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(54) **Title:** METHOD AND SYSTEM FOR PREDICTING HYDROCARBON DATA FOR UNCONVENTIONAL RESERVOIRS USING MACHINE LEARNING

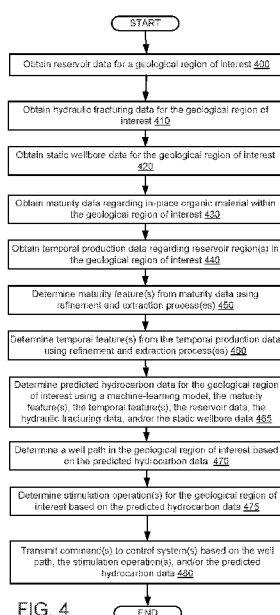


FIG. 4

(57) **Abstract:** A method may include obtaining reservoir data, hydraulic fracturing data, and static wellbore data for a geological region of interest. The method may further include obtaining temporal production data for the geological region of interest. The temporal production data may include a predetermined production rate with respect to a predetermined period of time. The method may further include determining various temporal features based on the temporal production data and an extraction process. The extraction process may include a deconvolution function that separates a portion of the temporal features from the predetermined production rate. The method may further include determining, using a machine-learning model, predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the reservoir data, the hydraulic fracturing data, the static wellbore data, and the temporal features. The method may further include transmitting a command to a well control system based on the predicted HIP data.

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METHOD AND SYSTEM FOR PREDICTING HYDROCARBON DATA FOR UNCONVENTIONAL RESERVOIRS USING MACHINE LEARNING

BACKGROUND

[0001] The composition of hydrocarbons in place (HIP) for unconventional reservoirs is an important consideration for reserve calculations, exploitation planning, and economic evaluation. HIP properties at initial reservoir conditions in nanopore spaces may be different from their bulk state, and HIP is typically expected to be heavier and more viscous in smaller nanopores than its counterpart in the bulk state. However, HIP compositions for unconventional reservoirs are hard to estimate as the pore space is miniscule and the physics in the confined nanopores may not be well understood for a particular geological context.

SUMMARY

[0002] This summary is provided to introduce a selection of concepts that are further described below in the detailed description. This summary is not intended to identify key or essential features of the claimed subject matter, nor is it intended to be used as an aid in limiting the scope of the claimed subject matter.

[0003] In general, in one aspect, embodiments relate to a method that includes obtaining first reservoir data, first hydraulic fracturing data, and first static wellbore data for a geological region of interest. The method further includes obtaining first temporal production data for the geological region of interest. The first temporal production data includes a predetermined production rate with respect to a predetermined period of time. The method further includes determining, by a computer processor, a plurality of temporal features based on the first temporal production data and a first extraction process. The first extraction process includes a deconvolution function that separates a portion of the plurality of temporal features from the predetermined production rate. The

method further includes determining, by the computer processor and using a machine-learning model, first predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the first reservoir data, the first hydraulic fracturing data, the first static wellbore data, and the plurality of temporal features. The method further includes transmitting, by the computer processor, a command to a well control system based on the first predicted HIP data.

[0004] In general, in one aspect, embodiments relate to a system that includes a stimulation control system coupled to a wellbore, and a reservoir simulator coupled to the stimulation control system. The reservoir simulator includes a computer processor, and the reservoir simulator performs a method. The reservoir simulator obtains first reservoir data, first hydraulic fracturing data, and first static wellbore data for a geological region of interest. The reservoir simulator further obtains temporal production data for the geological region of interest. The temporal production data includes a predetermined production rate with respect to a predetermined period of time. The reservoir simulator further determines a plurality of temporal features based on the temporal production data and a first extraction process. The first extraction process includes a deconvolution function that separates a portion of the plurality of temporal features from the predetermined production rate. The reservoir simulator further determines, using a machine-learning model, first predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the first reservoir data, the first hydraulic fracturing data, the first static wellbore data, and the plurality of temporal features. The stimulation control system performs a hydraulic stimulation operation based on the first predicted HIP data.

[0005] In general, in one aspect, embodiments relate to a system that includes a drilling system that includes a plurality of sensors and a drill string that includes a drill bit. The drilling system is coupled to a wellbore. The system further includes a reservoir simulator coupled to the drilling system. The reservoir

simulator includes a computer processor and performs a method. The reservoir simulator obtains reservoir data, hydraulic fracturing data, and static wellbore data for a geological region of interest. The reservoir simulator further obtains temporal production data for the geological region of interest. The temporal production data includes a predetermined production rate with respect to a predetermined period of time. The reservoir simulator further determines various temporal features based on the temporal production data and an extraction process. The extraction process includes a deconvolution function that separates a portion of the temporal features from the predetermined production rate. The reservoir simulator further determines, using a machine-learning model, predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the reservoir data, the hydraulic fracturing data, the static wellbore data, and the temporal features. The drilling system performs a drilling operation for a well path based on the predicted HIP data.

[0006] In some embodiments, maturity data is obtained regarding in-place organic material within a geological region of interest. A maturity feature may be determined, using an extraction process, from the maturity data. The maturity feature may be used by the machine-learning model to determine predicted HIP data. In some embodiments, maturity data includes a maturity map that describes various kerogen quantities in a geological region of interest. The maturity map may be acquired using various drill cutting samples or various core samples from various wells. In some embodiments, a selection of various wells is obtained. Training data may be obtained that includes reservoir data, hydraulic fracturing data, static production data, and temporal production data for the wells. A training operation may be performed on a machine-learning model iteratively using the training data until predicted HIP data is generated by the machine-learning model that satisfies a predetermined criterion.

[0007] In some embodiments, temporal production data includes gas production rate data. An extraction process may separate various predetermined gas rates and various respective gas time periods using a plurality of exponential decay curves. Various temporal features may correspond to the predetermined gas rates and the respective gas time periods. In some embodiments, temporal production data includes gas specific density data, carbon dioxide composition data, $\delta^{13}\text{C}$ composition data, methane composition data, liquid phase data, choke size data, and/or well head pressure data. In some embodiments, predicted HIP data includes molar ratio data of gas phase. In some embodiments, reservoir data includes geological data regarding one or more formation layers reservoir fluid data, reservoir pore pressure data, gamma ray log data, density log data, neutron log data, resistivity log data, permeability data, and/or porosity data, or open fracture data. In some embodiments, hydraulic fracturing data includes fracturing fluid data for a stimulation operation, injection rate data for a stimulation operation, injection consequence data, and/or hydraulic fracture geometry data. In some embodiments, static wellbore data includes well location data, well tubing data, and/or number of fractures adjacent to a wellbore. In some embodiments, a sweet spot region in a geological region of interest is determined using predicted HIP data. A stimulation operation may be determined based on the sweet spot region and predicted HIP data. The command may be transmitted to a well control system that causes performance of a stimulation operation. In some embodiments, a well path in a geological region of interest may be determined using predicted HIP data. A well control system may be a drilling system. A command may cause the drilling system to perform a drilling operation based on a well path. In some embodiments, a machine-learning model is an artificial neural network that includes an input layer, various hidden layers, and an output layer. In some embodiments, a user device coupled to a stimulation control system. A user device may provide a graphical user interface for presenting predicted HIP data.

[0008] In light of the structure and functions described above, embodiments disclosed herein may include respective means adapted to carry out various steps and functions defined above in accordance with one or more aspects and any one of the embodiments of one or more aspect described herein.

[0009] Other aspects and advantages of the claimed subject matter will be apparent from the following description and the appended claims.

BRIEF DESCRIPTION OF DRAWINGS

[0010] Specific embodiments of the disclosed technology will now be described in detail with reference to the accompanying figures. Like elements in the various figures are denoted by like reference numerals for consistency.

[0011] FIGs. 1, 2A, 2B, and 3 show systems in accordance with one or more embodiments.

[0012] FIG. 4 shows a flowchart in accordance with one or more embodiments.

[0013] FIGs. 5A, 5B, 5C, 5D, 5E, and 6 shows examples in accordance with one or more embodiments.

[0014] FIG. 7 shows a flowchart in accordance with one or more embodiments.

[0015] FIGs. 8A and 8B show an example in accordance with one or more embodiments.

[0016] FIG. 9 shows a computer system in accordance with one or more embodiments.

DETAILED DESCRIPTION

[0017] In the following detailed description of embodiments of the disclosure, numerous specific details are set forth in order to provide a more thorough understanding of the disclosure. However, it will be apparent to one of ordinary skill in the art that the disclosure may be practiced without these specific

details. In other instances, well-known features have not been described in detail to avoid unnecessarily complicating the description.

[0018] Throughout the application, ordinal numbers (e.g., first, second, third, etc.) may be used as an adjective for an element (i.e., any noun in the application). The use of ordinal numbers is not to imply or create any particular ordering of the elements nor to limit any element to being only a single element unless expressly disclosed, such as using the terms "before", "after", "single", and other such terminology. Rather, the use of ordinal numbers is to distinguish between the elements. By way of an example, a first element is distinct from a second element, and the first element may encompass more than one element and succeed (or precede) the second element in an ordering of elements.

[0019] In general, embodiments of the disclosure include systems and methods for determining predicted hydrocarbon data that may include hydrocarbon-in-place (HIP) data. In particular, predicted HIP data may include data that describes the original composition of HIP using various inputs to a machine-learning model, such as one or more artificial neural networks. The inputs may include static data (e.g., static wellbore parameters, geological data regarding formation layers, fracture geometry data, hydraulic fracturing data, etc.), temporal production data (e.g., production data based on the gas phase or liquid phase over a predetermined period of time at various production wells), and/or maturity data regarding levels of kerogen or other organic matter in various geological region. More specifically, temporal production data may include various temporal production curves as functions of time, e.g., the acquired data at a production well that includes phase ratios (e.g. gas vs liquid volume ratios with time), gas densities and other properties, such as the gas composition that can be expressed as light component fractions (e.g. the portion of methane relative to the total gaseous phase), and the liquid densities and other properties, such as the stable isotopic composition of the liquid. Maturity data may include maturity values or levels at a particular location, such as the position of one or

more wells on a total organic composition (TOC) maturation map. Static data may include static wellbore data such as choke size, the vertical length of the horizontal section, and the horizontal section the production spot, the distance between the production spot and the heel of any well from a group of wells. Other static data may include reservoir data, such as individual geological and petrophysical features of a geological region. Using these inputs, predicted hydrocarbon data of HIP may be further used in a well path planning operation and/or a stimulation operation for control systems (e.g., a stimulation control system or a control system in a drilling system) for one or more wells.

[0020] Furthermore, some embodiments predict hydrocarbon data of HIP for unconventional reservoirs, particularly the original composition of HIP (e.g., amounts of various gases, such as carbon dioxide and nitrogen as well as compositions of hydrocarbons in place (HIP), such as C1, C2, C3-6, etc.). Because of the nano space confinement and the nano pore throats of a flow path in an unconventional reservoir, hydrocarbon compositional separation due to physical segregation and chemical fractionation of the hydrocarbons may occur when flows occur. To predict the composition of hydrocarbons in place (HIP) in a particular geological region, the nature of the pore space at a nanoscale level and various hydrocarbon states, such as adsorbed or capillary-condensed states, may need to be accounted for in a prediction process. To address the complexity of physical and chemical fractionation, specific characteristics of hydrocarbon movement may be analyzed in unconventional reservoirs to address these processes in a machine-learning process. More specifically, hydrocarbon production from an unconventional reservoir may be controlled by the maturity of the in-place organic material. Likewise, various thermodynamic-property differences between different hydrocarbon components may result in different physical separations and chemical fractionation among the hydrocarbon components.

[0021] Turning to FIG. 1, FIG. 1 shows a schematic diagram in accordance with one or more embodiments. As shown, FIG. 1 illustrates a well environment (100) that may include a well (102) having a wellbore (104) extending into a formation (106). The wellbore (104) may include a bored hole that extends from the surface into a target zone of the formation (106), such as a reservoir. The formation (106) may include various formation characteristics of interest, such as formation porosity, formation permeability, resistivity, density, water saturation, and the like. Porosity may indicate how much space exists in a particular rock within an area of interest in the formation (106), where oil, gas, and/or water may be trapped. Permeability may indicate the ability of liquids and gases to flow through the rock within the area of interest. Resistivity may indicate how strongly rock and/or fluid within the formation (106) opposes the flow of electrical current. For example, resistivity may be indicative of the porosity of the formation (106) and the presence of hydrocarbons. More specifically, resistivity may be relatively low for a formation that has high porosity and a large amount of water, and resistivity may be relatively high for a formation that has low porosity or includes a large amount of hydrocarbons. Water saturation may indicate the fraction of water in a given pore space.

[0022] Keeping with FIG. 1, the well environment (100) may include a reservoir simulator (160), one or more additional computer programs, and various well systems, such as a drilling system (110), a logging system (112), a control system (114), and a well completion system (not shown). The drilling system (110) may include a drill string, drill bit, a mud circulation system and/or the like for use in boring the wellbore (104) into the formation (106). The control system (114) may include hardware and/or software for managing drilling operations and/or maintenance operations. For example, the control system (114) may include one or more programmable logic controllers (PLCs) that include hardware and/or software with functionality to control one or more processes performed by the drilling system (110). Specifically, a programmable logic controller may control valve states, fluid levels, pipe pressures, warning alarms, and/or pressure releases

throughout a drilling rig. In particular, a programmable logic controller may be a ruggedized computer system with functionality to withstand vibrations, extreme temperatures, wet conditions, and/or dusty conditions, for example, around a drilling rig. Without loss of generality, the term “control system” may refer to a drilling operation control system that is used to operate and control the equipment, a data acquisition and monitoring system that is used to acquire equipment data and to monitor one or more well operations, or a well interpretation software system that is used to analyze and understand well events, such as drilling progress. A logging system may be similar to a control system with a specific focus on managing one or more logging tools.

