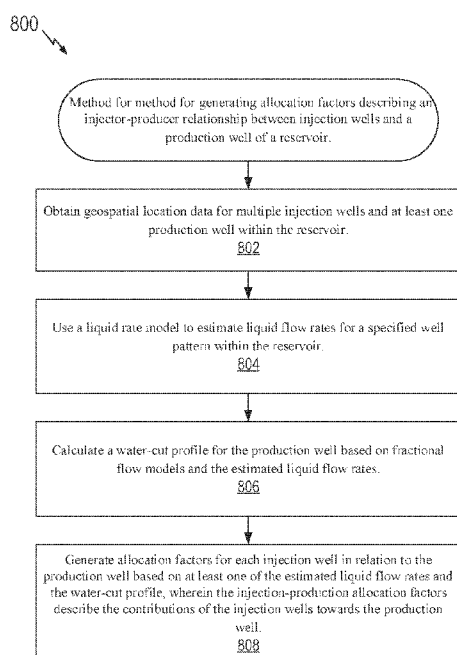


FIG. 8

(57) Abstract: Certain aspects of the disclosure provide a method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir. The method generally includes obtaining geospatial location data for multiple injection wells and at least one production well within the reservoir; using a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model incorporates a distance parameter representing the spatial separation between each injection well and the production well; calculating a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and generating allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.

TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, WS,
ZA, ZM, ZW.

(84) Designated States (*unless otherwise indicated, for every kind of regional protection available*): ARIPO (BW, CV, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SC, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, ME, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:

— *with international search report (Art. 21(3))*

FEEDBACK LOOP MODEL FOR INJECTOR-PRODUCER RELATIONSHIP IN HYDROCARBON RESERVOIRS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims the benefit of and priority to U.S. Provisional Patent Application No. 63/376,140, filed on September 19, 2022, the entire contents of which are hereby incorporated by reference.

BACKGROUND

[0002] The injection of fluids into reservoirs is a widely practiced technique for improving the recovery of petroleum assets. The injection of water/gas/enhanced oil recovery (EOR) agents perturbs the petroleum reservoir condition and generates a signal that can be analyzed at the producing wells. Models of such EOR techniques are leverages for parameter selection, including, for example, injector-producer relationship models. Assumptions in traditional approaches to injector-producer relationship modeling include the existence of a history-matched simulation model. However, in practice, it is difficult to update simulation models and thus to achieve satisfactory history-matching results.

SUMMARY

[0003] Certain aspects of the disclosure provide a method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir, the method comprising: obtaining geospatial location data for multiple injection wells and at least one production well within the reservoir; using a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model: incorporates a distance parameter representing the spatial separation between each injection well and the production well; and utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data; calculating a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and generating allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.

[0004] Certain aspects provide a method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir, the method comprising: obtaining location data for a plurality of injection wells of a reservoir and for a production well of the reservoir; evaluating a liquid rate model configured to generate a liquid flow rate estimation specific to a well pattern of the reservoir using a trained capacitance-resistance model, wherein: the trained capacitance-resistance model incorporates a distance parameter for each injection well representing a distance between the production well and each respective injection well, and the trained capacitance-resistance model relies on parameters that are iteratively fine-tuned through a refinement process until a predicted output aligns with production data specific to the production well; evaluating a water-cut profile model configured to generate a water-cut profile for the production well based on a fractional flow model and the liquid flow rate estimation; and generating injection-production allocation factors for the injection wells based on at least one of the liquid flow rate estimation and the water-cut profile, wherein the injection-production allocation factors describe the contributions of the injection wells towards the production well.

[0005] Other aspects provide processing systems configured to perform the aforementioned methods as well as those described herein; non-transitory, computer-readable media comprising instructions that, when executed by a processors of a processing system, cause the processing system to perform the aforementioned methods as well as those described herein; a computer program product embodied on a computer readable storage medium comprising code for performing the aforementioned methods as well as those further described herein; and a processing system comprising means for performing the aforementioned methods as well as those further described herein.

[0006] The following description and the related drawings set forth in detail certain illustrative features of one or more aspects.

DESCRIPTION OF THE DRAWINGS

[0007] The appended figures depict certain aspects and are therefore not to be considered limiting of the scope of this disclosure.

[0008] FIG. 1 depicts an example of a system that includes various management components to manage various aspects of a geologic environment, according to an embodiment.

[0009] FIG. 2 depicts details of an injector-producer feedback system for deriving injection-production allocation factors in accordance with examples of the present disclosure.

[0010] FIG. 3 depicts additional details of an injector-producer feedback system in accordance with examples of the present disclosure.

[0011] FIG. 4 provides additional details with respect to the capacitance-resistance modeling in accordance with examples of the present disclosure.

[0012] FIG. 5 depicts sample outcomes from a liquid rate model in accordance with examples of the present disclosure.

[0013] FIG. 6 illustrates example water-cut profiles in accordance with examples of the present disclosure.

[0014] FIG. 7 presents a schematic diagram featuring injection wells and production wells.

[0015] FIG. 8 illustrates an example method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir.

[0016] FIG. 9 depicts an example processing system on which aspects of the present disclosure can be performed.

[0017] To facilitate understanding, identical reference numerals have been used, where possible, to designate identical elements that are common to the drawings. It is contemplated that elements and features of one embodiment may be beneficially incorporated in other embodiments without further recitation.

DETAILED DESCRIPTION

[0018] Aspects of the present disclosure provide apparatuses, methods, processing systems, and computer-readable mediums for deriving injection-production allocation factors in accordance with examples of the present disclosure.

[0019] Waterflooding, an enhanced oil recovery (EOR) technique, is designed to augment the yield of hydrocarbons from subterranean hydrocarbon reservoirs. The method entails the strategic

injection of water/gas/EOR agents into a reservoir via designated injection wells. These injection wells are positioned either within the vicinity of or directly within the reservoir itself. The purpose of this water injection is two-fold. First, it serves to maintain the internal pressure of the reservoir, which is subject to decline during the extraction process. Maintaining adequate reservoir pressure helps to facilitate the movement of hydrocarbons toward production wells. Second, as the injected water permeates through the reservoir's porous rock layers, it expels hydrocarbons lodged within the pore spaces and fractures of rock. Subsequently, the mobilized hydrocarbons are extracted via a separate set of wells commonly referred to as production or producer wells, typically situated at a distance from the injection sites.

[0020] The efficacy of waterflooding depends on several geological variables, including rock permeability, porosity, the type of rock, and the existence of natural fissures. Waterflooding generally surpasses conventional production methods that rely solely on the reservoir's innate energy—such as pressure—to move hydrocarbons to the surface. While waterflooding has been proven to be a cost-efficient strategy for boosting hydrocarbon extraction from aging fields, capturing a significant quantity of residual hydrocarbons that would otherwise remain unrecovered once primary methods have been exhausted, its success is conditioned on specific reservoir properties and the effective arrangement of injection and production wells (e.g., a well pattern). During some waterflooding processes, a point is eventually reached where continuing the operation is no longer economically justifiable. This is because the costs associated with water injection, removal, and disposal surpass the net income generated from hydrocarbon production. Thus, engineers and geologists closely monitor and fine-tune various elements, such as the rate of water injection, the placement of wells, and reservoir management, to maximize hydrocarbon retrieval.

[0021] In accordance with examples of the present disclosure, derived injection-production allocation factors can provide an understanding of how water injected into a hydrocarbon reservoir is distributed among different production wells and enhance an understanding of the relationship between liquid injection rates and liquid production rates at different wells within a hydrocarbon field. As used herein, liquid injection and liquid production can refer to the controlled processes by which fluids are respectively introduced into and extracted from subsurface geological formations. Liquid injection generally denotes the introduction of fluids – such as water, brine, or other EOR agents – into the reservoir to maintain pressure and displace hydrocarbons toward

production wells. Liquid production refers to the extraction of fluids from the reservoir, which may include not only crude oil or other hydrocarbons, but also produced water and other byproducts. In embodiments, an injector-producer feedback system can take into account how changes in the rate of injection at one well might affect the production rates at surrounding wells, aiming to find the best overall operating conditions for an entire well pattern. In examples, a well pattern refers to the geometric arrangement of wells in a hydrocarbon reservoir for the purpose of maximizing hydrocarbon recovery. Various well patterns are employed based on the geological characteristics of the reservoir, fluid properties, and recovery mechanisms involved. The injector-producer feedback system can include workflows incorporating machine learning and enhanced traditional models to estimate the total hydrocarbon liquid production rates, water-cut profiles, and injection-production allocation factors to assess and predict reservoir performance, plan for interventions, and make various types of operational and financial decisions. Such liquid production rates and water-cut profiles can be generated at the pattern level (e.g., for an entire well pattern) and at the well-pair level (e.g., between an injection well and a production well in a well pattern).

[0022] In embodiments, workflows of the injector-producer feedback system can be used as a complementary or replacement model to high-fidelity reservoir simulation models. The workflows may rely on relatively minimal data comprising elements such as production and injection profiles and well positional data specifically tailored for waterflood assets, where a waterflood asset refers to a hydrocarbon reservoir or a specific zone within a larger reservoir that is currently under waterflood operations or is a candidate for such operations. In embodiments, a feedback mechanism is employed to facilitate workflow execution that surpasses the efficiency of current simulation models. The enhanced efficiency of the workflows makes them suitable for integration into broader solution frameworks that employ edge technologies, including but not limited to advanced monitoring and predictive capabilities. Furthermore, such workflows operate with heightened efficiency due to a reduced parameter set and can employ iterative approaches to incorporate linearization techniques, thereby minimizing computational load and complexity.

[0023] Embodiments of the present disclosure utilize machine learning (ML) models trained with historical production data to derive the contribution of injection wells with respect to the production wells. Additionally, a post-processing method can connect the injector-producer feedback system to controllers such as a Pattern Flood Management (PFM) tool.

[0024] Utilizing machine learning based approaches that drive efficiency, the injector-producer feedback system can model injector-producer relationships despite lacking full history matched dynamic models and potentially without many tedious, time-consuming processes of analysis. The injector-producer feedback system can integrate with analyzers and controllers to facilitate real-time monitoring, optimization, and automated adjustments of injection and production parameters. This integration allows for more efficient resource allocation, quicker response to reservoir dynamics, and ultimately, enhanced hydrocarbon recovery rates.

Example Management Component

[0025] **FIG. 1** illustrates an example of a system 100 that includes various management components 110 to manage various aspects of a geologic environment 150 (e.g., an environment that includes a sedimentary basin, a reservoir 151, one or more faults 153-1, one or more geobodies 153-2, etc.). For example, the management components 110 may allow for direct or indirect management of sensing, drilling, injecting, extracting, etc., with respect to the geologic environment 150. In turn, further information about the geologic environment 150 may become available as feedback 160 (e.g., optionally as input to one or more of the management components 110).

[0026] In the example of **FIG. 1**, the management components 110 include a seismic data component 112, an additional information component 114 (e.g., well/logging data), a processing component 116, a simulation component 120, an attribute component 130, an analysis/visualization component 142, and other workflow component 144. In operation, seismic data and other information provided per components 112 and 114 may be input to simulation component 120.

[0027] In an example embodiment, the simulation component 120 may rely on entities 122. Entities 122 may include earth entities or geological objects such as wells, surfaces, bodies, reservoirs, etc. In system 100, the entities 122 can include virtual representations of actual physical entities that are reconstructed for purposes of simulation. Entities 122 may include entities based on data acquired via sensing, observation, etc. (e.g., the seismic data 112 and other information 114). An entity 122 may be characterized by one or more properties (e.g., a geometrical pillar grid entity of an earth model may be characterized by a porosity property). Such properties may represent one or more measurements (e.g., acquired data), calculations, etc.

[0028] In an example embodiment, the simulation component 120 may operate in conjunction with a software framework such as an object-based framework. In such a framework, entities 122 may include entities based on pre-defined classes to facilitate modeling and simulation. A commercially available example of an object-based framework is the MICROSOFT® .NET® framework (Redmond, Washington), which provides a set of extensible object classes. In the .NET® framework, an object class encapsulates a module of reusable code and associated data structures. Object classes can be used to instantiate object instances for use in by a program, script, etc. For example, borehole classes may define objects for representing boreholes based on well data.