[0023] Turning to the reservoir simulator (160), a reservoir simulator (160) may include hardware and/or software with functionality for storing and analyzing well log data (141), such as borehole image data, cutting data (142) from drilling cuttings analyzed in drilling fluid, hydraulic fracturing data (145), core sample data (150), seismic data, static wellbore data (155), reservoir data (159), such as porosity data and permeability data, temporal production data (157), and/or other types of data to generate and/or update one or more geological models (170), such as models for an unconventional reservoir. Borehole image data may be based on electrical and/or acoustic logging techniques, for example. Fracture image data may include outcrop images and other image types that include one or more fractures. Geological models may include geochemical or geomechanical models that describe structural relationships within a particular geological region. Cuttings data may describe an analysis or rock typing performed on drill cuttings from a drilling operation, such as using visual methods of describing rock and pore characteristics. Hydraulic fracturing data may describe parameters of one or more hydraulic fracturing operations and associated acquired data, such as measurements relating to any induced fractures and any related results. Static wellbore data may describe well parameters relating to one or more wellbores, such as well locations, well types, and other well data. Temporal production data may describe various parameters relating

to production at a well as a function of time within one or more production operations. These different data types may be acquired during exploration, reservoir characterization, hydraulic fracturing, and production operations.

[0024] While the reservoir simulator (160) is shown at a well site, in some embodiments, the reservoir simulator (160) may be remote from a well site. In some embodiments, the reservoir simulator (160) is implemented as part of a software platform for the control system (114). The software platform may obtain data acquired by the drilling system (110) and logging system (112) as inputs, which may include multiple data types from multiple sources. The software platform may aggregate the data from these systems (110, 112) in real time for rapid analysis. In some embodiments, the control system (114), the logging system (112), the reservoir simulator (160), and/or a user device coupled to one of these systems may include a computer system that is similar to the computer system (902) described below with regard to FIG. 9 and the accompanying description.

[0025] The logging system (112) may include one or more logging tools (113) for use in generating well logs of the formation (106). For example, a logging tool may be lowered into the wellbore (104) to acquire measurements as the tool traverses a depth interval (130) (e.g., a targeted reservoir section) of the wellbore (104). The plot of the logging measurements versus depth may be referred to as a “log” or “well log”. Well log data (141) may provide depth measurements of the wellbore (104) that describe such reservoir characteristics as formation porosity, formation permeability, resistivity, water saturation, and the like. The resulting logging measurements may be stored and/or processed, for example, by the control system (114), to generate corresponding well logs for the well (102). A well log may include, for example, a plot of a logging response time versus true vertical depth (TVD) across the depth interval (130) of the wellbore (104).

[0026] Turning to examples of logging techniques, multiple types of logging techniques are available for determining various reservoir characteristics. In some embodiments, gamma ray logging is used to measure naturally occurring gamma radiation to characterize rock or sediment regions within a wellbore. In particular, different rock components from different types of rock may emit different amounts and different spectra of natural gamma radiation. For example, gamma ray logs may distinguish between shales and sandstones/carbonate rocks because radioactive potassium may be common to minerals in shales. Likewise, the cation exchange capacity of clay within shales may also result in higher absorption of uranium and thorium further increasing the amount of gamma radiation produced by shales.

[0027] Turning to nuclear magnetic resonance (NMR) logging, an NMR logging tool may measure the induced magnetic moment of hydrogen nuclei (i.e., protons) contained within the fluid-filled pore space of porous media (e.g., reservoir rocks). Thus, NMR logs may measure the magnetic response of fluids present in the pore spaces of the reservoir rocks. In so doing, NMR logs may measure both porosity and permeability, as well as the types of fluids present in the pore spaces. Thus, NMR logging may be a subcategory of electromagnetic logging that responds to the presence of hydrogen protons rather than a rock matrix. Because hydrogen protons may occur primarily in pore fluids, NMR logging may directly or indirectly measure the volume, composition, viscosity, and distribution of pore fluids.

[0028] Turning to spontaneous potential (SP) logging, SP logging may determine the permeabilities of rocks in the formation (106) by measuring the amount of electrical current generated between drilling fluid produced by the drilling system (110) and formation water that is held in pore spaces of the reservoir rock. Porous sandstones with high permeabilities may generate more electricity than impermeable shales. Thus, SP logs may be used to identify sandstones from shales.

[0029] Another type of electrical logging technique is resistivity logging. Resistivity logging may measure the electrical resistivity of rock or sediment in and around the wellbore (104). In particular, resistivity measurements may determine what types of fluids are present in the formation (106) by measuring how effective these rocks are at conducting electricity. Because fresh water and oil are poor conductors of electricity, they have high resistivities. As such, resistivity measurements obtained via such logging can be used to determine corresponding reservoir water saturation (S_w).

[0030] Another electrical logging technique is dielectric logging. For example, dielectric permittivity may be defined as a physical quantity that describes the propagation of an electromagnetic field through a dielectric medium. As such, dielectric permittivity may describe a physical medium's ability to polarize in response to an electromagnetic field, and thus reduce the total electric field inside the physical medium. In a portion of reservoir rock, water may have a large dielectric permittivity that is higher than any associated rock or hydrocarbon fluids within the portion. In particular, water permittivity may depend on a frequency of an electromagnetic wave, water pressure, water temperature, and salinity of the reservoir rock mixture. Likewise, a multi-frequency dielectric logging tool may determine a value of the water-filled porosity in the reservoir rock.

[0031] Keeping with dielectric logging, a dielectric logging tool may determine a dielectric constant (i.e., relative-permittivity) measurement. For example, the dielectric logging tool may include an antenna that detects the changes in amplitudes and phase angles that are relative dielectric constants between different fluids at a fluid interface. As such, a dielectric logging tool may generate a dielectric log of the high-frequency dielectric properties of a formation. In particular, a dielectric log may include two curves, where one curve may describe the relative dielectric permittivity of the analyzed rock and the other curve may describe the resistivity of the analyzed rock. Relative

dielectric permittivity may be used to distinguish hydrocarbons from water of differing salinities. However, the effect of salinity may be more important than the salinity effect with a high-frequency dielectric log (also called an “electromagnetic propagation log”).

[0032] Turning to sonic logging or acoustic logging, the logging system (112) may measure the speed that acoustic waves travel through rocks in the formation (106) to determine porosity in the formation (106). This type of logging may generate borehole compensated (BHC) logs, which are also called sonic logs. In general, sound waves may travel faster through high-density shales than through lower-density sandstones. Other types of logging include density logging and neutron logging. Density logging may determine porosity measurements by directly measuring the density of the rocks in the formation (106). Furthermore, neutron logging may determine porosity measurements by assuming that the reservoir pore spaces within the formation (106) are filled with either water or oil and then measuring the amount of hydrogen atoms (i.e., neutrons) in the pores.

[0033] Turning to coring, reservoir characteristics may be determined using core sample data (e.g., core sample data (150)) acquired from a well site. For example, certain reservoir characteristics can be determined via coring (e.g., physical extraction of rock specimens) to produce core specimens and/or logging operations (e.g., wireline logging, logging-while-drilling (LWD) and measurement-while-drilling (MWD)). Coring operations may include physically extracting a rock specimen from a region of interest within the wellbore (104) for detailed laboratory analysis. For example, when drilling an oil or gas well, a coring bit may cut core plugs (or “cores” or “core specimens”) from the formation (106) and bring the core plugs to the surface, and these core specimens may be analyzed at the surface (e.g., in a lab) to determine various characteristics of the formation (106) at the location where the specimen was obtained.

[0034] Turning to various coring technique examples, conventional coring may include collecting a cylindrical specimen of rock from the wellbore (104) using a coring bit, a core barrel, and a core catcher. The coring bit may have a hole in its center that allows the core bit to drill around a central cylinder of rock. Subsequently, the resulting core specimen may be acquired by the coring bit and disposed inside the core barrel. More specifically, the core barrel may include a special storage chamber within a coring tool for holding the core specimen. Furthermore, the core catcher may provide a grip to the bottom of a core and, as tension is applied to the drill string, the rock under the core breaks away from the undrilled formation below coring tool. Thus, the core catcher may retain the core specimen to avoid the core specimen falling through the bottom of the drill string. In some embodiments, a micro computed tomography (micro-CT) scan is performed on a core sample. Several types of micro-CT scanning may be used, such as a desktop micro-CT scanner that uses an X-ray generation tube, and a synchrotron X-ray micro-tomography. In particular, a micro-CT scanner may use various X-rays to penetrate from different viewpoints in a core sample to produce an attenuated projection profile that is used for later reconstruction using a filtered back projection algorithm.

[0035] Keeping with FIG. 1, geosteering may be used to position the drill bit or drill string of the drilling system (110) relative to a boundary between different subsurface layers (e.g., overlying, underlying, and lateral layers of a pay zone) during drilling operations. In particular, geological model may be used by the drilling system (110) for steering the drill bit in the direction of desired hydrocarbon concentrations. In some embodiments, a well path of a wellbore (104) may be updated by the control system (114) using a geological model. For example, a control system (114) may communicate geosteering commands to the drilling system (110) based on well log data updates or predicted hydrocarbon data that are further adjusted by the reservoir simulator (160) using a geological model. As such, the control system (114) may generate one or more control signals for drilling equipment (or a logging system may generate for logging

equipment) based on an updated well path design and/or an updated geological model. As such, a geosteering system may use various sensors located inside or adjacent to the drill string to determine different rock formations within a well path. In some geosteering systems, drilling tools may use resistivity or acoustic measurements to guide the drill bit during horizontal or lateral drilling.

[0036] FIG. 2A illustrates a system in accordance with one or more embodiments. As shown in FIG. 2A, a drilling system (200) may include a top drive drill rig (210) arranged around the setup of a drill bit logging tool (220). A top drive drill rig (210) may include a top drive (211) that may be suspended in a derrick (212) by a travelling block (213). In the center of the top drive (211), a drive shaft (214) may be coupled to a top pipe of a drill string (215), for example, by threads. The top drive (211) may rotate the drive shaft (214), so that the drill string (215) and a drill bit logging tool (220) cut the rock at the bottom of a wellbore (216). A power cable (217) supplying electric power to the top drive (211) may be protected inside one or more service loops (218) coupled to a control system (244). As such, drilling fluid may be pumped into the wellbore (216) using the drive shaft (214) and/or the drill string (215). Likewise, the drilling system may also include a mud pump, a mud line, mud pits, a mud return, and other components related to the circulation or recirculation of drilling fluid within the wellbore (216). The control system (244) may be similar to various control systems described above in FIG. 1 and the accompanying description.

[0037] In some embodiments, the drilling system (200) includes a bottomhole assembly (BHA). The bottomhole assembly may refer to a lower portion of the drill string (215) that includes a drill bit (224), bit sub (i.e., a substitute adapter), and a drill collar. The bottomhole assembly may also include a mud motor, stabilizers, heavy-weight drillpipe, jarring devices ("jars"), crossovers for various threadforms, directional drilling and measuring equipment, measurements-while-drilling tools, logging-while-drilling tools and other specialized devices. The bottomhole assembly may produce force for the drill

bit to break rock and provide the drilling system with directional control of a wellbore. Different types of bottomhole assemblies may be used, such as a rotary assembly, a fulcrum assembly, and a pendulum assembly.

[0038] Moreover, when completing a well, casing may be inserted into the wellbore (216). The sides of the wellbore (216) may require support, and thus the casing may be used for supporting the sides of the wellbore (216). As such, a space between the casing and the untreated sides of the wellbore (216) may be cemented to hold the casing in place. The cement may be forced through a lower end of the casing and into an annulus between the casing and a wall of the wellbore (216). More specifically, a cementing plug may be used for pushing the cement from the casing. For example, the cementing plug may be a rubber plug used to separate cement slurry from other fluids, reducing contamination and maintaining predictable slurry performance. A displacement fluid, such as water, or an appropriately weighted drilling fluid, may be pumped into the casing above the cementing plug. This displacement fluid may be pressurized fluid that serves to urge the cementing plug downward through the casing to extrude the cement from the casing outlet and back up into the annulus.

[0039] As further shown in FIG. 2A, sensors (221) may be included in a sensor assembly (223), which is positioned adjacent to a drill bit (224) and coupled to the drill string (215). Sensors (221) may also be coupled to a processor assembly that includes a processor, memory, and an analog-to-digital converter (222) for processing sensor measurements. For example, the sensors (221) may include acoustic sensors, such as accelerometers, measurement microphones, contact microphones, and hydrophones. Likewise, the sensors (221) may include other types of sensors, such as transmitters and receivers to measure resistivity, gamma ray detectors, etc. The sensors (221) may include hardware and/or software for generating different types of well logs (such as acoustic logs or density logs) that may provide well data about a wellbore, including porosity of wellbore sections, gas saturation, bed boundaries in a geologic formation, fractures in the wellbore

or completion cement, and many other pieces of information about a formation. If such well data is acquired during drilling operations (i.e., logging-while-drilling), then the information may be used to make adjustments to drilling operations in real-time. Such adjustments may include rate of penetration (ROP), drilling direction, altering mud weight, and many others drilling parameters.

[0040] In some embodiments, acoustic sensors may be installed in a drilling fluid circulation system of a drilling system (200) to record acoustic drilling signals in real-time. Drilling acoustic signals may transmit through the drilling fluid to be recorded by the acoustic sensors located in the drilling fluid circulation system. The recorded drilling acoustic signals may be processed and analyzed to determine well data, such as lithological and petrophysical properties of the rock formation. This well data may be used in various applications, such as steering a drill bit using geosteering, casing shoe positioning, etc.

[0041] The control system (244) may be coupled to the sensor assembly (223) in order to perform various program functions for up-down steering and left-right steering of the drill bit (224) through the wellbore (216). More specifically, the control system (244) may include hardware and/or software with functionality for geosteering a drill bit through a formation in a lateral well using sensor signals, such as drilling acoustic signals or resistivity measurements. For example, the formation may be a reservoir region, such as a pay zone, bed rock, or cap rock.