[0029] In the example of **FIG. 1**, the simulation component 120 may process information to conform to one or more attributes specified by the attribute component 130, which may include a library of attributes. Such processing may occur prior to input to simulation component 120 (e.g., consider the processing component 116). As an example, simulation component 120 may perform operations on input information based on one or more attributes specified by the attribute component 130. In an example embodiment, the simulation component 120 may construct one or more models of the geologic environment 150, which may be relied on to simulate behavior of the geologic environment 150 (e.g., responsive to one or more acts, whether natural or artificial). In the example of **FIG. 1**, the analysis/visualization component 142 may allow for interaction with a model or model-based results (e.g., simulation results, etc.). As an example, output from the simulation component 120 may be input to one or more other workflows, as indicated by workflow component 144.

[0030] As an example, simulation component 120 may include one or more features of a simulator such as the ECLIPSE ® reservoir simulator (SLB, Houston Texas), the INTERSECT ® reservoir simulator (SLB, Houston Texas), etc. As an example, a simulation component, a simulator, etc. may include features to implement one or more meshless techniques (e.g., to solve one or more equations, etc.). As an example, a reservoir or reservoirs may be simulated with respect to one or more enhanced recovery techniques (e.g., consider a thermal process such as SAGD, etc.).

[0031] In an example embodiment, the management components 110 may include features of a commercially available framework such as the PETREL® seismic to simulation software

framework (SLB, Houston, Texas). The PETREL® framework provides components that allow for optimization of exploration and development operations. The PETREL® framework includes seismic to simulation software components that can output information for use in increasing reservoir performance, for example, by improving asset team productivity. Through use of such a framework, various professionals (e.g., geophysicists, geologists, and reservoir engineers) can develop collaborative workflows and integrate operations to streamline processes. Such a framework may be considered an application and may be considered a data-driven application (e.g., where data is input for purposes of modeling, simulating, etc.).

[0032] In an example embodiment, various aspects of the management components 110 may include add-ons or plug-ins that operate according to specifications of a framework environment. For example, a commercially available framework environment marketed as the OCEAN® framework environment (SLB, Houston, Texas) allows for integration of add-ons (or plug-ins) into a PETREL® framework workflow. The OCEAN® framework environment leverages .NET® tools (Microsoft Corporation, Redmond, Washington) and offers stable, user-friendly interfaces for efficient development. In an example embodiment, various components may be implemented as add-ons (or plug-ins) that conform to and operate according to specifications of a framework environment (e.g., according to application programming interface (API) specifications, etc.).

[0033] FIG. 1 also shows an example of framework 170 that includes a model simulation layer 180 along with a framework services layer 190, a framework core layer 195 and a modules layer 175. The framework 170 may include the commercially available OCEAN® framework where the model simulation layer 180 is the commercially available PETREL® model-centric software package that hosts OCEAN® framework applications. In an example embodiment, the PETREL® software may be considered a data-driven application. The PETREL® software can include a framework for model building and visualization.

[0034] As an example, a framework may include features for implementing one or more mesh generation techniques. For example, a framework may include an input component for receipt of information from interpretation of seismic data, one or more attributes based at least in part on seismic data, log data, image data, etc. Such a framework may include a mesh generation component that processes input information, optionally in conjunction with other information, to generate a mesh.

[0035] In the example of **FIG. 1**, the model simulation layer 180 may provide domain objects 182, act as a data source 184, provide for rendering 186 and provide for various user interfaces 188. Rendering 186 may provide a graphical environment in which applications can display their data while user interfaces 188 may provide a common look and feel for application user interface components.

[0036] As an example, domain objects 182 can include entity objects, property objects and optionally other objects. Entity objects may be used to geometrically represent wells, surfaces, bodies, reservoirs, etc., while property objects may be used to provide property values as well as data versions and display parameters. For example, an entity object may represent a well where a property object provides log information as well as version information and display information (e.g., to display the well as part of a model).

[0037] In the example of **FIG. 1**, data may be stored in one or more data sources 184 (or data stores, generally physical data storage devices), which may be at the same or different physical sites and accessible via one or more networks. The model simulation layer 180 may be configured to model projects. As such, a particular project may be stored where stored project information may include inputs, models, results, and cases. Thus, upon completion of a modeling session, a user may store a project. At a later time, the project can be accessed and restored using the model simulation layer 180, which can recreate instances of the relevant domain objects 182.

[0038] In the example of **FIG. 1**, the geologic environment 150 may include layers (e.g., stratification) that include a reservoir 151 and one or more other features such as the fault 153-1, the geobody 153-2, etc. As an example, the geologic environment 150 may be outfitted with any of a variety of sensors, detectors, actuators, etc. For example, equipment 152 may include communication circuitry to receive and to transmit information with respect to one or more networks 155. Such information may include information associated with downhole equipment 154, which may be equipment to acquire information, to assist with resource recovery, etc. Other equipment 156 may be located remote from a well site and include sensing, detecting, emitting or other circuitry. Such equipment may include storage and communication circuitry to store and to communicate data, instructions, etc. As an example, one or more satellites may be provided for purposes of communications, data acquisition, etc. For example, **FIG. 1** shows a satellite in communication with the network 155 that may be configured for communications, noting that the

satellite may additionally or instead include circuitry for imagery (e.g., spatial, spectral, temporal, radiometric, etc.).

[0039] FIG. 1 also shows the geologic environment 150 as optionally including equipment 157 and 158 associated with a well that includes a substantially horizontal portion that may intersect with one or more fractures 159. For example, consider a well in a shale formation that may include natural fractures, artificial fractures (e.g., hydraulic fractures) or a combination of natural and artificial fractures. As an example, a well may be drilled for a reservoir that is laterally extensive. In such an example, lateral variations in properties, stresses, etc. may exist where an assessment of such variations may assist with planning, operations, etc. to develop a laterally extensive reservoir (e.g., via fracturing, injecting, extracting, etc.). As an example, equipment 157 and/or 158 may include components, a system, systems, etc. for fracturing, seismic sensing, analysis of seismic data, assessment of one or more fractures, etc.

[0040] As mentioned, system 100 may be used to perform one or more workflows. A workflow may be a process that includes a number of worksteps. A workstep may operate on data, for example, to create new data, to update existing data, etc. As an example, a workflow may operate on one or more inputs and create one or more results, for example, based on one or more algorithms. As an example, a system may include a workflow editor for creation, editing, executing, etc. of a workflow. In such an example, the workflow editor may provide for selection of one or more pre-defined worksteps, one or more customized worksteps, etc. As an example, a workflow may be a workflow implementable in the PETREL® software, for example, that operates on seismic data, seismic attribute(s), etc. As an example, a workflow may be a process implementable in the OCEAN® framework. As an example, a workflow may include one or more worksteps that access a module such as a plug-in (e.g., external executable code, etc.).

[0041] FIG. 2 depicts details of an injector-producer feedback system 200 for deriving injection-production allocation factors in accordance with examples of the present disclosure. As depicted in FIG. 2, the injector-producer feedback system 200 may include workflows 204, 210, and 214 that work to derive injection-production allocation factors, such as one or more efficiency parameters. More specifically, a liquid rate workflow 204 can train a liquid rate model to output a total rate of liquid hydrocarbon production for one or more wells. In examples, an output of the liquid rate workflow 204 may be a trained liquid rate model that is capable of providing a rate at

which liquid hydrocarbons, mainly oil and condensates, are estimated to be extracted from either a single well or an entire field. Such production estimation serves as an important metric for evaluating the economic viability and operational efficiency of a well or reservoir. In examples, the liquid rate workflow 204 may implement a machine learning model trained using production data 202 and well location data 206. Production data 202 can include production well profiles and injector well profiles. The well location data 206 can include geospatial locations of production and injection wells; alternatively, or in addition, the well location data 206 may be distances between each injection well and each production well. The liquid rate model can utilize one or more capacitance-resistance models (CR models) to forecast liquid production rates in systems that have both injection and production wells. An example liquid production rate signal for a well may vary over time, as depicted in **FIG. 2** as 208. In addition, the composition of the liquid is subject to variation, where differing ratios of water, oil, and other liquids may change over time.

[0042] In accordance with examples of the present disclosure, a water-cut workflow 210 of the injector-producer feedback system can generate water-cut profiles (e.g., 212) for one or more production wells using a flow-allocation model, also referred to as a water-cut model. In examples, the water-cut workflow 210 can implement a trained a water-cut model, where the trained water-cut model is trained using production data 202. A water-cut profile (e.g., 212) provides data on the ratio of water produced in comparison to the total volume of liquids (both hydrocarbons and water) extracted from a production well. This profile can vary over time and across different regions of a reservoir. A rising water-cut often indicates that a reservoir is maturing and could be a sign that enhanced recovery techniques might need to be considered. In examples, water-cut is usually expressed as a percentage and is an important parameter for reservoir management.

[0043] In accordance with examples of the present disclosure, a workflow 214 of the injector-producer feedback system 200 can generate or derive injection-production allocation factors that quantify the relative contribution or efficiency of each production or injection well involved in waterflood operations within a reservoir. The injection-production allocation factors can be used to provide an indication of balance or imbalance in the subsurface and may further be relied on to provide water-cut models at the well-pair level. An example output of the workflow 214 is depicted as 218, illustrating various efficiencies of production or injection wells.

[0044] FIG. 3 depicts additional details of the injector-producer feedback system 200 in accordance with examples of the present disclosure. As previously discussed, liquid rate workflow 204 may include a liquid rate model, such as liquid rate model 302. The liquid rate model 302 can utilize capacitance-resistance (CR) modeling 312 to forecast liquid production rates in systems that have both injection and production wells. CR models reduce the intricate dynamics of fluid movement through porous formations into simpler representations of "capacitances" and "resistances." In CR models, capacitance is linked to the storage potential of the reservoir, usually associated with the pore volume between injection and production wells. Resistance reflects the flow resistance in the porous medium, which can depend on a variety of factors including permeability, viscosity, and the distance between wells.

[0045] Equations governing CR models are typically non-linear in nature, which tends to extend the time required for analysis and optimization. The task of optimizing CR models is intricate, involving a multitude of adjustable parameters that may encompass reservoir characteristics, fluid properties, and operational variables. Consequently, CR model optimization is not just resource-intensive but also demands a detailed grasp of several variables for effective fine-tuning. In accordance with embodiments of the present disclosure, capacitance-resistance modeling 312 can mitigate such optimization complexity by reducing the number of parameters included in the CR model equations. This reduction in parameters allows for easier evaluation and optimization, enabling a CR model to be fine-tuned using a linear approach. For instance, classical CR models can predict the production flow rate of a producer at a point in time according to the following equation:

$$\dot{q}_j(n) = \lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}} + \sum_{i=1}^{i=I} \lambda_{ij} \ddot{q}_i(\tau_{ij})$$

where, $\dot{q}_j(n)$ is the CRM predicted production flow rate of producer at time n , $q(t_0)$ is the initial production rate, τ_p is the time constant due to reservoir primary energy, τ_{ij} is the time constant for flow between injector i and producer j , λ_p is the flow coefficient for reservoir primary energy, λ_{ij} is the flow coefficient for flow between Producer j and Injector i , $\ddot{q}_i$ is the convoluted injection rates, and I is the total number of injectors per pattern. In examples, rather than using a time constant to describe the flow between production wells and injector wells, capacitance-resistance

modeling 312 can consider a distance-dependent parameter, such as the spatial distance between production wells and injection wells. Thus, capacitance-resistance modeling 312 can predict production flow rate of a producer at a point in time according to the following equation:

$$\dot{q}_j(n) = \lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}} + \sum_{i=1}^{i=I} \lambda_{ij} \ddot{q}_i \left(\frac{d_{ij}}{div} \right)$$

where, d_{ij} is the distance between Producer j and Injector i , and div is a flow factor parameter. Utilizing the above equation, the total number of parameters needed for evaluation can be reduced from a multiple of the number of injection wells per pattern to a sum of the number of injection wells per pattern together with a constant. Additionally, capacitance-resistance modeling 312 can simplify the complexity involved in evaluating CR models by initially estimating values for various optimization parameters and iteratively refining such values until an acceptable amount of error is achieved, as further described in **FIG. 4**. Consequently, embodiments described herein can include workflows that enhance process efficiency such that CR models can be applied to hydrocarbon fields that have a large number of wells and provide high frequency data (e.g., daily data).

[0046] Understanding the effects of multi-phase flow – often involving oil, water, and gas – is important for accurately predicting reservoir behavior, optimizing hydrocarbon production, and implementing effective recovery strategies. Some versions of CR models focus solely on total liquid output (combining both oil and water) and may overlook the complications introduced by multi-phase flow. Therefore, it is common to train CR models using production data from periods where a single phase, such as water or oil, is the predominant component. This is relevant in areas of the hydrocarbon field where water has yet to be significantly produced. However, by limiting CR models to training periods having a dominant phase, the CR model may become specialized for conditions where the chosen phase is dominant and may not perform well when multiple phases become important. That is, the CR model may be less adept at understanding the interactions between multiple phases and their collective impact on reservoir performance. In accordance with examples of the present disclosure, a multiphase flow factor (MPFF) modeling workflow 314 can include CR models that account for multi-phase flow effects, such that the training periods of the CR models can be extended to include those periods that capture a wider array of production events, including but not limited to, phase transitions like gas breakouts, multi-phase interactions

such as water or gas coning, and other factors that impact reservoir quality like the movement of saturation fronts and changes in wettability. In examples, capacitance-resistance modeling 312, or other CR model, can predict a production flow rate of a producer at a point in time according to the following equation:

$$\dot{q}_j(n) = \text{MPFF}(t) \cdot \left[\lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}} + \sum_{i=1}^{i=l} \lambda_{ij} \ddot{q}_i \left(\frac{d_{ij}}{div} \right) \right]$$

where MPFF(t) is a multiphase flow factor. The multiphase flow factor can take into account the interaction of oil and water at differing levels of concentrations. In some examples, the liquid rate model parameters 316 can consider MPFF during training. In some examples, the liquid rate model parameters 316 can exclude MPFF during training. In some embodiments, a machine learning model can be utilized to train the liquid rate model 302. In some embodiments, a machine learning model can be utilized to determine which features (e.g., injection rates, reservoir characteristics) are most influential in predicting an output to focus on certain optimization parameters over others when performing an optimization process. Alternatively, or in addition, a machine learning model can be utilized perform a co-optimization where both the CR model optimization parameters and the machine learning model parameters are adjusted simultaneously to minimize an objective function during parameter optimization. Additional details directed to training and utilizing a machine learning model are provided with respect to **FIG. 4**.

[0047] As previously discussed, the workflow 210 of the injector-producer feedback system 200 can generate water-cut profiles for one or more production wells using a water-cut model, such as water-cut model 304. In examples, water-cut modeling 320 can generate a trained water-cut model as water-cut model parameters 324 using production data 202. To obtain a water-cut profile, water-cut modeling 320 may incorporate a fractional flow model, such as one that employs the Koval method, to describe the sweep efficiency in waterflood operations. The Koval method is characterized by a Koval factor, which is a measure of reservoir heterogeneity. In the context of CR models, the Koval factor and the pore volume between production wells and injection wells can be important subsurface parameters for optimizing waterflood strategies, accurately predicting reservoir behavior, and maximizing hydrocarbon extraction. These parameters can significantly

influence fluid flow dynamics, sweep efficiency, and overall reservoir performance, allowing for more effective and sustainable resource management.

[0048] Two approaches are generally available for utilizing water-cut modeling to estimate water production in hydrocarbon fields where water-cut profiles have already been established. The first approach involves initiating water-cut modeling from the beginning of production, while the second introduces an added degree of freedom, allowing water-cut modeling to commence calculations from any selected time point. Allowing water-cut modeling to commence calculations from a selected point in time is beneficial for scenarios where historical data are incomplete or when one is interested in simulating future behavior based on current conditions. In accordance with embodiments of the present disclosure, water-cut modeling 320 may utilize the Koval method together with an additional parameter V_{p_hist} 322 that accounts for the cumulative historical injected pore-volume. This additional parameter, V_{p_hist} 322, provides flexibility when selecting a training period such that water-cut modeling 320 can be applied to wells with long histories of production. In examples, output of water-cut modeling 320 can include water-cut model parameters. Alternatively, or in addition, a water-cut model 304 can be trained on production data 202 utilizing a previously trained liquid rate model 302. In some embodiments, a machine learning model can be utilized to train the water-cut model 304 or otherwise obtain optimized parameters utilizing an iterative approach together with the machine learning model.

[0049] In accordance with examples of the present disclosure, a workflow 214 of the injector-producer feedback system 200 can generate injection-production allocation factors that quantify the relative contribution or efficiency of each production well or injection well involved in waterflood operations within a reservoir. The injection-production allocation factors can be used to provide an indication of balance or imbalance in the subsurface. A "balanced" subsurface condition generally refers to a condition where the injection and production rates across different wells in a specific pattern are optimally aligned. In such a state, the injected fluids, often water or gas, efficiently drive oil towards the production wells, facilitating optimal oil recovery. A balanced state is usually characterized by uniform pressure distribution across the reservoir, efficient sweep efficiency, meaning that the injected fluid is effectively pushing the oil towards the production wells without bypassing large volumes of recoverable reserves, low water or gas cut in production wells, implying that the ratio of undesired fluids (water or gas) to oil in the production stream is low, and a maximized reservoir life and oil recovery.

[0050] An "imbalance" occurs when there is a misalignment between injection and production rates across different wells in a pattern, leading to suboptimal conditions for oil recovery. Signs of an imbalanced system might include irregular pressure distribution within the reservoir, leading to areas of both high and low pressure, poor sweep efficiency, with injected fluids bypassing significant portions of recoverable oil, high water or gas cut in production wells, meaning a larger volume of water or gas is being produced relative to oil, which is economically undesirable, and reduced reservoir life/decreased total recoverable oil. By generating allocation factors that indicate either balance or imbalance, reservoir engineers can identify which wells or patterns are operating optimally and which ones require adjustments. Actions like changing injection rates, shutting in or opening new wells, or even employing enhanced oil recovery techniques can then be precisely targeted to correct these imbalances and improve overall reservoir performance. In some examples, allocation factors that indicate either balance or imbalance can be flagged or logged such that the allocation factors are brought to the attention of those responsible.

[0051] In examples, the injection production allocation factor modeling 306 can generate injections rates for a well pattern. As an injection well can feed multiple production wells, the sum of injection well contributions to all neighboring producers will equal the actual injection rates in a balanced system, where the contributions to all neighboring producers can be obtained from the liquid rate model 302. That is, a trained liquid rate model 302 can be utilized to sum the injection well contributions to all neighboring producers. Thus, in a balanced system, the sum of actual injection rates will equal the sum of calculated injection rates, where the sum of actual injection rates can be obtained from actual production data 202.

[0052] Further, an enhancement of a production system can utilize information at the individual well-pair level, e.g., between each injection well and production well. In accordance with examples of the present disclosure, insights into system imbalances can be identified at the well-pair level and are generated through injection-production allocation factor modeling 332. As previously stated, the liquid rate model 302 generates liquid flow rate estimations specific to a well pattern (e.g., injection wells together with a production well form a pattern). In examples, an allocation factor can be determined for a well-pair (e.g., the contribution of an injector i towards production at producer j) and can be expressed as:

$$F_{ij} = \frac{\lambda_{ij} \bar{q}_l(d_{ij}/div)}{\lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}} + \sum_{i=1}^I \lambda_{ij} \bar{q}_l(d_{ij}/div)}$$

[0053] In an unbalanced example, such as where a reservoir undergoes expansion, a reservoir source allocation factor can be expressed as the following:

$$F_{pj} = \frac{\lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}}}{\lambda_p q(t_0) e^{-\frac{t-t_0}{\tau_p}} + \sum_{i=1}^I \lambda_{ij} \bar{q}_l(d_{ij}/div)}$$

[0054] For injection allocation factors, the contribution of injector i to all production wells is calculated as:

$$F_{ij} q_j,$$

where a reservoir sink allocation factor can be expressed as:

$$q_i - \sum_{j=1}^J F_{ij} q_j$$

[0055] Both the reservoir source allocation factor and the reservoir sink allocation factor can provide an indication of balance/imbalance in a subsurface area. In some examples, the imbalanced systems determination 330 can generate reservoir sink allocation factors and reservoir source allocation factors.

[0056] The trained water-cut model 304 predicts water-cut profiles at the pattern level. However, a Buckley-Leverette analytical model and subsequent optimization can be utilized to generate water-cut profiles for a well-pair (e.g., between each injection well and production well in the pattern). That is, water-cut modelling 336 leverages Buckley-Leverette methodology to rank wells based on a production well water-cut profile, wells' geometrical relationships, and liquid rate allocation results. To optimize system performance, water-cut modelling 336 deploys an iterative optimization routine designed to explore a range of water-cut scenarios. Each such scenario is subject to meeting predefined conditions established at the overarching pattern level. The optimization process is initialized by applying Buckley-Leverette Theory, an approach that

effectively accelerates the convergence rate of the optimization, thereby achieving optimal system settings in a more timely and efficient manner.

[0057] FIG. 4 provides additional details with respect the capacitance-resistance modeling 312 in accordance with examples of the present disclosure. In examples, capacitance-resistance modeling 312 can be used to forecast liquid production rates in systems that have both injection and production wells. Capacitance-resistance modeling 312 includes a CR model 408 that comprises injection terms 410, primary reservoir terms 412, and primary model parameters 414. Injection terms 410 can include, but are not limited to, injection rates (the amount of fluid (usually water or gas) injected into the reservoir over time), injection efficiency (term accounting for not all injected fluids contributing equally to production due to factors like reservoir heterogeneity or varying connectivity between injector and producer wells), and injection history (past injection profiles used to calibrate the model, typically through a history-matching process). Primary reservoir terms 412 can include, but are not limited to initial conditions (e.g., initial pressures, saturations, and fluid distributions) reservoir properties (e.g., rock and fluid properties like permeability, porosity, fluid viscosities, and compressibility), and boundary conditions (e.g., boundary effects like natural aquifer influx or the impact of neighboring fields). Primary model parameters 414 can include, but are not limited to time constants (e.g., characteristic times for fluids to flow from injectors to producers), efficiency factors (e.g., multipliers that weigh the contributions of individual injectors to the producers), and capacitance and resistance (e.g., terms used to model the storage and flow properties of the reservoir and wellbore system). The CR model 408 can be trained utilizing production data 202 and well location data 206.

[0058] In examples, an initialization and training process can occur at 404, where governing equations and factors are initialized and a machine learning model 411 is trained at 418. More specifically, values for τ_p and div can be preconfigured or otherwise assumed at 416 to reduce the computational complexity associated with evaluating an otherwise non-linear CR model equation of CR model 408. Once governing equations and factors have been assumed at 416, the CR model 408 can enter a training and optimization portion 430 to obtain one or more optimized parameters utilized to generate injector-producer allocation factors. In some examples, λ_p (the flow coefficient for reservoir primary energy) and λ_{ij} (the flow coefficient for flow between Producer j and Injector i) are at least some of the optimized parameters to be obtained during training and

optimization portion 430. Using the assumed values at 416 and an iterative approach, a flow rate of a production well at a point in time can be calculated at 436 and compared to an actual production flow rate at 438 using production data 202 to obtain an error amount. In examples where the error amount is less than a threshold, flow and time factors preconfigured or assumed at 416 can be assumed to be optimized, or matched, and the training and optimization portion 430 can end, yielding one or more model parameters 440 that may be utilized in a model to obtain injector-producer allocation factors. Alternatively, where the error is greater than a threshold, values for τ_p and div can be adjusted at 432 and the training and optimization portion 430 can resume at 436 until a solution converges.