[0042] Turning to geosteering, geosteering may be used to position the drill bit (224) or drill string (215) relative to a boundary between different subsurface layers (e.g., overlying, underlying, and lateral layers of a pay zone) during drilling operations. In particular, measuring rock properties during drilling may provide the drilling system (200) with the ability to steer the drill bit (224) in the direction of desired hydrocarbon concentrations. As such, a geosteering system may use various sensors located inside or adjacent to the drill string (215) to determine different rock formations within a well path. In some geosteering

systems, drilling tools may use resistivity or acoustic measurements to guide the drill bit (224) during horizontal or lateral drilling.

[0043] Turning to FIG. 2B. FIG. 2B illustrates some embodiments for steering a drill bit through a lateral pay zone using a geosteering system (290). As shown in FIG. 2B, the geosteering system (290) may include the drilling system (200) from FIG. 2A. In particular, the geosteering system (290) may include functionality for monitoring various sensor signatures (e.g., an acoustic signature from acoustic sensors) that gradually or suddenly change as a well path traverses a cap rock (230), a pay zone (240), and a bed rock (250). Because of the sudden change in lithology between the cap rock (230) and the pay zone (240), for example, a sensor signature of the pay zone (240) may be different from the sensor signature of the cap rock (230). When the drill bit (224) drills out of the pay zone (240) into the cap rock (230), a detected amplitude spectrum of a particular sensor type may change suddenly between the two distinct sensor signatures. In contrast, when drilling from the pay zone (240) downward into the bed rock (250), the detected amplitude spectrum may gradually change.

[0044] During the lateral drilling of the wellbore (216), preliminary upper and lower boundaries of a formation layer's thickness may be derived from a geophysical survey and/or an offset well obtained before drilling the wellbore (216). If a vertical section (235) of the well is drilled, the actual upper and lower boundaries of a formation layer (i.e., actual pay zone boundaries (A, A')) and the pay zone thickness (i.e., A to A') at the vertical section (235) may be determined. Based on this well data, an operator may steer the drill bit (224) through a lateral section (260) of the wellbore (216) in real time. In particular, a logging tool may monitor a detected sensor signature proximate the drill bit (224), where the detected sensor signature may continuously be compared against prior sensor signatures, e.g., of the cap rock (230), pay zone (240), and bed rock (250), respectively. As such, if the detected sensor signature of drilled rock is the same or similar to the sensor signature of the pay zone (240), the drill bit (224) may

still be drilling in the pay zone (240). In this scenario, the drill bit (224) may be operated to continue drilling along its current path and at a predetermined distance (0.5h) from a boundary of a formation layer. If the detected sensor signature is same as or similar to the prior sensor signatures of the cap rock (230) or the bed rock (250), respectively, then the control system (244) may determine that the drill bit (224) is drilling out of the pay zone (240) and into the upper or lower boundary of the pay zone (240). At this point, the vertical position of the drill bit (224) at this lateral position within the wellbore (216) may be determined and the upper and lower boundaries of the pay zone (240) may be updated, (for example, positions B and C in FIG. 2B). In some embodiments, the vertical position at the opposite boundary may be estimated based on the predetermined thickness of the pay zone (240), such as positions B' and C'.

[0045] Turning to FIG. 3, FIG. 3 shows a schematic diagram in accordance with one or more embodiments. As shown in FIG. 3, FIG. 3 illustrates a hydraulic stimulation operation that forms additional microfractures (312) within a formation (302). More specifically, a wellbore (304) may be located within formation (302), where a casing string (306) is positioned within the wellbore (304). Following a hydraulic fracturing process, for example, large fractures (310) may exist within the formation (302) and extend outward from the wellbore (304). In particular, hydrocarbon reserves may be trapped within certain low permeability formations, such as sand, carbonate, and/or shale formations. Thus, stimulation treatments may be performed by a stimulation control system coupled to a well completion assembly or well completion system that enhances well productivity at one or more wells, where one type of stimulation treatment is hydraulic fracturing. In some embodiments, for example, hydraulic fracturing includes injecting high viscosity fluids into a wellbore at a sufficiently high injection rate so that enough pressure is produced within the wellbore to split the formation. As such, a stimulation operation may be determined that achieves a desired height and/or length of one or more induced fractures.

[0046] Keeping with FIG. 3, various stimulation procedures may be employed that use one or more techniques to ensure that an induced fracture becomes conductive after injection ceases. For example, during acid fracturing of carbonate formations, acid-based fluids may be injected into the formation to create an etched fracture and conductive channels. These conductive channels may be left open upon closure of the induced fracture. With sand or shale formations, a proppant may be included with the hydraulic fracturing fluid such that the induced fracture remains open during or following a stimulation treatment. Likewise, in carbonate formations, a stimulation treatment may include both acid fracturing fluids and proppants. Accordingly, heat produced within a formation, acid, or aqueous water transmitted into the formation may all play a role in producing reactions causing one or more microfractures in a formation.

[0047] Keeping with hydraulic fracturing, a hydraulic fracturing operation may include well completion assembly with one or more inflatable packers as well as a work string or casing string (306) that extends within a wellbore. A casing string may include steel casing or pipe that may be divided into surface casing, intermediate casing, and/or production casing. Packers may include inflatable packers that seal an annulus defined between well completion equipment and an inner wall of the wellbore in order to divide a formation into multiple wellbore intervals. These wellbore intervals may be separately or simultaneously stimulated during a hydraulic stimulation operation using a stimulation control system. Thus, in a hydraulic fracturing operation, a hydraulic fracturing fluid may be pumped through the casing string (306) and into a targeted formation using various perforations (i.e., open holes) in the casing string (306).

[0048] By injecting the hydraulic fracturing fluid at pressures high enough to cause the rock within the targeted formation to fracture, the hydraulic fracturing operation may “break down” the formation. As high-pressure fluid injection continues, a fracture may continue to propagate into a fracture network. This

high pressure for injecting the hydraulic fracturing fluid may be referred to as the “propagation pressure” or “extension pressure.” As an induced fracture continues to grow, a proppant, such as sand, may be added to the fracturing fluid. Once a desired fracture network is formed, the fluid flow may be reversed and the liquid portion of the fracturing fluid is removed. The proppant is intentionally left behind to prevent the fractures from closing onto themselves due to the weight of the overlying rock layers and stresses within the formation. Accordingly, the proppant may “prop” or support the induced fractures to remain open, by remaining sufficiently permeable for hydrocarbon fluids to flow through the induced fracture. Thus, a proppant may form a packed bed of particles with interstitial void space connectivity within a formation. Accordingly, a higher permeability fracture may result from the hydraulic fracturing operation.

[0049] In some embodiments, for example, a hydraulic fracturing fluid with an activator is injected into the formation (302), where the fluid migrates within the large fractures (310). Upon a reaction caused by the activator, the injection fluid may produce one or more gases and heat, thereby causing the microfractures (312) to be created within the formation (302). Thus, a stimulation treatment may provide pathways for the hydrocarbon deposits trapped within the formation (202) to migrate and be recovered by a production well. In other words, hydraulic stimulation operations may be applied to formations that easily fracture to produce more microfractures with little plastic deformation under compression.

[0050] Furthermore, fracture monitoring may be important to understanding and optimizing hydraulic fracturing treatments. For example, a hydraulic stimulation manager may perform diagnostics that determine various stimulation effects such as fracture geometry, proppant placement in one or more fractures, and/or fracture conductivity. This fracture monitoring may be performed using a distributed acoustic sensing (DAS) system implemented within a wellbore. In

some embodiments, a DAS system includes various fiber-optic sensors (e.g., distributed over a single mode optical fiber several kilometers in length). As such, backscattered light may be measured and further analyzed using signal processing techniques to enable a DAS system to segregate an optical fiber into an array of individual acoustic receivers. More specifically, various pulses of light may be transmitted along the optical fiber, where characteristics of the backscattered light may change due to acoustic vibrations disturbing the casing of the optical fiber. Through DAS processing, the location of these disturbances may be identified.

[0051] Keeping with DAS systems, pumping operations may produce various acoustic signals along a wellbore and the adjacent fractures, where the acoustic sensing data depends upon geometrical and physical attributes of the propagating fractures. Accordingly, a quantitative DAS inversion may determine various fracture properties in hydraulic fracture monitoring. For example, a wellbore may be profiled in real time by removing DAS pump noise data and matching acquired data to a forward model regarding pulse propagation in the wellbore and adjacent fractures. Thus, DAS inversion may identify various hydraulic stimulation features such as tubing expansion, fluid-to-fluid interfaces, an adjacent hydraulic fracture, presence of a porous reservoir, and/or an annular compartment. During initial phases of a hydraulic stimulation operation, DAS inversion may determine location information of wireline logging equipment within a wellbore. For example, DAS techniques may verify whether perforating guns and packer-setting devices are disposed at desired depths in the wellbore. In some embodiments, DAS inversion is performed using additional data from distributed temperature sensors (DTS) and/or micro-seismic monitoring techniques.

[0052] In certain unconventional formations, for example, an important element that determines whether it is economically viable to develop a reservoir is the presence of one or more sweet spots in the reservoir. A sweet spot may be

generally defined herein as the area within a reservoir that represents the best production or potential for production. In a particular geological region, the sweet spot may be determined based on a lack of ductility, a destruction of internal cohesion, an ability for a rock to deform and fail with a low degree of inelastic behavior, and a rock's capability for self-sustaining fracturing. Likewise, sweet spots may include intervals within organic shales, which possess the highest relative hydrocarbon yield for drilling purposes.

[0053] Keeping with sweet spots, sweet spot identification may be used by a reservoir simulator to identify one or more drilling location for unconventional wells. In particular, a sweet spot may be determined with certain reservoir characteristics such as reservoir quality and completion quality based on predicted hydrocarbon data, reservoir data, well log data, seismic data, etc. As such, various technologies may be used to extract resources from unconventional reservoirs at certain sweet spots, such as hydraulic fracturing and horizontal wells.

[0054] With respect to proppant systems, a well completion system may include a proppant system. A proppant system may include transfer devices, such as chutes and conveyor belts, for transferring a propping agent (also called simply "proppant") to a fluid mixing system. Likewise, a proppant system may include one or more proppant storage devices, such as a silo, and a housing. In particular, a silo may use fill ports for acquiring propping agents, which may be subsequently transferred to a fluid mixing system using drain valves and/or outlet ports. The proppant system may then dispense the propping agent to the fluid mixing system for producing a stimulation fluid.

[0055] Moreover, a stimulation treatment for a formation may be updated by a reservoir simulator using a geological model (e.g., one of the geological models (170)). For example, a reservoir simulator may use a geological model to perform one or more stimulation simulations using different injection fluid

pressure rates, different types of proppants, acid-based treatments and non-acid treatments, etc., to determine a desired stimulation scenario for the formation.

[0056] Returning to FIG. 1, a reservoir simulator or another computer program may include hardware and/or software with functionality for generating and/or updating one or more machine-learning models (165) for use in analyzing the formation (106). For example, the reservoir simulator or another computer program may store well logs and core sample data (150), and further analyze the well log data, the core sample data, seismic data, and/or other types of data to generate and/or update one or more machine-learning models (165) and/or one or more geological models (170). Thus, different types of machine-learning models may be trained, such as convolutional neural networks, U-Net models, deep neural networks, recurrent neural networks, support vector machines, decision trees, inductive learning models, deductive learning models, supervised learning models, unsupervised learning models, reinforcement learning models, etc. In some embodiments, two or more different types of machine-learning models are integrated into a single machine-learning architecture, e.g., a machine-learning model may include decision trees and neural networks. In some embodiments, the reservoir simulator (160) or another computer program may generate augmented or synthetic data to produce a large amount of interpreted data for training a particular model.

[0057] With respect to artificial neural networks, for example, a neural network may include one or more hidden layers, where a hidden layer includes one or more neurons. A neuron may be a modelling node or object that is loosely patterned on a neuron of the human brain. In particular, a neuron may combine data inputs with a set of coefficients, i.e., a set of network weights for adjusting the data inputs. These network weights may amplify or reduce the value of a particular data input, thereby assigning an amount of significance to various data inputs for a task being modeled. Through machine learning, a neural network may determine which data inputs should receive greater priority in determining

one or more specified outputs of the neural network. Likewise, these weighted data inputs may be summed such that this sum is communicated through a neuron's activation function to other hidden layers within the neural network. As such, the activation function may determine whether and to what extent an output of a neuron progresses to other neurons where the output may be weighted again for use as an input to the next hidden layer.

[0058] Turning to convolutional neural networks, a convolutional neural network (CNN) is a type of artificial neural network that may be used in computer vision and image recognition, e.g., for processing pixel data. For example, a convolutional neural network may include functionality for performing an application of a filter to an input (e.g., an input image) that results in a particular activation, where repeated filter application may result in an output map of activations called a feature map. A feature map may indicate the locations and strength of one or more detected features in the input to the convolutional neural network. Thus, a convolutional neural network may have the ability to automatically learn multiple filters in parallel specific to a training dataset under the constraints of a specific predictive modeling problem, such as image classification.

[0059] In some embodiments, a reservoir simulator (160) or another computer program uses one or more ensemble learning methods in connection to the machine-learning models (165). For example, an ensemble learning method may use multiple types of machine-learning models to obtain better predictive performance than available with a single machine-learning model. In some embodiments, for example, an ensemble architecture may combine multiple base models to produce a single machine-learning model. One example of an ensemble learning method is a BAGGING model (i.e., BAGGING refers to a model that performs Bootstrapping and Aggregation operations) that combines predictions from multiple neural networks to add a bias that reduces variance of a single trained neural network model. Another ensemble learning method

includes a stacking method, which may involve fitting many different model types on the same data and using another machine-learning model to combine various predictions. In some embodiments, two or more different types of machine-learning models are integrated into a single machine-learning architecture, e.g., a machine-learning model may include support vector machines and neural networks. In some embodiments, a reservoir simulator may generate augmented data or synthetic data to produce a large amount of interpreted data for training a particular model.