[0059] In addition, primary reservoir terms 412 and injection terms 410 can be prepared such that historical data can be used to train a machine learning model 411 on the relationship between reservoir and injection terms (features) and production data (target). In examples, following an iteration involving the solving of the linearized governing equations at 436, the trained machine learning model 422 can make predictions or estimate parameters based on the current system state (e.g., current reservoir conditions, injection rates, etc. predicted from production data 202). Thus, the trained machine learning model's 422 outputs can be evaluated (e.g., 424) to emphasize or understand the relative importance of each feature (e.g., individual well contributions to overall production). Insights gained from the trained machine learning model 422 prediction can be used to update the parameters, boundary conditions, or even the structure of the governing equations at 432. The governing equations can be evaluated at 436 and an error amount can be evaluated at 438. In addition to comparing the predictions from the governing equations to production data 202, predictions from the trained machine learning model 422 can be compared to production data 202. In examples where an error amount exceeds a level, such as a predetermined threshold, the trained machine learning model 422 can be retrained or be subjected to fine-tuning at 444. By integrating the trained machine learning model 422 into a feedback loop, data-driven insights can be leveraged to continuously refine and improve the physics-based governing equations. This hybrid approach can offer a more robust and adaptive framework for understanding and predicting complex systems like reservoir behavior.

[0060] In some examples, the governing equation can resemble:

$$\dot{q}_j(n) = \lambda_p q_{n0} * f(\tau_p) + \sum \lambda_{ij} \ddot{q}_i \left(\frac{d_{ij}}{div} \right)$$

[0061] FIG. 5 depicts sample outcomes from the liquid rate model, both with and without the inclusion of the MPFF (Multi-Phase Flow Factor) variable. In outcome 502, the estimated liquid production rate 504 diverges more from the actual recorded value 506 when compared to outcome 508. In the latter, the predicted rate 510 shows a closer alignment with the true measurement 512.

[0062] FIG. 6 illustrates example water-cut profiles, comparing results that incorporate the additional Vp_hist parameter 322 and those that do not. In the case of outcome 602, the water-cut profile 608 is derived from a traditional model and exhibits close alignment with the empirically observed profile 604. The integration of an additional parameter, denoted as Vp_hist 322, allows for the consideration of cumulative historical injected pore-volume. Consequently, a training phase can commence at a specified starting point 618, which does not necessarily correspond to the onset of production history 610. Utilizing this added Vp_hist 322 parameter, the newly generated water-cut profile 616 closely approximates the observed water-cut profile 614 as depicted in outcome 612.

[0063] FIG. 7 presents a schematic diagram 700 featuring injection wells 704A-704E and production wells 708A-708C. In certain configurations, a well pattern may be established consisting of injection wells 704A-704D and a singular production well 708A. Within these setups, the injection wells 704A-704D can contribute to the total liquid rate yielded by production wells 708A. Utilizing injection-production allocation factor modeling 332, the injector-producer feedback system 200 can generate injector-producer allocation metrics that quantify the collective contribution from injection wells 704A-704D to the output of production wells 708A. In specific instances, water-cut modeling 336 can produce individualized water-cut profiles that denote the unique contributions of injection wells 704A-704B to production well 708A. As further depicted in FIG. 7, the well pattern may be imbalanced where liquid from injection well 704A is not directed to a production well, such as in instance 716. Further, in some instances, an injection well can contribute to more than production well, such as injection well 704E. The injector-producer feedback system 200 can generate injector-producer allocation metrics or factors that take this into account.

Example Operations for Generating Allocation Factors Describing an Injector-Producer Relationship

[0064] FIG. 8 depicts an example method 800 for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir. Method 800 may be performed by one or more processor(s) of a computing device, such as processor(s) 906 of computing system 900 described below with respect FIG. 9.

[0065] Method 800 begins, at step 802, with obtaining geospatial location data for multiple injection wells and at least one production well within the reservoir.

[0066] Method 800 proceeds to step 804, using a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir. In some aspects, the liquid rate model incorporates a distance parameter representing the spatial separation between each injection well and the production well. In some aspects, the liquid rate model utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data. In some aspects, the liquid rate model is a capacitance-resistance model. In some aspects, step 804 can include iteratively fine-tuning the model parameters in the capacitance-resistance model through a process of refinement, wherein the refinement process utilizes an error metric based on a comparison of predicted outputs with actual production data. In some aspects, the refinement process includes converting a non-linear CR model equation into a linearized form for computational efficiency. In some aspects, the capacitance-resistance model is implemented in conjunction with a machine learning model thereby creating a hybrid predictive framework. In some aspects, the machine learning model is a supervised learning algorithm comprising at least one of a random forest, gradient boosting, or neural network. In some aspects, the liquid rate model incorporates a multi-phase flow factor (MPFF) to account for interactions between oil and water phases. In some aspects, the capacitance-resistance model is used in conjunction with real-time monitoring systems to provide dynamic updates to the production flow rate predictions. In some aspects, step 804 includes comparing predicted production flow rates generated by the capacitance-resistance model with actual production data to evaluate an accuracy of the capacitance-resistance model.

[0067] Method 800 proceeds to step 806, with calculating a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates. In some

aspects, step 806 includes evaluating a water-cut profile model configured to generate water-cut profiles based on a Koval method, where the water-cut profile model is configured to commence calculations from a selected time point based on historical production data and incorporates an additional parameter accounting for the cumulative historical injected pore volume. In some aspects, calculating the water-cut profile for the production well based on the fractional flow models and the estimated liquid flow rates includes generating a water-cut profile at the well-pair level such that water-cut values are specific to each injection well and production well-pair.

[0068] Method 800 proceeds to step 808, with generating allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the injection-production allocation factors describe the contributions of the injection wells towards the production well. In some aspects, step 808 includes generating injection-production allocation factors at both a well-pair level and a pattern level. In some aspects, the allocation factors at the pattern level are generated by aggregating well-pair level allocation factors. In some aspects, the injection-production allocation factors indicate imbalances in subsurface conditions. In some aspects, the injection-production allocation factors indicate balance in subsurface conditions.

[0069] In some embodiments, the methods of the present disclosure may be executed by a computing system. **FIG. 9** illustrates an example of such a computing system 900, in accordance with some embodiments. The computing system 900 may include a computer or computer system 902A, which may be an individual computer system 902A or an arrangement of distributed computer systems. The computer system 902A includes one or more analysis modules 904 that are configured to perform various tasks according to some embodiments, such as one or more methods disclosed herein. To perform these various tasks, the analysis module 904 executes independently, or in coordination with, one or more processors 906 which is (or are) connected to one or more storage media 908. The processor(s) 906 is (or are) also connected to a network interface 912 to allow the computer system 902A to communicate over a data network 914 with one or more additional computer systems and/or computing systems, such as 902B, 902C, and/or 902D (note that computer systems 902B, 902C and/or 902D may or may not share the same architecture as computer system 902A, and may be located in different physical locations, e.g., computer systems 902A and 902B may be located in a processing facility, while in communication

with one or more computer systems such as 902C and/or 902D that are located in one or more data centers, and/or located in varying countries on different continents).

[0070] A processor 906 may include a microprocessor, microcontroller, processor module or subsystem, programmable integrated circuit, programmable gate array, or another control or computing device.

[0071] The storage media 908 may be implemented as one or more computer-readable or machine-readable storage media. Note that while in the example embodiment of **FIG. 9** storage media 908 is depicted as within computer system 902A, in some embodiments, storage media 908 may be distributed within and/or across multiple internal and/or external enclosures of computing system 902A and/or additional computing systems. Storage media 908 may include one or more different forms of memory including semiconductor memory devices such as dynamic or static random access memories (DRAMs or SRAMs), erasable and programmable read-only memories (EPROMs), electrically erasable and programmable read-only memories (EEPROMs) and flash memories, magnetic disks such as fixed, floppy and removable disks, other magnetic media including tape, optical media such as compact disks (CDs) or digital video disks (DVDs), BLURAY® disks, or other types of optical storage, or other types of storage devices. Note that the instructions discussed above may be provided on one computer-readable or machine-readable storage medium, or may be provided on multiple computer-readable or machine-readable storage media distributed in a large system having possibly plural nodes. Such computer-readable or machine-readable storage medium or media is (are) considered to be part of an article (or article of manufacture). An article or article of manufacture may refer to any manufactured single component or multiple components. The storage medium or media may be located either in the machine running the machine-readable instructions, or located at a remote site from which machine-readable instructions may be downloaded over a network for execution.

[0072] In some embodiments, computing system 900 contains one or more machine learning module(s) 910. In the example of computing system 900, computer system 902A includes the machine learning module 910. In some embodiments, a single machine learning module may be used to perform some aspects of one or more embodiments of the methods disclosed herein. In other embodiments, a plurality of machine learning modules may be used to perform some aspects of methods herein.

[0073] It should be appreciated that computing system 900 is merely one example of a computing system, and that computing system 900 may have more or fewer components than shown, may combine additional components not depicted in the example embodiment of **FIG. 9**, and/or computing system 900 may have a different configuration or arrangement of the components depicted in **FIG. 9**. The various components shown in **FIG. 9** may be implemented in hardware, software, or a combination of both hardware and software, including one or more signal processing and/or application specific integrated circuits.

[0074] Further, the steps in the processing methods described herein may be implemented by running one or more functional modules in information processing apparatus such as general-purpose processors or application specific chips, such as ASICs, FPGAs, PLDs, or other appropriate devices. These modules, combinations of these modules, and/or their combination with general hardware are included within the scope of the present disclosure.

[0075] Computational interpretations, models, and/or other interpretation aids may be refined in an iterative fashion; this concept is applicable to the methods discussed herein. This may include use of feedback loops executed on an algorithmic basis, such as at a computing device (e.g., computing system 900, **FIG. 9**), and/or through manual control by a user who may make determinations regarding whether a given step, action, template, model, or set of curves has become sufficiently accurate for the evaluation of the subsurface three-dimensional geologic formation under consideration.

[0076] The foregoing description, for purpose of explanation, has been described with reference to specific embodiments. However, the illustrative discussions above are not intended to be exhaustive or limiting to the precise forms disclosed. Many modifications and variations are possible in view of the above teachings. Moreover, the order in which the elements of the methods described herein are illustrated and described may be re-arranged, and/or two or more elements may occur simultaneously. The embodiments were chosen and described in order to best explain the principles of the disclosure and its practical applications, to thereby enable others skilled in the art to best utilize the disclosed embodiments and various embodiments with various modifications as are suited to the particular use contemplated.

Example Clauses

[0078] Implementation examples are described in the following numbered clauses:

[0079] Clause 1: A method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir, the method comprising: obtaining geospatial location data for multiple injection wells and at least one production well within the reservoir; using a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model: incorporates a distance parameter representing the spatial separation between each injection well and the production well; and utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data; calculating a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and generating allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.

[0080] Clause 2: The method of clause 1, wherein the liquid rate model is a capacitance-resistance model.

[0081] Clause 3: The method of any one of Clauses 1-2, further comprising iteratively fine-tuning the model parameters in the capacitance-resistance model through a process of refinement, wherein the refinement process utilizes an error metric based on a comparison of predicted outputs with actual production data.

[0082] Clause 4: The method of any one of Clauses 1-3, wherein the refinement process includes converting a non-linear CR model equation into a linearized form for computational efficiency.

[0083] Clause 5: The method of any one of Clauses 1-4, wherein the capacitance-resistance model is implemented in conjunction with a machine learning model thereby creating a hybrid predictive framework.

[0084] Clause 6: The method of any one of Clauses 1-5, wherein the machine learning model is a supervised learning algorithm comprising at least one of a random forest, gradient boosting, or neural network.

[0085] Clause 7: The method of any one of Clauses 1-6, wherein the liquid rate model incorporates a multi-phase flow factor (MPFF) to account for interactions between oil and water phases.

[0086] Clause 8: The method of any one of Clauses 1-7, further comprising evaluating a water-cut profile model configured to generate water-cut profiles based on a Koval method, wherein the water-cut profile model is configured to commence calculations from a selected time point based on historical production data and incorporates an additional parameter accounting for the cumulative historical injected pore volume.

[0087] Clause 9: The method of any one of Clauses 1-8, further comprising generating injection-production allocation factors at both a well-pair level and a pattern level.

[0088] Clause 10: The method of any one of Clauses 1-9, wherein the allocation factors at the pattern level are generated by aggregating well-pair level allocation factors.

[0089] Clause 11: The method of any one of Clauses 1-10, wherein the injection-production allocation factors indicate imbalances in subsurface conditions.

[0090] Clause 12: The method of any one of Clauses 1-11, wherein the injection-production allocation factors indicate balance in subsurface conditions.

[0091] Clause 13: The method of any one of Clauses 1-12, wherein the capacitance-resistance model is used in conjunction with real-time monitoring systems to provide dynamic updates to the production flow rate predictions.

[0092] Clause 14: The method of any one of Clauses 1-13, wherein the calculating the water-cut profile for the production well based on the fractional flow models and the estimated liquid flow rates includes generating a water-cut profile at the well-pair level such that water-cut values are specific to each injection well and production well-pair.

[0093] Clause 15: The method of any one of Clauses 1-14, further comprising comparing predicted production flow rates generated by the capacitance-resistance model with actual production data to evaluate an accuracy of the capacitance-resistance model.

[0094] Clause 16: The method of any one of Clauses 1-15, wherein the allocation factors are generated on a periodic basis using updated production data to provide dynamic injector-producer relationship updates.

[0095] Clause 17: The method of any one of Clauses 1-16, wherein the location data, production data, and injection data are obtained from a distributed control system operatively coupled to sensors at the injection wells and production well.

[0096] Clause 18: The method of any one of Clauses 1-17, wherein the water-cut profile is generated using a fractional flow model that incorporates a history matching parameter accounting for cumulative historical water influx.

[0097] Clause 19: The method of any one of Clauses 1-18, wherein the allocation factors comprise efficiency factors representing proportional contributions of each injection well to the production well.

[0098] Clause 20: A method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir, the method comprising: obtaining location data for a plurality of injection wells of a reservoir and for a production well of the reservoir; evaluating a liquid rate model configured to generate a liquid flow rate estimation specific to a well pattern of the reservoir using a trained capacitance-resistance model, wherein: the trained capacitance-resistance model incorporates a distance parameter for each injection well representing a distance between the production well and each respective injection well, and the trained capacitance-resistance model relies on parameters that are iteratively fine-tuned through a refinement process until a predicted output aligns with production data specific to the production well; evaluating a water-cut profile model configured to generate a water-cut profile for the production well based on a fractional flow model and the liquid flow rate estimation; and generating injection-production allocation factors for the injection wells based on at least one of the liquid flow rate estimation and the water-cut profile, wherein the injection-production allocation factors describe the contributions of the injection wells towards the production well.

[0099] Clause 21: A processing system, comprising: a memory comprising computer-executable instructions; and a processor configured to execute the computer-executable instructions and cause the processing system to perform a method in accordance with any one of Clauses 1-20.

[0100] Clause 22: A processing system, comprising means for performing a method in accordance with any one of Clauses 1-20.

[0101] Clause 23: A non-transitory computer-readable medium storing program code for causing a processing system to perform the steps of any one of Clauses 1-20.

[0102] Clause 24: A computer program product embodied on a computer-readable storage medium comprising code for performing a method in accordance with any one of Clauses 1-20.

Additional Considerations

[0103] The preceding description is provided to enable any person skilled in the art to practice the various embodiments described herein. The examples discussed herein are not limiting of the scope, applicability, or embodiments set forth in the claims. Various modifications to these embodiments will be readily apparent to those skilled in the art, and the generic principles defined herein may be applied to other embodiments. For example, changes may be made in the function and arrangement of elements discussed without departing from the scope of the disclosure. Various examples may omit, substitute, or add various procedures or components as appropriate. For instance, the methods described may be performed in an order different from that described, and various steps may be added, omitted, or combined. Also, features described with respect to some examples may be combined in some other examples. For example, an apparatus may be implemented, or a method may be practiced using any number of the aspects set forth herein. In addition, the scope of the disclosure is intended to cover such an apparatus or method that is practiced using other structure, functionality, or structure and functionality in addition to, or other than, the various aspects of the disclosure set forth herein. It should be understood that any aspect of the disclosure disclosed herein may be embodied by one or more elements of a claim.

[0104] As used herein, the word “exemplary” means “serving as an example, instance, or illustration.” Any aspect described herein as “exemplary” is not necessarily to be construed as preferred or advantageous over other aspects.

[0105] As used herein, a phrase referring to “at least one of” a list of items refers to any combination of those items, including single members. As an example, “at least one of: a, b, or c” is intended to cover a, b, c, a-b, a-c, b-c, and a-b-c, as well as any combination with multiples of the same element (e.g., a-a, a-a-a, a-a-b, a-a-c, a-b-b, a-c-c, b-b, b-b-b, b-b-c, c-c, and c-c-c or any

other ordering of a, b, and c). Reference to an element in the singular is not intended to mean only one unless specifically so stated, but rather “one or more.” For example, reference to an element (e.g., “a processor,” “a memory,” etc.), unless otherwise specifically stated, should be understood to refer to one or more elements (e.g., “one or more processors,” “one or more memories,” etc.). The terms “set”, and “group” are intended to include one or more elements and may be used interchangeably with “one or more.” Where reference is made to one or more elements performing functions (e.g., steps of a method), one element may perform all functions, or more than one element may collectively perform the functions. When more than one element collectively performs the functions, each function need not be performed by each of those elements (e.g., different functions may be performed by different elements) and/or each function need not be performed in whole by only one element (e.g., different elements may perform different sub-functions of a function). Similarly, where reference is made to one or more elements configured to cause another element (e.g., an apparatus) to perform functions, one element may be configured to cause the other element to perform all functions, or more than one element may collectively be configured to cause the other element to perform the functions. Unless specifically stated otherwise, the term “some” refers to one or more.

[0106] As used herein, the term “determining” encompasses a wide variety of actions. For example, “determining” may include calculating, computing, processing, deriving, investigating, looking up (e.g., looking up in a table, a database, or another data structure), ascertaining and the like. Also, “determining” may include receiving (e.g., receiving information), accessing (e.g., accessing data in a memory) and the like. Also, “determining” may include resolving, selecting, choosing, establishing and the like.

[0107] The methods disclosed herein comprise one or more steps or actions for achieving the methods. The method steps and/or actions may be interchanged with one another without departing from the scope of the claims. In other words, unless a specific order of steps or actions is specified, the order and/or use of specific steps and/or actions may be modified without departing from the scope of the claims. Further, the various operations of methods described above may be performed by any suitable means capable of performing the corresponding functions. The means may include various hardware and/or software component(s) and/or module(s), including, but not limited to a circuit, an application specific integrated circuit (ASIC), or processor. Generally, where there are

operations illustrated in figures, those operations may have corresponding counterpart means-plus-function components with similar numbering.

[0108] The following claims are not intended to be limited to the embodiments shown herein but are to be accorded the full scope consistent with the language of the claims. Within a claim, reference to an element in the singular is not intended to mean “one and only one” unless specifically so stated, but rather “one or more.” Unless specifically stated otherwise, the term “some” refers to one or more. No claim element is to be construed under the provisions of 35 U.S.C. §112(f) unless the element is expressly recited using the phrase “means for” or, in the case of a method claim, the element is recited using the phrase “step for.” All structural and functional equivalents to the elements of the various aspects described throughout this disclosure that are known or later come to be known to those of ordinary skill in the art are expressly incorporated herein by reference and are intended to be encompassed by the claims. Moreover, nothing disclosed herein is intended to be dedicated to the public regardless of whether such disclosure is explicitly recited in the claims.

WHAT IS CLAIMED IS:

1. A method for generating allocation factors describing an injector-producer relationship between injection wells and a production well of a reservoir, the method comprising:
 - obtaining geospatial location data for multiple injection wells and at least one production well within a reservoir;
 - using a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model:
 - incorporates a distance parameter representing the spatial separation between each injection well and the production well, and
 - utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data;
 - calculating a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and
 - generating allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.
2. The method of claim 1, wherein the liquid rate model is a capacitance-resistance model.
3. The method of claim 2, further comprising iteratively fine-tuning the model parameters in the capacitance-resistance model through a process of refinement, wherein the refinement process utilizes an error metric based on a comparison of predicted outputs with actual production data.
4. The method of claim 3, wherein the refinement process includes converting a non-linear CR model equation into a linearized form for computational efficiency.
5. The method of claim 2, wherein the capacitance-resistance model is implemented in conjunction with a machine learning model thereby creating a hybrid predictive framework.

6. The method of claim 5, wherein the machine learning model is a supervised learning algorithm comprising at least one of a random forest, gradient boosting, or neural network.

7. The method of claim 2, wherein the capacitance-resistance model is used in conjunction with real-time monitoring systems to provide dynamic updates to liquid flow rate estimations.

8. The method of claim 2, further comprising comparing predicted production flow rates generated by the capacitance-resistance model with actual production data to evaluate an accuracy of the capacitance-resistance model.

9. The method of claim 1, wherein the liquid rate model incorporates a multi-phase flow factor (MPFF) to account for interactions between oil and water phases.

10. The method of claim 1, further comprising evaluating a water-cut profile model configured to generate water-cut profiles based on a Koval method, wherein the water-cut profile model is configured to commence calculations from a selected time point based on historical production data and incorporates an additional parameter accounting for the cumulative historical injected pore volume.

11. The method of claim 1, further comprising generating injection-production allocation factors at both a well-pair level and a pattern level.

12. The method of claim 11, wherein the allocation factors at the pattern level are generated by aggregating well-pair level allocation factors.

13. The method of claim 1, wherein the allocation factors indicate imbalances in subsurface conditions.

14. The method of claim 1, wherein the allocation factors indicate balance in subsurface conditions.

15. The method of claim 1, wherein the calculating the water-cut profile for the production well based on the fractional flow models and the estimated liquid flow rates includes

generating a water-cut profile at the well-pair level such that water-cut values are specific to each injection well and production well-pair.

16. The method of claim 1, wherein the allocation factors are generated on a periodic basis using updated production data to provide dynamic injector-producer relationship updates.

17. The method of claim 1, wherein the location data, production data, and injection data are obtained from a distributed control system operatively coupled to sensors at the injection wells and production well.

18. The method of claim 1, wherein the water-cut profile is generated using a fractional flow model that incorporates a history matching parameter accounting for cumulative historical water influx.

19. A system for generating allocation factors describing an injector-producer relationship, the system comprising:

one or more processors; a memory communicatively coupled to the one or more processors and storing instructions which, when executed by the one or more processors, cause the system to:

obtain geospatial location data for multiple injection wells and at least one production well within a reservoir;

use a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model:

incorporates a distance parameter representing the spatial separation between each injection well and the production well, and

utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data;

calculate a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and

generate allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.

20. A non-transitory computer-readable medium comprising computer executable instructions, which when executed by one or more processors, cause a processing system to:
- obtain geospatial location data for multiple injection wells and at least one production well within a reservoir;
 - use a liquid rate model to estimate liquid flow rates for a specified well pattern within the reservoir, wherein the liquid rate model:
 - incorporates a distance parameter representing the spatial separation between each injection well and the production well, and
 - utilizes model parameters that are iteratively adjusted to minimize differences between predicted and actual production data;
 - calculate a water-cut profile for the production well based on fractional flow models and the estimated liquid flow rates; and
 - generate allocation factors for each injection well in relation to the production well based on at least one of the estimated liquid flow rates and the water-cut profile, wherein the allocation factors describe contributions of the injection wells towards the production well.