[0060] In some embodiments, various types of machine-learning algorithms (e.g., machine-learning algorithm (175)) may be used to train the model, such as a backpropagation algorithm. In a backpropagation algorithm, gradients are computed for each hidden layer of a neural network in reverse from the layer closest to the output layer proceeding to the layer closest to the input layer. As such, a gradient may be calculated using the transpose of the weights of a respective hidden layer based on an error function (also called a “loss function”). The error function may be based on various criteria, such as mean squared error function, a similarity function, etc., where the error function may be used as a feedback mechanism for tuning weights in the machine-learning model.

[0061] In some embodiments, a machine-learning model is trained using multiple epochs. For example, an epoch may be an iteration of a model through a portion or all of a training dataset. As such, a single machine-learning epoch may correspond to a specific batch of training data, where the training data is divided into multiple batches for multiple epochs. Thus, a machine-learning model may be trained iteratively using epochs until the model achieves a predetermined criterion, such as predetermined level of prediction accuracy or training over a specific number of machine-learning epochs or iterations. Thus, better training of a model may lead to better predictions by a trained model.

[0062] With respect to artificial neural networks, for example, an artificial neural network may include one or more hidden layers, where a hidden layer includes

one or more neurons. A neuron may be a modelling node or object that is loosely patterned on a neuron of the human brain. In particular, a neuron may combine data inputs with a set of coefficients, i.e., a set of network weights for adjusting the data inputs. These network weights may amplify or reduce the value of a particular data input, thereby assigning an amount of significance to various data inputs for a task being modeled. Through machine learning, a neural network may determine which data inputs should receive greater priority in determining one or more specified outputs of the artificial neural network. Likewise, these weighted data inputs may be summed such that this sum is communicated through a neuron's activation function to other hidden layers within the artificial neural network. As such, the activation function may determine whether and to what extent an output of a neuron progresses to other neurons where the output may be weighted again for use as an input to the next hidden layer.

[0063] Turning to recurrent neural networks, a recurrent neural network (RNN) may perform a particular task repeatedly for multiple data elements in an input sequence, with the output of the recurrent neural network being dependent on past computations. As such, a recurrent neural network may operate with a memory or hidden cell state, which provides information for use by the current cell computation with respect to the current data input. For example, a recurrent neural network may resemble a chain-like structure of RNN cells, where different types of recurrent neural networks may have different types of repeating RNN cells. Likewise, the input sequence may be time-series data, where hidden cell states may have different values at different time steps during a prediction or training operation. For example, where a deep neural network may use different parameters at each hidden layer, a recurrent neural network may have common parameters in an RNN cell, which may be performed across multiple time steps. To train a recurrent neural network, a supervised learning algorithm such as a backpropagation algorithm may also be used. In some embodiments, the backpropagation algorithm is a backpropagation through time (BPTT) algorithm. Likewise, a BPTT algorithm

may determine gradients to update various hidden layers and neurons within a recurrent neural network in a similar manner as used to train various deep neural networks. In some embodiments, a recurrent neural network is trained using a reinforcement learning algorithm such as a deep reinforcement learning algorithm. For more information on reinforcement learning algorithms, see the discussion below.

[0064] Embodiments are contemplated with different types of RNNs. For example, classic RNNs, long short-term memory (LSTM) networks, a gated recurrent unit (GRU), a stacked LSTM that includes multiple hidden LSTM layers (i.e., each LSTM layer includes multiple RNN cells), recurrent neural networks with attention (i.e., the machine-learning model may focus attention on specific elements in an input sequence), bidirectional recurrent neural networks (e.g., a machine-learning model that may be trained in both time directions simultaneously, with separate hidden layers, such as forward layers and backward layers), as well as multidimensional LSTM networks, graph recurrent neural networks, grid recurrent neural networks, etc. With regard to LSTM networks, an LSTM cell may include various output lines that carry vectors of information, e.g., from the output of one LSTM cell to the input of another LSTM cell. Thus, an LSTM cell may include multiple hidden layers as well as various pointwise operation units that perform computations such as vector addition.

[0065] In some embodiments, a reservoir simulator uses one or more ensemble learning methods in connection to one or more machine-learning models. For example, an ensemble learning method may use multiple types of machine-learning models to obtain better predictive performance than available with a single machine-learning model. In some embodiments, for example, an ensemble architecture may combine multiple base models to produce a single machine-learning model. One example of an ensemble learning method is a BAGGING model (i.e., BAGGING refers to a model that performs Bootstrapping

and Aggregation operations) that combines predictions from multiple neural networks to add a bias that reduces variance of a single trained neural network model. Another ensemble learning method includes a stacking method, which may involve fitting many different model types on the same data and using another machine-learning model to combine various predictions.

[0066] While FIGs. 1, 2A, 2B, and 3 show various configurations of components, other configurations may be used without departing from the scope of the disclosure. For example, various components in FIGs. 1, 2A, 2B, and 3 may be combined to create a single component. As another example, the functionality performed by a single component may be performed by two or more components.

[0067] Turning to FIG. 4, FIG. 4 shows a flowchart in accordance with one or more embodiments. Specifically, FIG. 4 describes a general method for determining predicted hydrocarbon data. One or more blocks in FIG. 4 may be performed by one or more components (e.g., reservoir simulator (160) or another computer program, control system (114), control system (244)) as described in FIGs. 1, 2A, 2B, and 3. While the various blocks in FIG. 4 are presented and described sequentially, one of ordinary skill in the art will appreciate that some or all of the blocks may be executed in different orders, may be combined or omitted, and some or all of the blocks may be executed in parallel. Furthermore, the blocks may be performed actively or passively.

[0068] In Block 400, reservoir data are obtained for a geological region of interest in accordance with one or more embodiments. Reservoir data may include pressure-volume-temperature (PVT) data for reservoir fluid, reservoir pore pressure data, such as the initial pore pressure, permeability data, porosity data, and natural fractures' information for open and sealed fractures in various reservoir regions. Reservoir data may also include geological data regarding formation layers, such as lithological, sedimentary, and similar data, as well as fracability data that describes the composition of major rock minerals in a

region or in situ-stress. Reservoir data may be acquired using well logging tools, coring techniques, seismic surveys, and other techniques for acquired reservoir data on one or more formations in a reservoir.

[0069] Furthermore, a geological region of interest may be a portion of a geological area or volume that includes one or more wells or formations of interest desired or selected for further analysis, e.g., for determining a location of hydrocarbons or reservoir development purposes for a respective reservoir. As such, a geological region of interest may include one or more reservoir regions in an unconventional reservoir selected for running simulations.

[0070] In Block 410, hydraulic fracturing data are obtained for a geological region of interest in accordance with one or more embodiments. For example, hydraulic fracturing data may relate to one or more hydraulic fracturing operations, such as stimulation parameters relating to fracturing fluid, injection rate, injection consequence, etc. In some embodiments, hydraulic fracture data includes fracture geometry information that is obtained from seismic data for a particular geological region.

[0071] In Block 420, static wellbore data are obtained for a geological region of interest in accordance with one or more embodiments. For example, static wellbore data may relate wellbore parameters that do not change based on drilling, production, or stimulation operations, such as the location coordinates of a wellbore or casing type.

[0072] In Block 430, maturity data are obtained regarding in-place organic material within a geological region of interest in accordance with one or more embodiments. In some embodiments, for example, maturity data describes the maturation of kerogen or other organic materials in one or more geological regions. For example, maturity data may specify different maturity zone in a geological region, or a well's position relative to one or more maturity zones. Maturity data may be acquired from cuttings data corresponding to cuttings of wells in unconventional reservoirs for chemical assay analysis. Likewise,

maturity data may be organized as one or more maturity maps that may be charted for a basin in a geological region.

[0073] Moreover, hydrocarbon-in-place (HIP) compositions in unconventional plays, an objective may be determined by the quantity, quality (e.g., maturity), and/or types of kerogen in the underlying rock. For example, hydrocarbon produced and stored in the pore place inside the unconventional source rocks may have little hydrocarbon movement in the natural state. Thus, maturity data may approximately and loosely describe kerogen compositions that can be summed with HIP compositions to determine a total composition of organic components during the sedimentation of a geological region, if the amount and types of the original organic components can be determined. Moreover, light components may appear from kerogen as the kerogen matures (or as maturity increases). Heavier components, that likely come out of kerogen at a later time, may contribute to the liquid or gaseous phase of hydrocarbons-in-place.

[0074] Furthermore, two categories of methods may be used to determine the maturity of a rock samples. One example method is performed using a microscopy technique by examining the reflectance of vitrinite, a derivative of kerogen, under a microscope and determining the percentage of incident light reflected by the vitrinite (R_o). As such, the resultant vitrinite reflectance (R_o) may be used as a proxy of maturity of the kerogen. Another example method is to obtain a bulk temperature where kerogen is produced through a process called pyrolysis using analysis equipment such as rock-eval pyrolysis, which heats the rock sample to chemically alter the kerogen with increasing temperature, e.g., from 300°C to 600°C. Rock-eval pyrolysis may monitor the amount of hydrocarbon produced by heating the kerogen, where the temperature value at which the most of hydrocarbon is generated is called T_{max} . This temperature value can be directly used as a proxy for kerogen maturity or approximately converted to R_o .

[0075] Turning to FIG. 5A, FIG. 5A shows an example of a maturity map in accordance with one or more embodiments. In FIG. 5A, a maturity map of kerogen shows a well 1 and a well 2 that are located in a gas zone of a reservoir region. Well 1 and well 2 both in the gas window zone on the map, but wells 1 and 2 have different distances to different zone boundaries. More specifically, well 1 is very close to an oil window in the reservoir region, whereas well 2 is close to an overmature zone. Furthermore, FIG. 5B also shows a few examples of the temporal changes of compositional traits with time for produced hydrocarbons from unconventional reservoirs. As such, hydrocarbon movement in an unconventional reservoir may result from a large thermodynamic-property difference between different hydrocarbon components. Thus, physical separation and chemical fractionation may occur during the production. For example, during the production, hydrocarbon in the gas phase may normally move faster than hydrocarbons in the liquid phase. Likewise, inside the liquid, oil, and the gas facies, lighter components moves faster than the heavy component. Also, compositional separation and chemical fractionation may occur due to geological system's own dynamics. The physical separation and chemical fractionation during production may result in the difference between the composition of the produced hydrocarbon at the surface and the initial composition of hydrocarbon-in-place (HIP) before production and also in the changing properties of the produced hydrocarbon.

[0076] Returning to FIG. 4, in Block 440, temporal production data are obtained regarding one or more reservoir regions in a geological region of interest in accordance with one or more embodiments. Temporal production data may include production physiochemical data with respect to time, such as gas liquid ratios or various physical properties of different phases. Temporal production data may also describe relative components of each phase (e.g., the molar portion of C1 of the gas phase or C2 in the gas phase as C1 or C2 change over a particular period of time). Temporal production data may also include various dynamic production parameters, such as bottom hole pressure, maintained well

head pressure, and choke size with respect to time. Other examples of temporal production data include how the composition and/or the signatures change with time such as the isotopic composition of $\delta^{13}\text{C}$ of the whole gas phase or of a particular portion of the gas phase such as C1 or of the liquid phase can change with time. FIG. 5B shows various temporal curves regarding temporal production data. In particular, FIG. 5B illustrates various compositional changes (e.g. gas/liquid, C1/total gas, $\delta^{13}\text{C}$ in C1) and property changes (e.g., changes in gas density or liquid density) of produced fluid at the surface based on time from one or more unconventional reservoirs.

[0077] In Block 450, one or more maturity features are determined using one or more refinement and/or extraction process(es) in accordance with one or more embodiments. For example, two wells, Well1 and Well2 (e.g., as shown in FIG. 5A) are both in a zone of a gas window so the assignment of windows are the same for both wells. But the two wells may have different relative proximity to the two different maturation isolines. In FIG. 5A, Well1 is close to the line separating the oil window and gas window, whereas Well2 is close to the other boundary of gas window, beyond of which no production is likely. By analyzing the real distances of the two wells to the maturation isolines on a maturation map, the maturity features of the wells are further refined or extracted. For example, the ratio of the distance between Wellx and the upward maturation isoline and the distance between the same well and the downward maturation isoline can be used as another maturity feature, in addition to the feature of its zonal designation, to be used to describe the maturation level of the two wells.

[0078] In Block 460, one or more temporal production features are determined from the temporal production data using one or more refinement and/or extraction processes in accordance with one or more embodiments. For example, a machine-learning model, such as an artificial neural network, may require input features as inputs at an input layer in order to predict data.

However, because of the complexity in estimating hydrocarbon-in-place compositions, conventional input features may not be applicable with respect to temporal production data. As such, a reservoir simulator may apply one or more extraction processes to the temporal production data to determine temporal features. Examples of extraction processes include minima functions (e.g., identify minimum values), maxima functions (e.g., identify maximum values), length functions (e.g., identify length of relevant data points), autocorrelation functions, Fast Fourier transformations, linear regression functions, exponential regression functions, polynomial regression functions, logarithmic functions, and hybrid functions that use two or more different techniques to identify particular features in temporal production data (e.g., as shown in FIG. 5C).

[0079] In FIG. 5C, the left-hand graph and the right-hand graph have y-axis (vertical axis) units of M pounds and 100 pounds respectively. M pounds is equal to 1000 pounds, and 1 pound is equal to approximately 0.4536 kg.

[0080] In some embodiments, a machine-learning model is coupled to a deconvolution layer to perform the extraction process. FIG. 5D shows various temporal production data that is input to a deconvolution layer to extract temporal characteristics as input features to an artificial neural network that is shown in FIG. 5E. In some embodiments, deconvolution processing has a particular function associated with a given parameter type of temporal data. In other words, different temporal data types may use different extraction processes to determine temporal features. For illustration, an extraction process for $\delta^{13}\text{C}$ vs time may be different than an extraction process for a gas rate vs a respective gas time period.