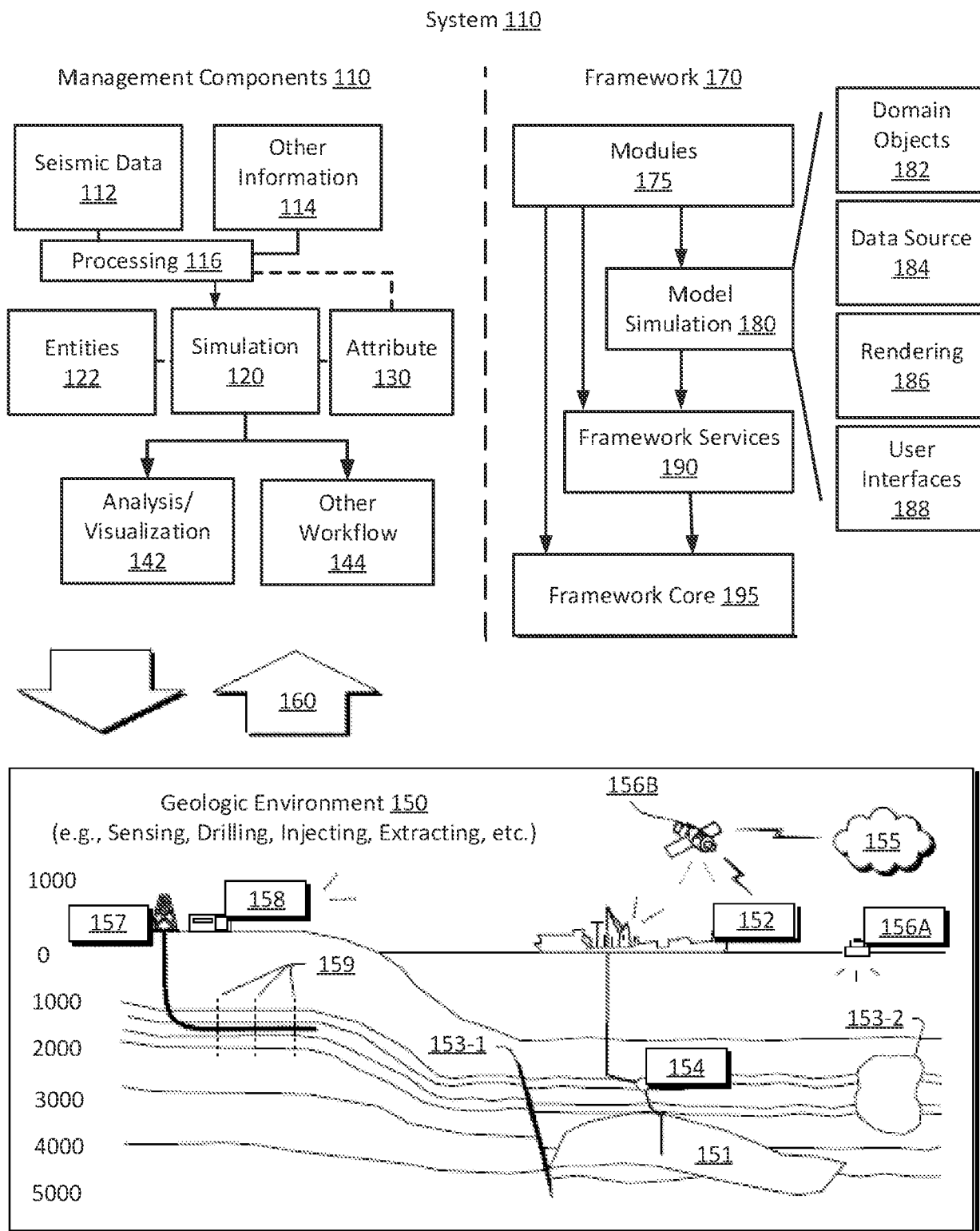


FIG. 1

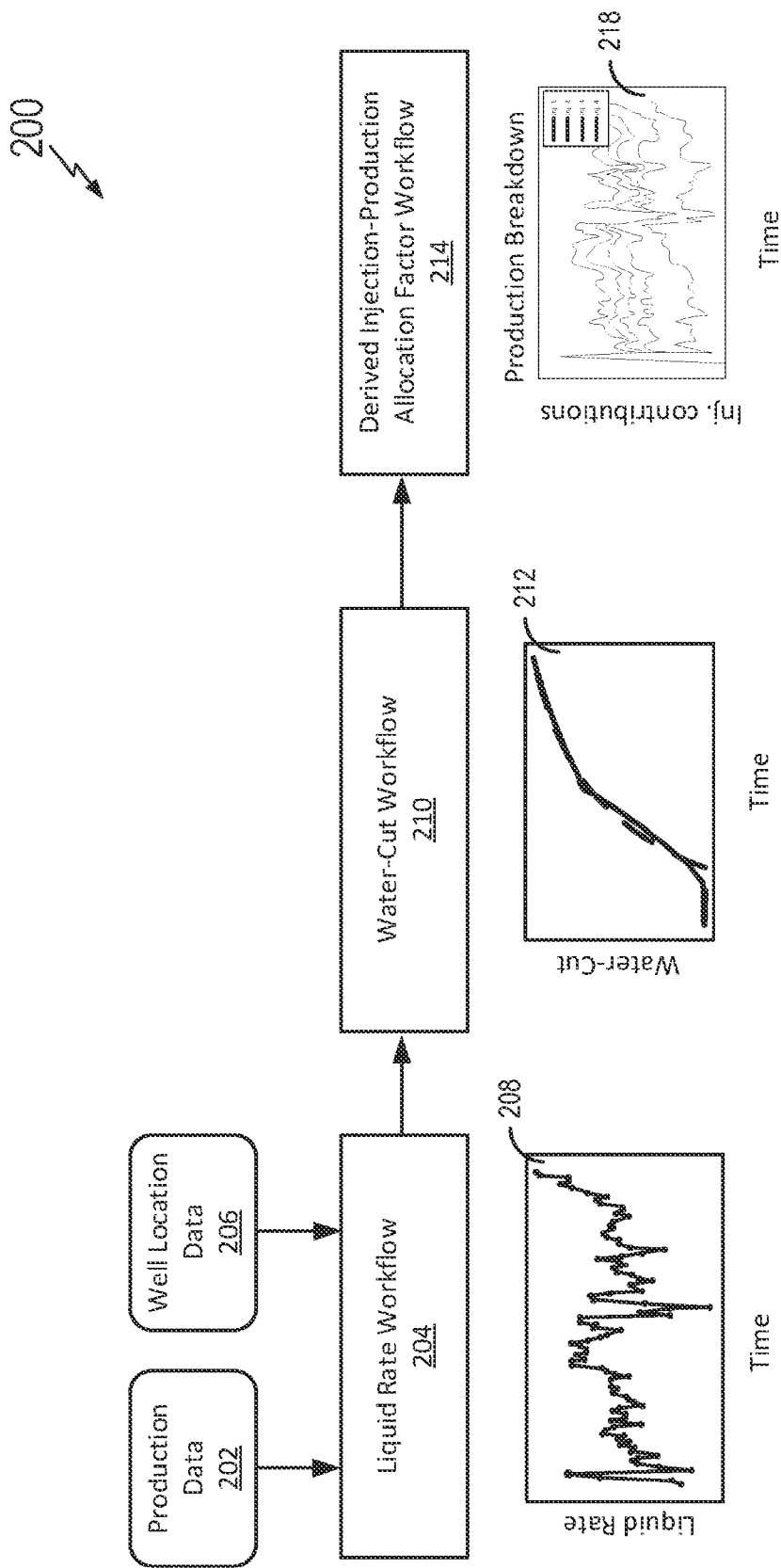


FIG. 2

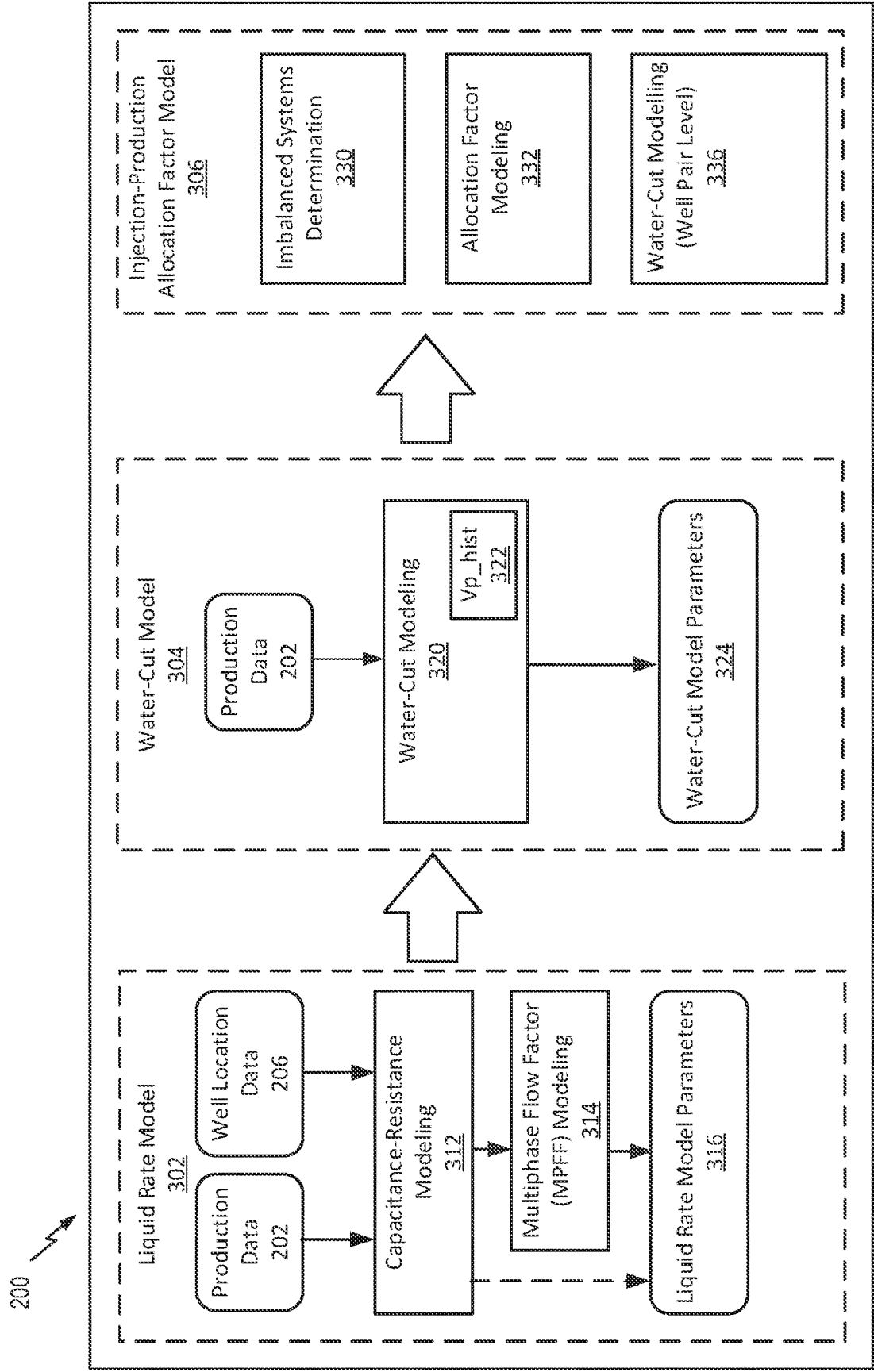


FIG. 3

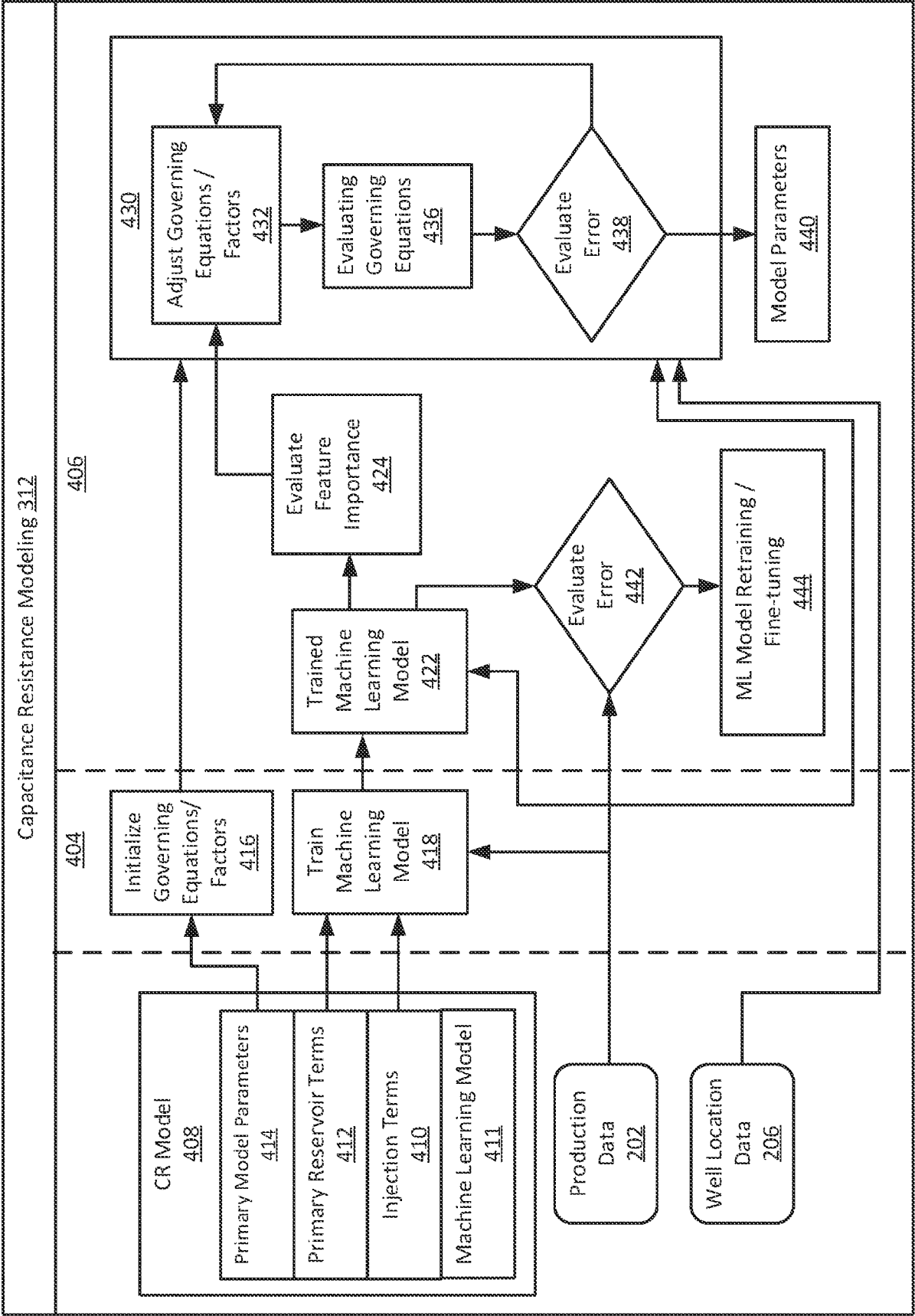


FIG. 4

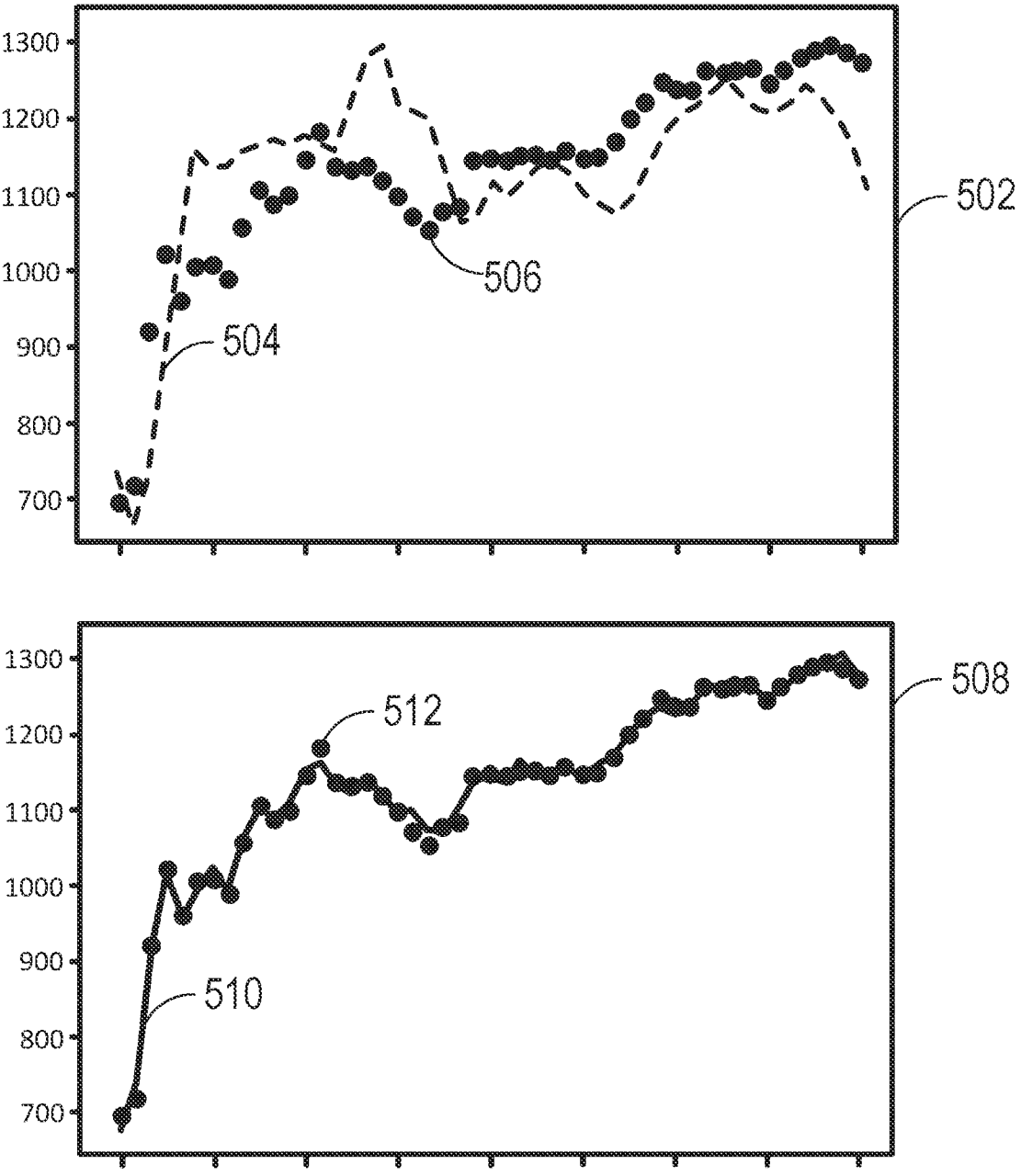


FIG. 5

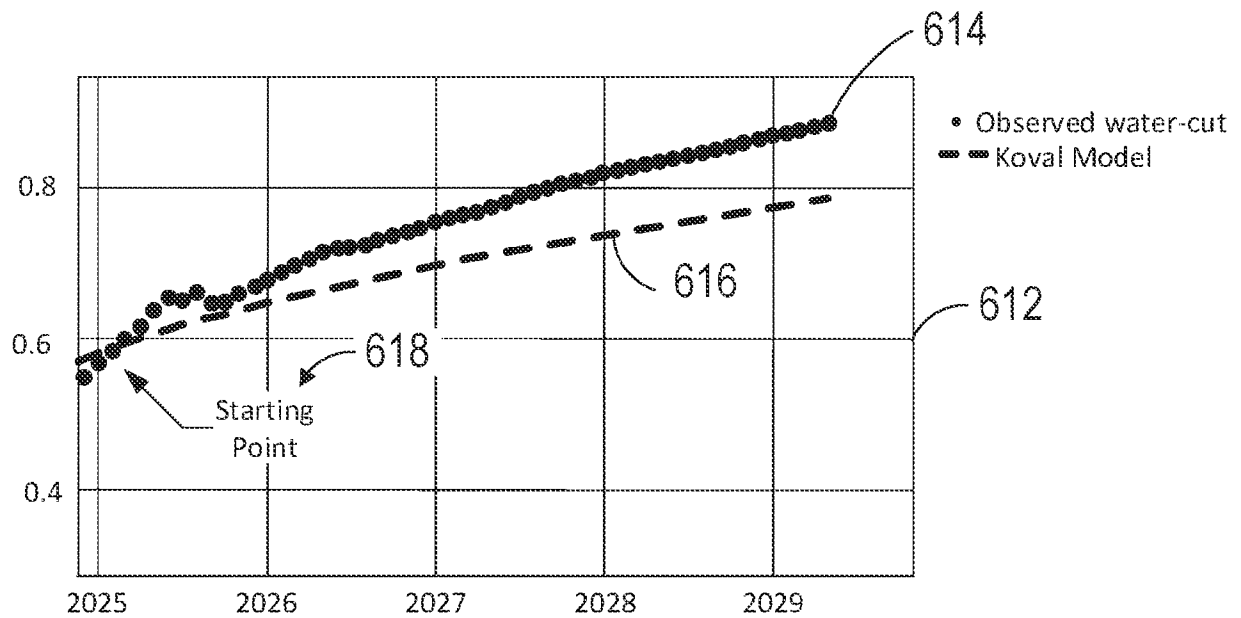
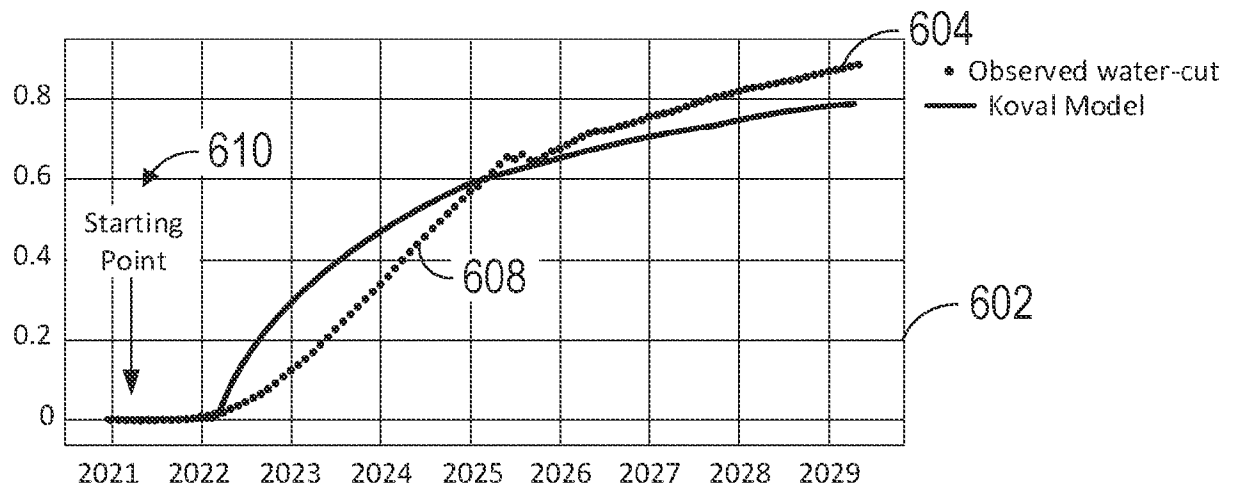