[0081] In some embodiments, gas rate with time is fitted with a number of exponential decays. As an example, an extraction process may deconvolve the gas rate with a respective gas time period into four decays with characteristic time and four predetermined gas rates using the following formula:

$$G(j) = \sum_{i=0}^4 g(i) * \exp \left(-\frac{t}{\tau(i)} \right) \quad \text{Equation (1)}$$

where $G(j)$ corresponds to a measured gas rate, $g(i)$ corresponds to a predetermined gas rate, and $\tau(i)$ is a characteristic time. In this case, eight temporal features (i.e., 4 predetermined gas rates and four decay curves) are extracted from the original gas rate curve for temporal features.

[0082] In Block 465, predicted hydrocarbon-in-place data, especially the compositions of the hydrocarbon-in-place (HIP), are determined for a geological region of interest using a machine-learning model, one or more maturity features, one or more temporal features, reservoir data, hydraulic fracturing data, and/or static wellbore data in accordance with one or more embodiments. In some embodiments, the predicted hydrocarbon data describes a hydrocarbon-in-place (HIP) composition in a geological region. Using maturity features and/or temporal features that describe production compositional traits, a machine-learning model may be used to predict hydrocarbon-in-place compositional data at an output layer. In addition, other input features may be used, such as static wellbore data (e.g., swell parameters that remain static during a production operation, such as the well position, tubing size, and the number of fractures), reservoir data, and/or hydraulic fracturing data. FIG. 5E shows an example of an artificial neural network that uses various input features to predict hydrocarbon-in-place data, such as its compositions of hydrogen sulfide (H₂S), nitrogen (N₂), carbon dioxide (CO₂), hydrocarbons (i.e., C₃-6 or C₄-C₁₂), and total organic carbon (TOC).

[0083] In Block 470, a well path is determined in a geological region of interest based on predicted hydrocarbon data in accordance with one or more embodiments.

[0084] In Block 475, one or more stimulation operations are determined for a geological region of interest based on predicted hydrocarbon data in accordance with one or more embodiments.

[0085] In Block 480, one or more commands are transmitted to one or more control systems based on a well path, one or more stimulation operations, and/or predicted hydrocarbon data in accordance with one or more embodiments. For example, commands may be transmitted to various control system to automate drilling operations or stimulation operations necessary for drilling or completing a well. Likewise, a user may select different stimulation parameters or adjusted drilling parameters based on predicted hydrocarbon data. A user selection may be obtained within a graphical user interface.

[0086] Turning to FIG. 6, FIG. 6 provides an example of an artificial neural network model in accordance with one or more embodiments. In FIG. 6, an artificial neural network X (651) determines predicted hydrocarbon-in-place data, especially its composition data for a target well X, i.e., predicted carbon dioxide data (691), predicted C1 data (692), predicted C2 data (693), predicted C3-6 data (694), and predicted C4-C12 data (695). More specifically, the artificial neural network X (651) requires the following inputs, i.e., kerogen maturity levels X (611), position data A (612) for target well X and its relative position on the maturation map, temporal gas phase features B (613), temporal liquid phase features C (614), static wellbore parameters D (615), hydraulic fracture related data (616), and reservoir fluid data F (617).

[0087] Turning to FIGs. 8A-8B, FIGs. 8A-8B shows an example of predicting hydrocarbon-in-place data, especially its composition data, in accordance with one or more embodiments. In FIG. 8A, a reservoir simulator or any other program (not shown) obtains maturity data, i.e., maturity data A (811) for maturity zone A and maturity data B (812) for maturity zone B in a particular geological region. The reservoir simulator also obtains various temporal production data, i.e., gas rate data A (821) $\delta^{13}\text{C}$ gas data A (823) and gas specific density data A (825) for a production well A, gas rate data B (822), $\delta^{13}\text{C}$ gas data B (824) and gas specific density data B (826) for production well B, liquid $\delta^{13}\text{C}$ data A (831) for production well A, liquid $\delta^{13}\text{C}$ data B (832) for

production well B, C12+ weight data A (833) for production well A, C12+ weight data B (834) for production well B, liquid specific density data A (835) for production well A, and liquid specific density data B (836) for production well B. In FIG. 8B, the reservoir simulator applies a maturity refinement and extraction function A (871) to maturity data (811, 812) to determine maturity features C (841). The reservoir simulator further applies a temporal gas phase deconvolution function B (872) to the gas rate data (821, 822), gas δ^{13} data (823, 824) and gas specific density data (825, 826), respectively, to determine temporal gas rate features D (842). The reservoir simulator further applies various temporal liquid phase deconvolution functions C (873) to liquid δ^{13} data (831, 832), C12+ weight data (833, 834), and liquid specific density data (835, 836), respectively, to determine temporal liquid phase features E (843). In a prediction operation A (890), the reservoir simulator uses the maturity features C (841), temporal gas rate features D (842), the temporal liquid phase features E (843), static wellbore data F (844), reservoir data G (845), and hydraulic fracturing data H (846) as inputs to a machine-learning model Y (891) to generate predicted hydrocarbon-in-place data Z (885), especially its composition data.

[0088] Turning to FIG. 7, FIG. 7 shows a flowchart in accordance with one or more embodiments. Specifically, FIG. 7 describes a general method for training a machine-learning model to predict hydrocarbon-in-place (HIP) data, especially its composition data. One or more blocks in FIG. 7 may be performed by one or more components (e.g., reservoir simulator (160) or another computer program, control system (114), control system (244)) as described in FIGs. 1, 2A, 2B, and 3. While the various blocks in FIG. 7 are presented and described sequentially, one of ordinary skill in the art will appreciate that some or all of the blocks may be executed in different orders, may be combined or omitted, and some or all of the blocks may be executed in parallel. Furthermore, the blocks may be performed actively or passively.

[0089] In Block 700, a target well is selected for an unconventional reservoir in accordance with one or more embodiments. For example, the target well may correspond to a possible location for a production well or an injection well. The target well may traverse a geological region of interest similar to the geological region described above in FIG. 4 and the accompanying description.

[0090] In Block 710, various training wells are determined that are associated with a target well based on a predetermined criterion in accordance with one or more embodiments. For example, the training wells may provide training data for a machine-learning model for target variables associated with reservoir data, static wellbore data, temporal production data, maturity data, and/or hydraulic fracturing data. Likewise, predetermined criteria may be user-defined based on a user selection in a user interface (e.g., a user may manually select different training wells, choose all available wells, or specify particular well attributes to automatically select the training wells). Moreover, a reservoir simulator may automatically determine the predetermined criterion based on historical data, such as similar wells to a possible unconventional reservoir associated with a target well.

[0091] In Block 720, a machine-learning model is obtained in accordance with one or more embodiments. For example, the machine-learning model may be a default model or a pre-trained model that has undergone one or more training operations to predict hydrocarbon data.

[0092] In Block 730, acquired hydrocarbon data is obtained for various training wells in accordance with one or more embodiments. In some embodiments, for example, HIP compositions are obtained for the selection of training wells. The collection of HIP fluid at the original state may be performed using several methods, such as by a wireline tool that acquires reservoir fluid shortly immediately after a well is drilled long before the start of the hydrocarbon production or by extraction of a pressurized core sample collected by a pressurized coring tool so the rock and all the original fluid can be preserved

and lifted to the surface. Acquired hydrocarbon data may also include temperature and the pressure of a hydrocarbon-in-place (HIP) fluid at the original reservoir conditions. Phase compositions of the acquired hydrocarbon samples may be analyzed in a laboratory accordingly.

[0093] In Block 740, acquired reservoir data, acquired hydraulic fracturing data, static wellbore data, and/or acquired maturity data are obtained based on various training wells in accordance with one or more embodiments. For example, the acquired maturity data may correspond to the maturation of the kerogen of the training wells, such as read from one or more maturation maps, and well position of training wells relative to other maturity zones. Reservoir data may include geological and petrophysical information regarding formation layers, such as the mineral composition, textural properties, petrophysical properties from various well logs, such as gamma ray logs, density logs, neutron logs, resistivities logs that describe resistivity at different depths, and dielectric logs. Acquired reservoir data may also include geological data derived from logs, core samples, and other data sources, such as permeability data, porosity data, and fracture data. Hydraulic fracturing data may include fracturing fluid data, injection rate data, and injection consequence data.

[0094] In Block 750, acquired temporal production data are obtained based on various training wells in accordance with one or more embodiments. For example, acquired temporal production data may be collected during one or more production operations at various training wells. Temporal production data may include gas volume per barrel of oil produced by a well, composition and related properties of production in the gaseous phase (e.g., gas specific density data, methane (CH₄) data, such as CH₄ 90 molarity percentage, carbon dioxide data, such as CO₂ 1 molarity percentage, $\delta^{13}\text{C}$ of methane, etc.), and composition and related properties of production in the liquid phase (e.g., American Petroleum Institute (API) number, a unique well identifier (UWI), specific density, color, C12 weight percentage on the liquid phase, C12-C25

weight percentages of the liquid phase, $\delta^{13}\text{C}$ data of the whole liquid or a component of the liquid). Temporal production data acquired for various training wells may also include various controlled dynamic parameters, such as the maintained well head pressure and choke size during a production operation.

[0095] In Block 760, one or more temporal features and/or one or more maturity features are determined using one or more refinement and extraction processes, acquired temporal production data, and/or acquired maturity data in accordance with one or more embodiments.

[0096] In Block 770, one or more training operations are performed on a machine-learning model using a machine-learning algorithm, acquired reservoir data, acquired hydraulic fracturing data, static wellbore data, acquired maturity data, and/or acquired temporal production data based on various training wells in accordance with one or more embodiments. For example, a machine-learning model may be trained using acquired temporal features, acquired maturity features, acquired reservoir data, acquired static wellbore data, and/or acquired reservoir data to match acquired hydrocarbon-in-place data (e.g., HIP composition data) from the training wells. In some embodiments, different combinations of acquired data may be used in training (e.g., some temporal production data may be excluded from a training operation) based on the available static data (e.g., static data for more than 500 training wells) is available. As such, static data may be used alone for training data or input data for predicting HIP compositions at various locations where temporal production data is not available.

[0097] In some embodiments, a training operation is performed on a selected number of samples, such as in a machine-learning epoch. For training an artificial neural network, a machine-learning algorithm may be expressed using the following equation:

$$\mathbf{H}^{[i]} = f^{[i]}(\mathbf{b}^{[i]} + \mathbf{w}^{[i]} * \mathbf{ic}) \quad \text{Equation (2)}$$

where H is an array of neurons values in the artificial neural network, b corresponds to an array of biases for neuron i , w corresponds to an array of weights, superscript i corresponds to an i layer of the artificial neural network, f is a predetermined activation function for the i layer (e.g., such as a tansig function or a relu function), and ic corresponds to an array of various input characteristics, such as temporal features or maturity features. Equation (2) may be rewritten as the following equation:

$$H^{[i]} = f^{[i]}(b^{[i]} + w^{[i]} * H^{[i-1]}) = f^{[i]}(z^{[i]}) \quad \text{Equation (3)}$$

where the weight array at layer I performs a convolution operation with array $H^{[i-1]}$ that includes neuron values for the previous layer of the artificial neural network, such as for a convolution neural network. In some embodiments, final activation needs to be a softmax activation function in order to categorize the predicted results of the artificial neural network. The softmax activation function may be expressed using the following equation:

$$H^{[output]} = softmax(z^{[output]})_j = \frac{\exp(z_j)}{\sum(\exp(z_j))} \quad \text{Equation (4)}$$

where the predicted hydrocarbon data, after reaching the best fit between $H^{[output]}$ and acquired hydrocarbon-in-place data (e.g., observed HIP compositions at the training wells), includes a trained model that encompasses the biases, weights, and activation functions used in the training operation.

[0098] In some embodiments, a reservoir simulator or another computer program checks the consistency of various temporal features, various maturity features, static wellbore data, reservoir data, and hydraulic fracturing data prior to performing a training operation. As such, a reservoir simulator may conduct quality control of training data and/or testing data to confirm that the data is consistent since the same type of data may be collected from different labs or different instruments.

[0099] In Block 780, a trained machine-learning model is generated for predicting hydrocarbon data for a target well in accordance with one or more embodiments.

[00100] In Block 790, hydrocarbon-in-place data are predicted using a trained machine-learning model in accordance with one or more embodiments. For example, the predicted HIP data may include composition data of a target well. A manual checkup may be performed on the predicted data, where the training operation may be repeated iteratively until the predicted data appears satisfactory. If the results do not appear satisfactory, for example, Blocks 770 through 790 can be repeated until satisfaction.

[00101] Embodiments may be implemented on a computer system. FIG. 9 is a block diagram of a computer system (902) used to provide computational functionalities associated with described algorithms, methods, functions, processes, flows, and procedures as described in the instant disclosure, according to an implementation. The illustrated computer (902) is intended to encompass any computing device such as a high performance computing (HPC) device, a server, desktop computer, laptop/notebook computer, wireless data port, smart phone, personal data assistant (PDA), tablet computing device, one or more processors within these devices, or any other suitable processing device, including both physical or virtual instances (or both) of the computing device. Additionally, the computer (902) may include a computer that includes an input device, such as a keypad, keyboard, touch screen, or other device that can accept user information, and an output device that conveys information associated with the operation of the computer (902), including digital data, visual, or audio information (or a combination of information), or a GUI.

[00102] The computer (902) can serve in a role as a client, network component, a server, a database or other persistency, or any other component (or a combination of roles) of a computer system for performing the subject matter described in the instant disclosure. The illustrated computer (902) is communicably coupled with

a network (930) or cloud. In some implementations, one or more components of the computer (902) may be configured to operate within environments, including cloud-computing-based, local, global, or other environment (or a combination of environments).

[00103] At a high level, the computer (902) is an electronic computing device operable to receive, transmit, process, store, or manage data and information associated with the described subject matter. According to some implementations, the computer (902) may also include or be communicably coupled with an application server, e-mail server, web server, caching server, streaming data server, business intelligence (BI) server, or other server (or a combination of servers).