FIG. 6

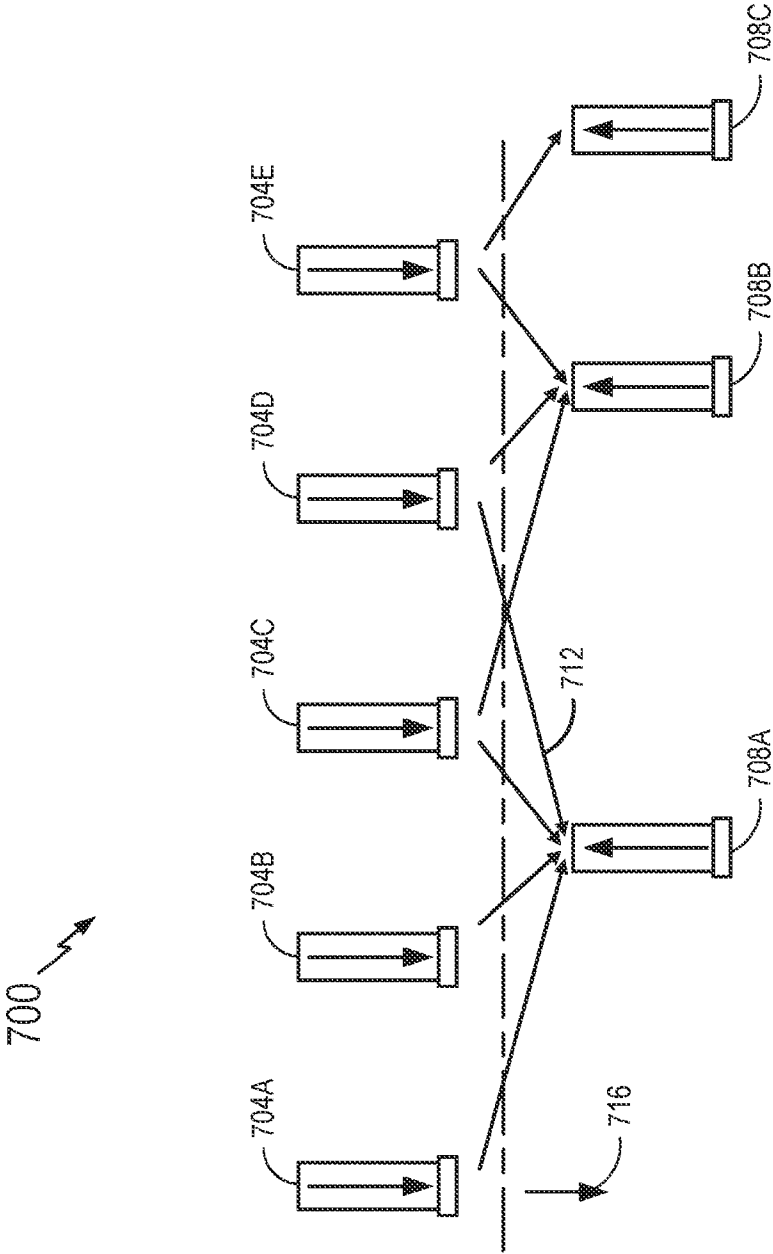
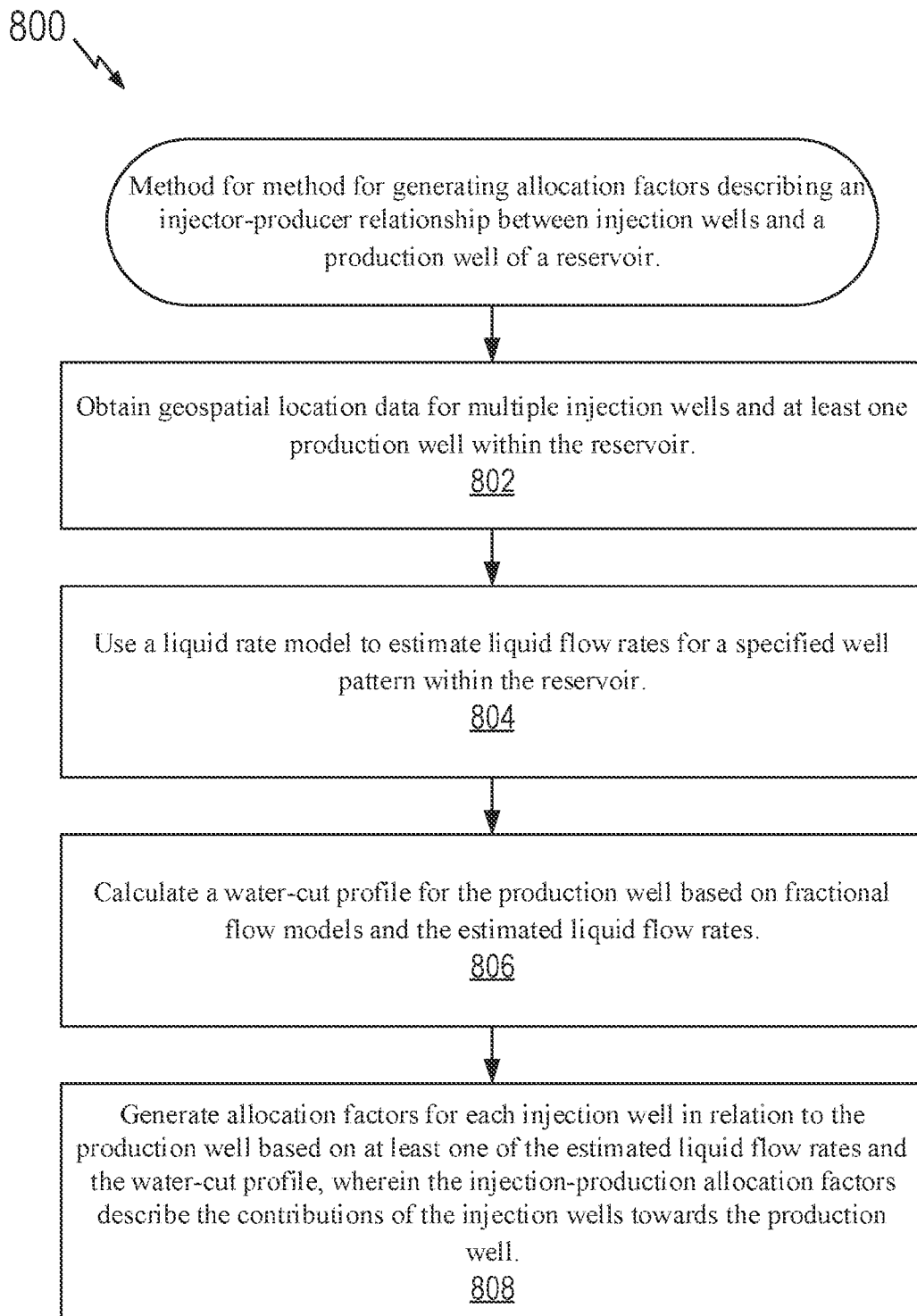


FIG. 7

**FIG. 8**

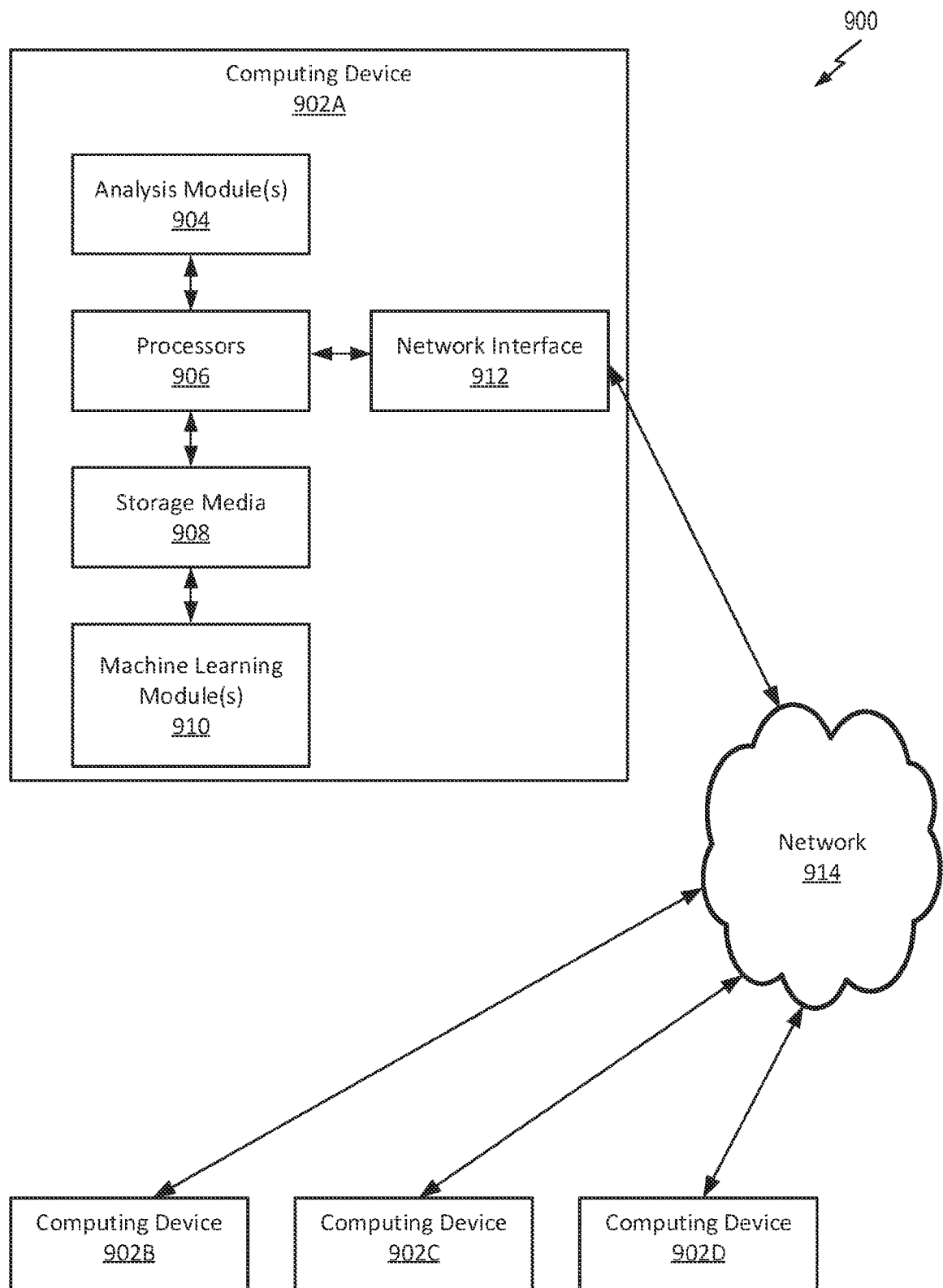


FIG. 9

INTERNATIONAL SEARCH REPORT

International application No.

PCT/US 23/74558

A. CLASSIFICATION OF SUBJECT MATTER

IPC - INV. E21B 21/08, G06G 7/50, E21B 43/16, G06N 3/02 (2024.01)

ADD. E21B 47/00 (2024.01)

CPC - INV. E21B 21/08, G06G 7/50, E21B 43/16, E21B 43/162, G06N 3/02

ADD. E21B 2200/20, E21B 47/00

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)

See Search History document

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

See Search History document

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

See Search History document

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y — A	US 2016/0177679 A1 (Chevron U.S.A. Inc.), 23 June 2016 (23.06.2016), entire document	1-3 and 5-20 4
Y — A	US 2009/0198477 A1 (Benish et al.) (hereinafter Benish), 06 August 2009 (06.08.2009), entire document	1-3 and 5-20 4
Y —	Nikitin et al. "Hybrid and automated machine learning approaches for oil fields development: The case study of Volve field, North Sea." In: Computers & Geosciences 161 (2022), Available online 18 February 2022 [online] [retrieved on 22 November 2023 (22.11.2023)] Retrieved from the Internet < URL: https://www.sciencedirect.com/science/article/pii/S0098300422000267?via%3Dihub >, entire document	5-6
Y —	Zhang et al. "Research on the influence of production fluctuation of high-production gas well on service security of tubing string." In: Oil & Gas Science and Technology – Rev. IFP Energies nouvelles 76, 54 (2021), [online] [retrieved on 22 November 2023 (22.11.2023)] Retrieved from the Internet < URL: https://hal.science/hal-03326393/document >, entire document	9
Y —	Tanveer et al. "Production Prediction of Water Drive Gas Reservoir using History Matching." In: International Journal of Petroleum and Petrochemical Engineering (IJPPE) Volume 5, Issue 4, 2019, PP 23-30, [online] [retrieved on 22 November 2023 (22.11.2023)] Retrieved from the Internet < URL: https://www.arcjournals.org/pdfs/ijppe/v5-i4/4.pdf >, entire document	18

☒ Further documents are listed in the continuation of Box C.☐ See patent family annex.

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"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search

23 November 2023

Date of mailing of the international search report

JAN 08 2024

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Kari Rodriguez

Telephone No. PCT Helpdesk: 571-272-4300

INTERNATIONAL SEARCH REPORT

International application No.

PCT/US 23/74558

C (Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	US 2014/0166280 A1 (Stone et al.), 19 June 2014 (19.06.2014), entire document	1-20
A	US 2021/0238971 A1 (SAUDI ARABIAN OIL COMPANY), 05 August 2021 (05.08.2021), entire document	1-20