[00104] The computer (902) can receive requests over network (930) or cloud from a client application (for example, executing on another computer (902)) and responding to the received requests by processing the said requests in an appropriate software application. In addition, requests may also be sent to the computer (902) from internal users (for example, from a command console or by other appropriate access method), external or third-parties, other automated applications, as well as any other appropriate entities, individuals, systems, or computers.

[00105] Each of the components of the computer (902) can communicate using a system bus (903). In some implementations, any or all of the components of the computer (902), both hardware or software (or a combination of hardware and software), may interface with each other or the interface (904) (or a combination of both) over the system bus (903) using an application programming interface (API) (912) or a service layer (913) (or a combination of the API (912) and service layer (913)). The API (912) may include specifications for routines, data structures, and object classes. The API (912) may be either computer-language independent or dependent and refer to a complete interface, a single function, or even a set of APIs. The service layer

(913) provides software services to the computer (902) or other components (whether or not illustrated) that are communicably coupled to the computer (902). The functionality of the computer (902) may be accessible for all service consumers using this service layer. Software services, such as those provided by the service layer (913), provide reusable, defined business functionalities through a defined interface. For example, the interface may be software written in JAVA, C++, or other suitable language providing data in extensible markup language (XML) format or other suitable format. While illustrated as an integrated component of the computer (902), alternative implementations may illustrate the API (912) or the service layer (913) as stand-alone components in relation to other components of the computer (902) or other components (whether or not illustrated) that are communicably coupled to the computer (902). Moreover, any or all parts of the API (912) or the service layer (913) may be implemented as child or sub-modules of another software module, enterprise application, or hardware module without departing from the scope of this disclosure.

[00106] The computer (902) includes an interface (904). Although illustrated as a single interface (904) in FIG. 9, two or more interfaces (904) may be used according to particular needs, desires, or particular implementations of the computer (902). The interface (904) is used by the computer (902) for communicating with other systems in a distributed environment that are connected to the network (930). Generally, the interface (904) includes logic encoded in software or hardware (or a combination of software and hardware) and operable to communicate with the network (930) or cloud. More specifically, the interface (904) may include software supporting one or more communication protocols associated with communications such that the network (930) or interface's hardware is operable to communicate physical signals within and outside of the illustrated computer (902).

[00107] The computer (902) includes at least one computer processor (905). Although illustrated as a single computer processor (905) in FIG. 9, two or more processors may be used according to particular needs, desires, or particular implementations of the computer (902). Generally, the computer processor (905) executes instructions and manipulates data to perform the operations of the computer (902) and any algorithms, methods, functions, processes, flows, and procedures as described in the instant disclosure.

[00108] The computer (902) also includes a memory (906) that holds data for the computer (902) or other components (or a combination of both) that can be connected to the network (930). For example, memory (906) can be a database storing data consistent with this disclosure. Although illustrated as a single memory (906) in FIG. 9, two or more memories may be used according to particular needs, desires, or particular implementations of the computer (902) and the described functionality. While memory (906) is illustrated as an integral component of the computer (902), in alternative implementations, memory (906) can be external to the computer (902).

[00109] The application (907) is an algorithmic software engine providing functionality according to particular needs, desires, or particular implementations of the computer (902), particularly with respect to functionality described in this disclosure. For example, application (907) can serve as one or more components, modules, applications, etc. Further, although illustrated as a single application (907), the application (907) may be implemented as multiple applications (907) on the computer (902). In addition, although illustrated as integral to the computer (902), in alternative implementations, the application (907) can be external to the computer (902).

[00110] There may be any number of computers (902) associated with, or external to, a computer system containing computer (902), each computer (902) communicating over network (930). Further, the term “client,” “user,” and other appropriate terminology may be used interchangeably as appropriate without

departing from the scope of this disclosure. Moreover, this disclosure contemplates that many users may use one computer (902), or that one user may use multiple computers (902).

[00111] In some embodiments, the computer (902) is implemented as part of a cloud computing system. For example, a cloud computing system may include one or more remote servers along with various other cloud components, such as cloud storage units and edge servers. In particular, a cloud computing system may perform one or more computing operations without direct active management by a user device or local computer system. As such, a cloud computing system may have different functions distributed over multiple locations from a central server, which may be performed using one or more Internet connections. More specifically, a cloud computing system may operate according to one or more service models, such as infrastructure as a service (IaaS), platform as a service (PaaS), software as a service (SaaS), mobile "backend" as a service (MBaaS), artificial intelligence as a service (AIaaS), serverless computing, and/or function as a service (FaaS).

[00112] Although only a few example embodiments have been described in detail above, those skilled in the art will readily appreciate that many modifications are possible in the example embodiments without materially departing from this invention. Accordingly, all such modifications are intended to be included within the scope of this disclosure as defined in the following claims.

CLAIMS

What is claimed:

1. A method, comprising:

obtaining first reservoir data, first hydraulic fracturing data, and first static wellbore data for a geological region of interest;

obtaining first temporal production data for the geological region of interest, wherein the first temporal production data comprises a predetermined production rate with respect to a predetermined period of time;

determining, by a computer processor (905), a plurality of temporal features based on the first temporal production data and a first extraction process, wherein the first extraction process comprises a deconvolution function that separates a portion of the plurality of temporal features from the predetermined production rate;

determining, by the computer processor (905) and using a machine-learning model, first predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the first reservoir data, the first hydraulic fracturing data, the first static wellbore data, and the plurality of temporal features; and

transmitting, by the computer processor (905), a command to a well control system based on the first predicted HIP data.

2. The method of claim 1, further comprising:

obtaining maturity data regarding in-place organic material within the geological region of interest; and

determining, using a second extraction process, a maturity feature from the maturity data,

wherein the maturity feature is used by the machine-learning model to determine the first predicted HIP data.

3. The method of claim 2,
wherein the maturity data comprise a maturity map that describes a plurality of kerogen quantities in the geological region of interest, and
wherein the maturity map is acquired using a plurality of drill cutting samples or a plurality of core samples from a plurality of wells.
4. The method of any preceding claim, further comprising:
obtaining a selection of a plurality of wells;
obtaining training data comprising second reservoir data, second hydraulic fracturing data, second static production data, and second temporal production data for the plurality of wells; and
performing a training operation on the machine-learning model iteratively using the training data until second predicted HIP data that is generated by the machine-learning model satisfies a predetermined criterion.
5. The method of any preceding claim,
wherein the first temporal production data comprises gas production rate data,
wherein the first extraction process separates a plurality of predetermined gas rates and a plurality of respective gas time periods using a plurality of exponential decay curves, and
wherein the plurality of temporal features correspond to the plurality of predetermined gas rates and the plurality of respective gas time periods.
6. The method of any preceding claim,
wherein the first temporal production data comprises gas specific density data, carbon dioxide composition data, $\delta^{13}\text{C}$ composition data, methane composition data, liquid phase data, choke size data, or well head pressure data.
7. The method of any preceding claim,
wherein the first predicted HIP data comprises molar ratio data of gas phase.

8. The method of any preceding claim,
wherein the first reservoir data comprises geological data regarding one or more formation layers reservoir fluid data, reservoir pore pressure data, gamma ray log data, density log data, neutron log data, resistivity log data, permeability data, and porosity data, or open fracture data.
9. The method of any preceding claim,
wherein the first hydraulic fracturing data comprises fracturing fluid data for a stimulation operation, injection rate data for a stimulation operation, injection consequence data, and hydraulic fracture geometry data.
10. The method of any preceding claim,
wherein the first static wellbore data comprises well location data, well tubing data, and number of fractures adjacent to a wellbore.
11. The method of any preceding claim, further comprising:
determining a sweet spot region in the geological region of interest using the first predicted HIP data; and
determining a stimulation operation based on the sweet spot region and the first predicted HIP data,
wherein the command that is transmitted to the well control system is configured to cause performance of the stimulation operation.
12. The method of any preceding claim, further comprising:
determining a well path in the geological region of interest using the first predicted HIP data,
wherein the well control system is a drilling system (110), and
wherein the command causes the drilling system (110) to perform a drilling operation based on the well path.
13. The method of any preceding claim,

wherein the machine-learning model is an artificial neural network (651) comprising an input layer, a plurality of hidden layers, and an output layer.

14. A system, comprising:

a stimulation control system coupled to a wellbore; and
a reservoir simulator (160) coupled to the stimulation control system, wherein the reservoir simulator (160) comprises a computer processor (905), the reservoir simulator (160) is configured to perform a method comprising:
obtaining first reservoir data, first hydraulic fracturing data, and first static wellbore data for a geological region of interest;
obtaining temporal production data for the geological region of interest, wherein the temporal production data comprises a predetermined production rate with respect to a predetermined period of time;
determining a plurality of temporal features based on the temporal production data and a first extraction process, wherein the first extraction process comprises a deconvolution function that separates a portion of the plurality of temporal features from the predetermined production rate; and
determining, using a machine-learning model, first predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the first reservoir data, the first hydraulic fracturing data, the first static wellbore data, and the plurality of temporal features,
wherein the stimulation control system is configured to perform a hydraulic stimulation operation based on the first predicted HIP data.

15. The system of claim 14, further comprising:

a user device coupled to the stimulation control system,

wherein the user device is configured to provide a graphical user interface for presenting the first predicted HIP data.

16. The system of claim 14 or claim 15, wherein the method further comprises:
obtaining maturity data regarding in-place organic material within the geological region of interest; and
determining, using a second extraction process, a maturity feature from the maturity data,
wherein the maturity feature is used by the machine-learning model to determine the first predicted HIP data.
17. The system of claim 16,
wherein the maturity data comprise a maturity map that describes a plurality of kerogen quantities in the geological region of interest, and
wherein the maturity map is acquired using a plurality of drill cutting samples or a plurality of core samples from a plurality of wells.
18. The system of any one of claims 14 to 17, wherein the method further comprises:
obtaining a selection of a plurality of wells;
obtaining training data comprising second reservoir data, second hydraulic fracturing data, second static production data, and second temporal production data for the plurality of wells; and
performing a training operation on the machine-learning model iteratively using the training data until second predicted HIP data that is generated by the machine-learning model satisfies a predetermined criterion.
19. A system, comprising:
a drilling system (110) comprising a plurality of sensors and a drill string comprising a drill bit, wherein the drilling system (110) is coupled to a wellbore; and

a reservoir simulator (160) coupled to the drilling system (110), wherein the reservoir simulator (160) comprises a computer processor (905), the reservoir simulator (160) is configured to perform a method comprising: obtaining reservoir data, hydraulic fracturing data, and static wellbore data for a geological region of interest; obtaining temporal production data for the geological region of interest, wherein the temporal production data comprises a predetermined production rate with respect to a predetermined period of time; determining a plurality of temporal features based on the temporal production data and a first extraction process, wherein the first extraction process comprises a deconvolution function that separates a portion of the plurality of temporal features from the predetermined production rate; and determining, using a machine-learning model, predicted hydrocarbon-in-place (HIP) data for the geological region of interest using the reservoir data, the hydraulic fracturing data, the static wellbore data, and the plurality of temporal features, wherein the drilling system (110) is configured to perform a drilling operation for a well path based on the predicted HIP data.

20. The system of claim 19, wherein the method further comprises:

obtaining maturity data regarding in-place organic material within the geological region of interest; and determining, using a second extraction process, a maturity feature from the maturity data, wherein the maturity feature is used by the machine-learning model to determine the predicted HIP data.

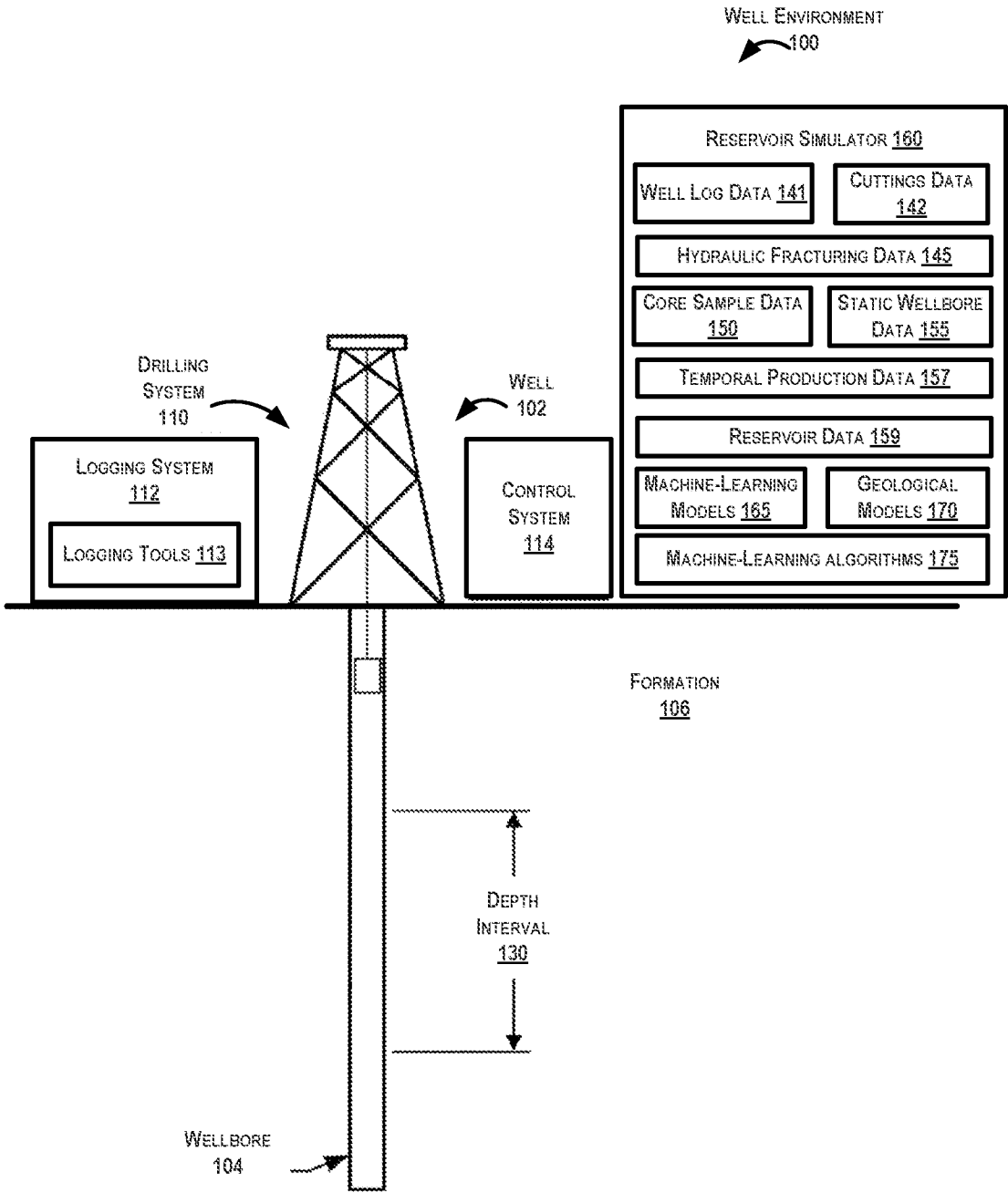


FIG. 1

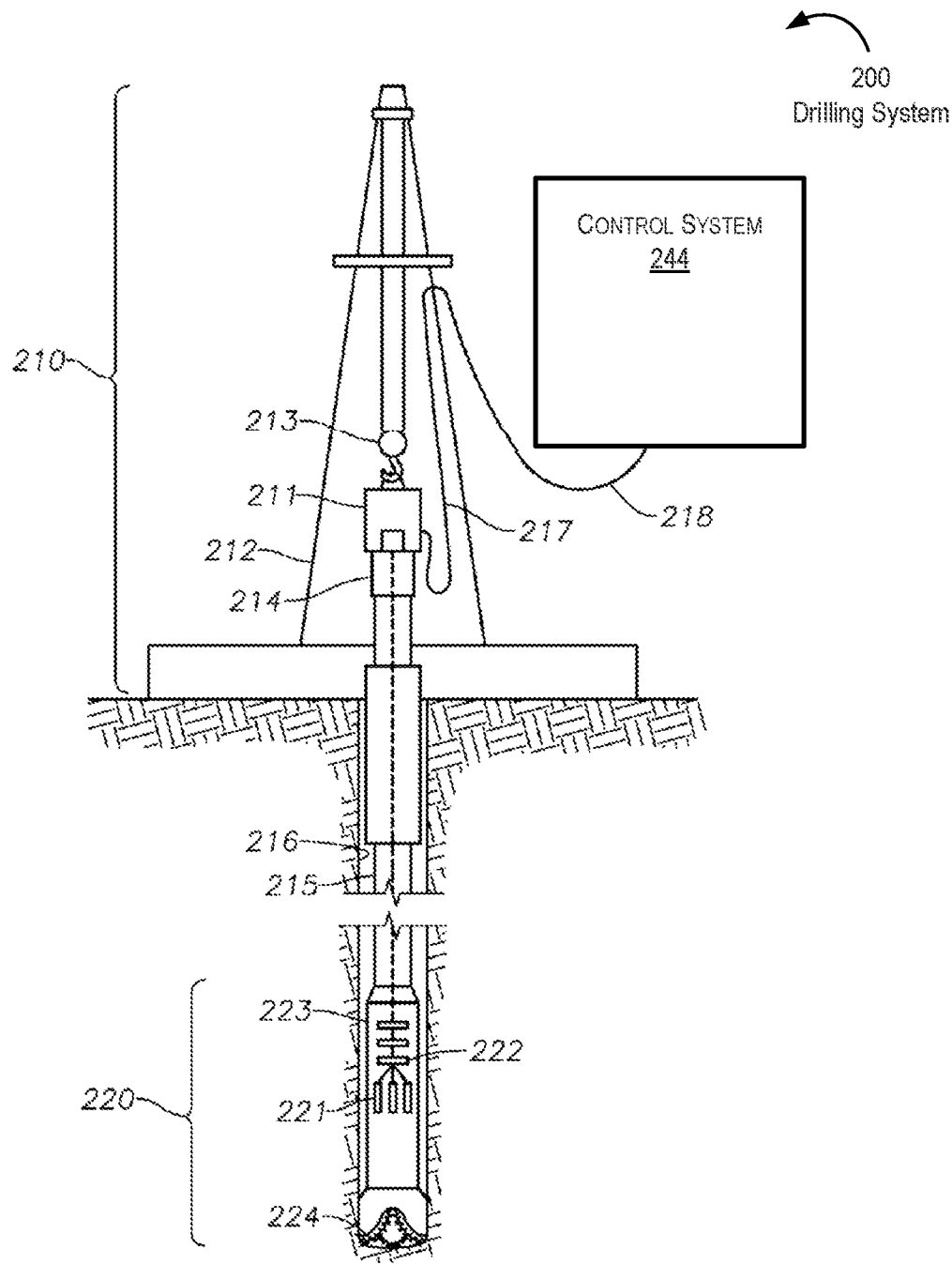


FIG. 2A

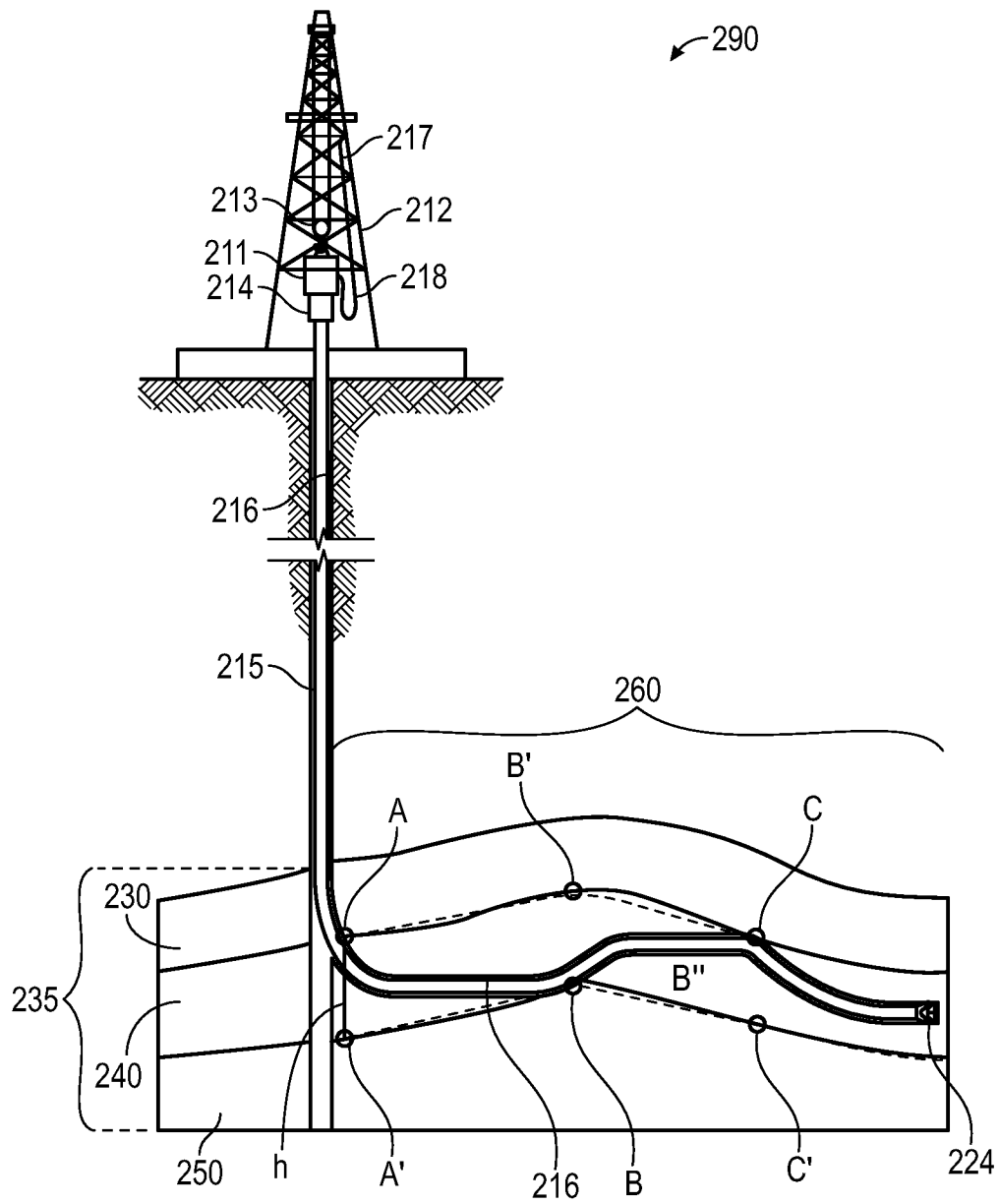


FIG. 2B

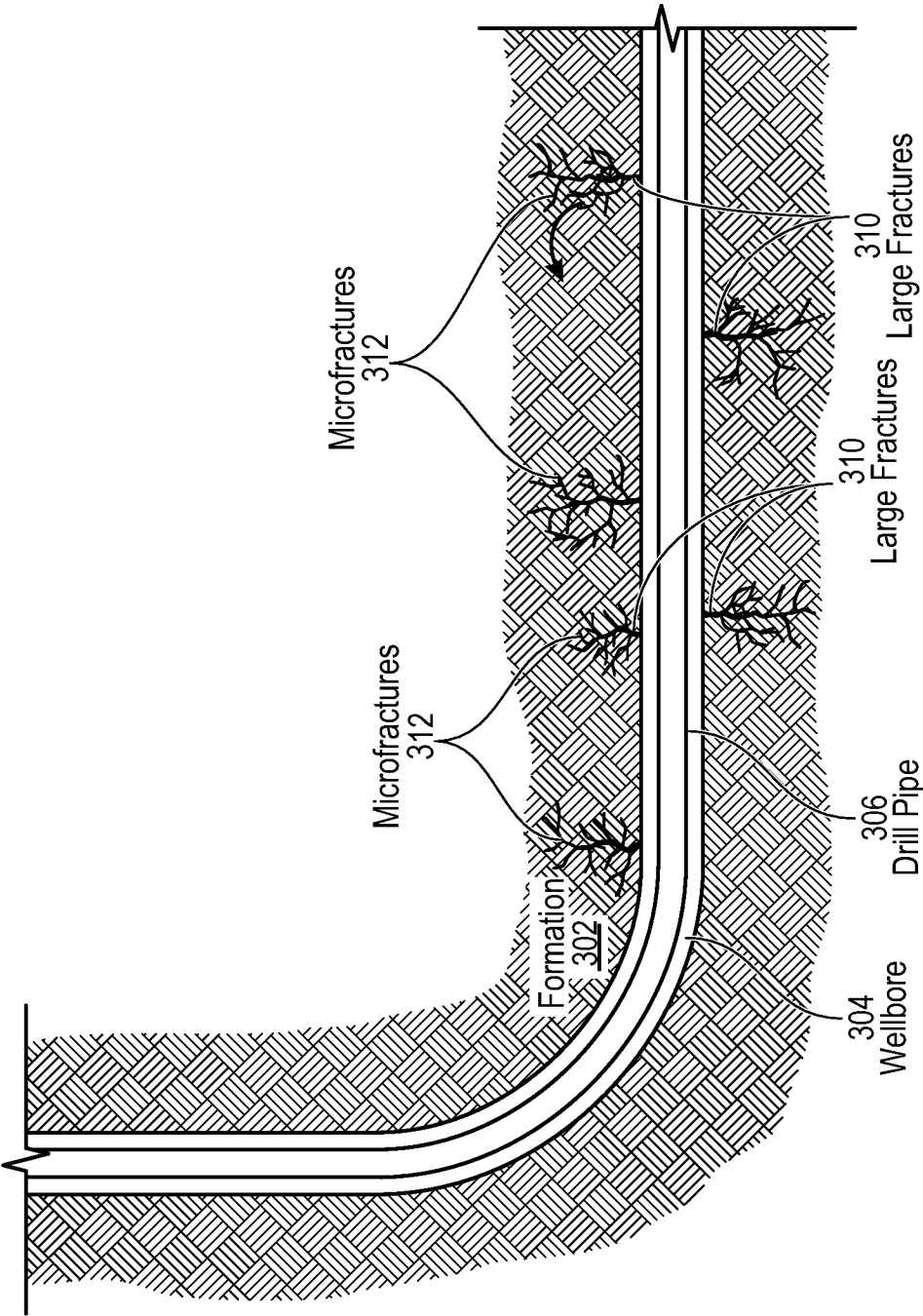


FIG.3

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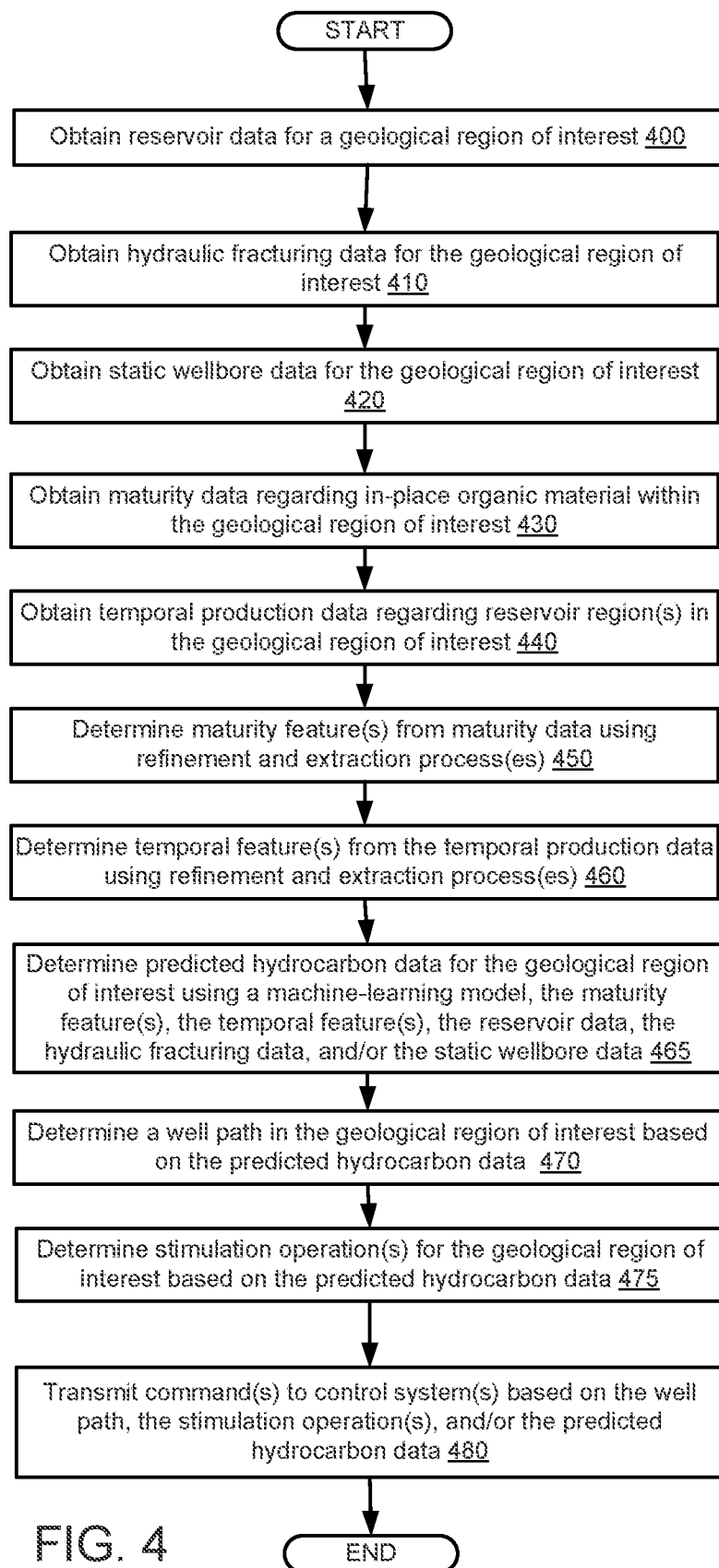


FIG. 4

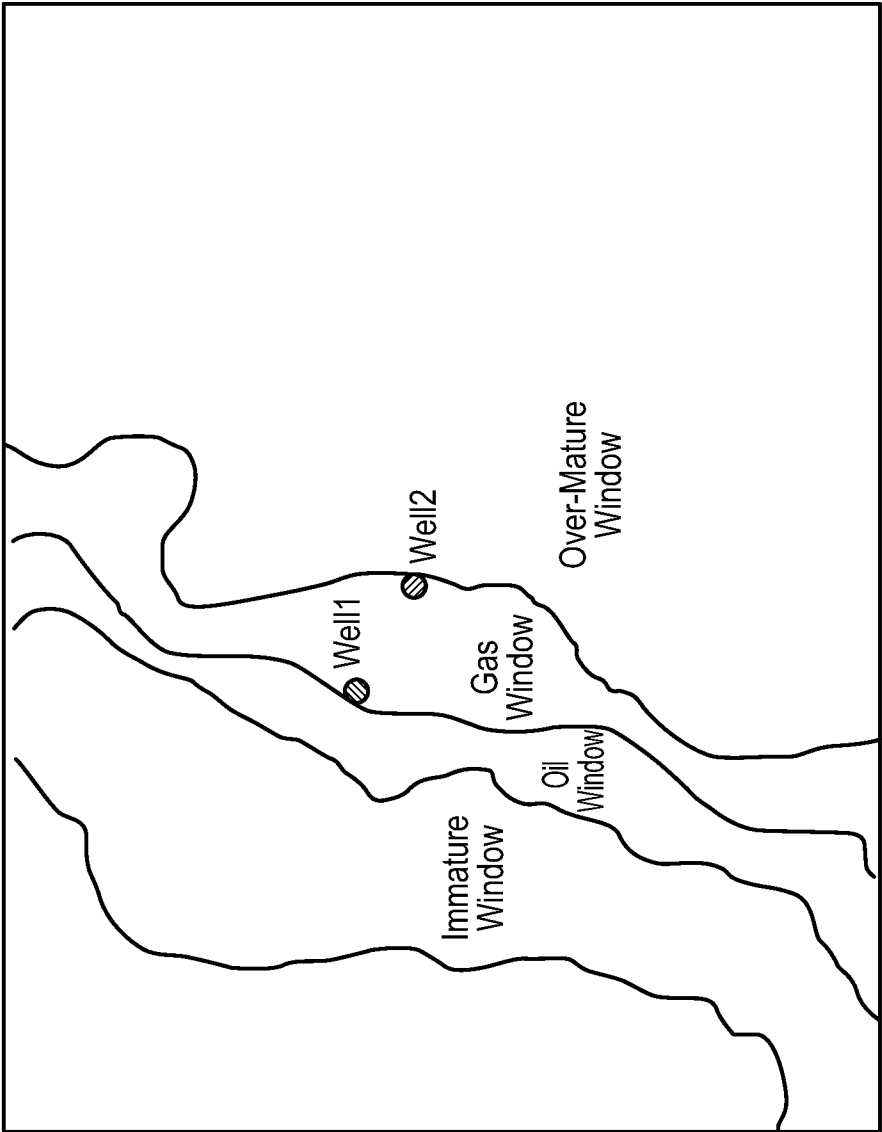


FIG. 5A

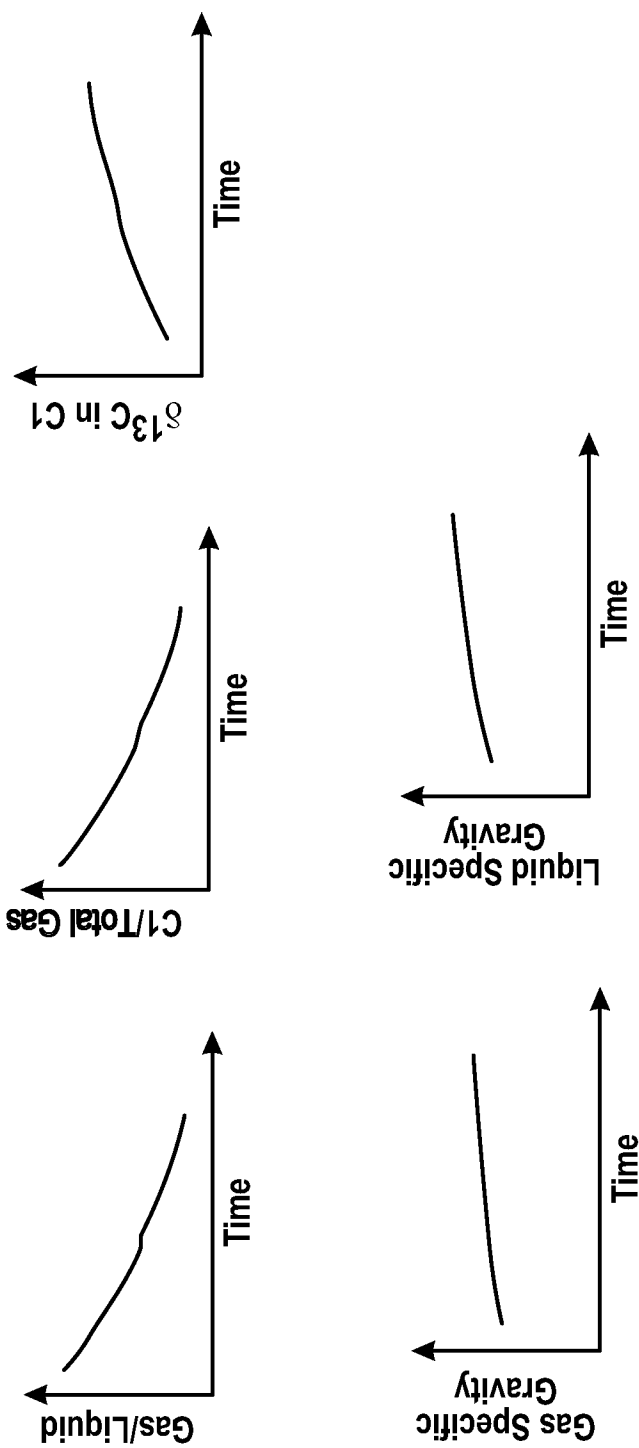


FIG. 5B

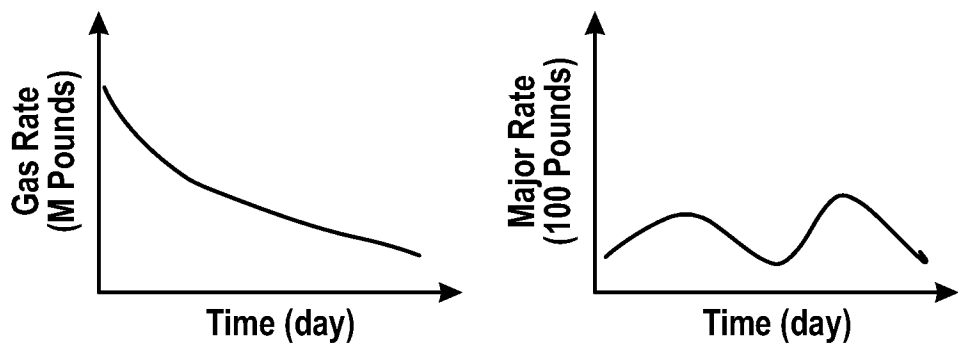


FIG. 5C

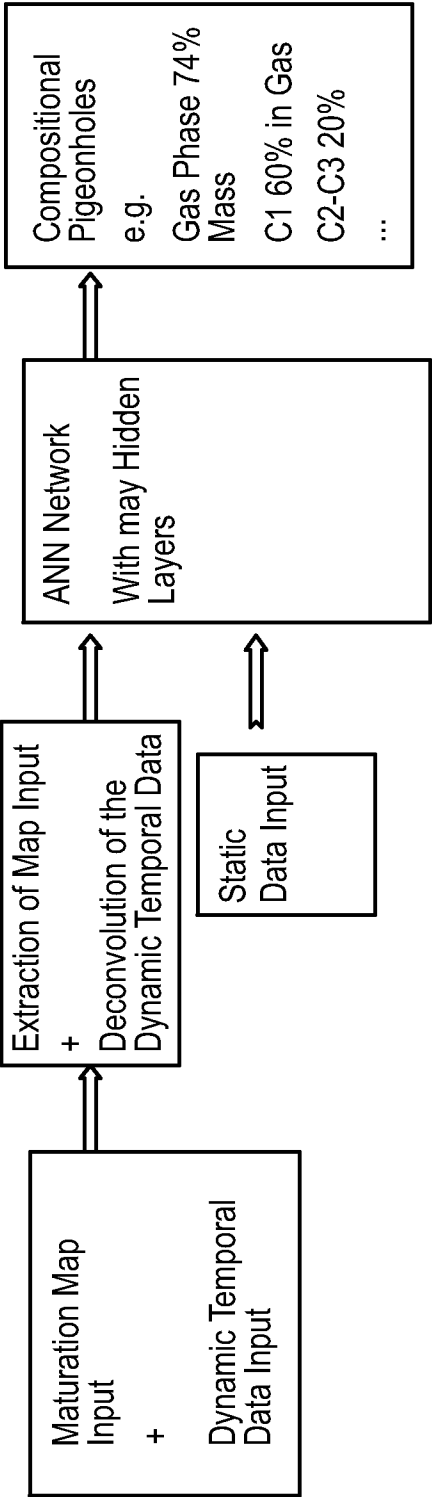


FIG. 5D

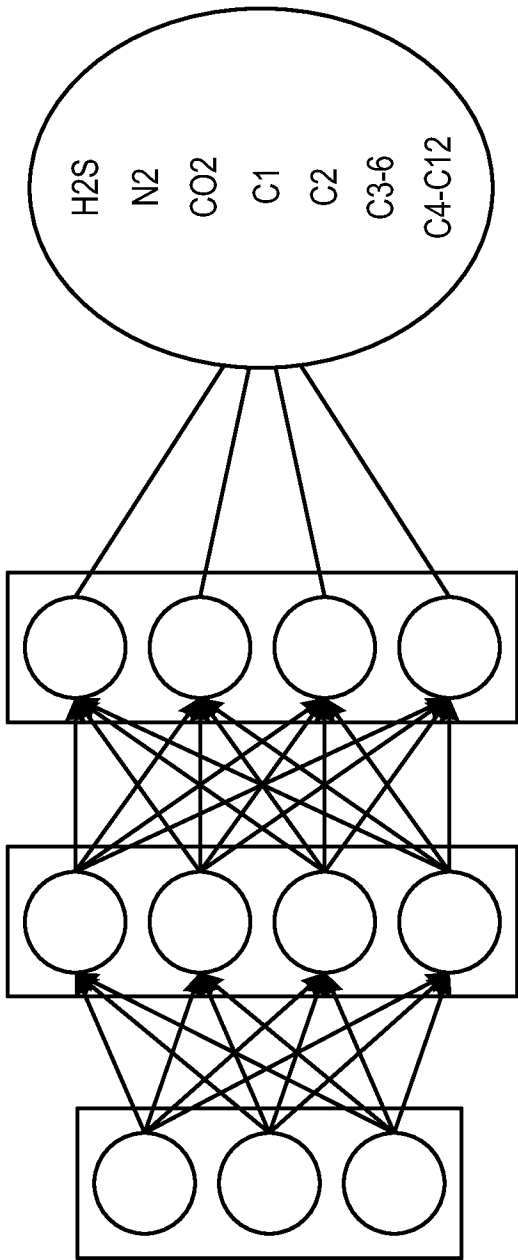
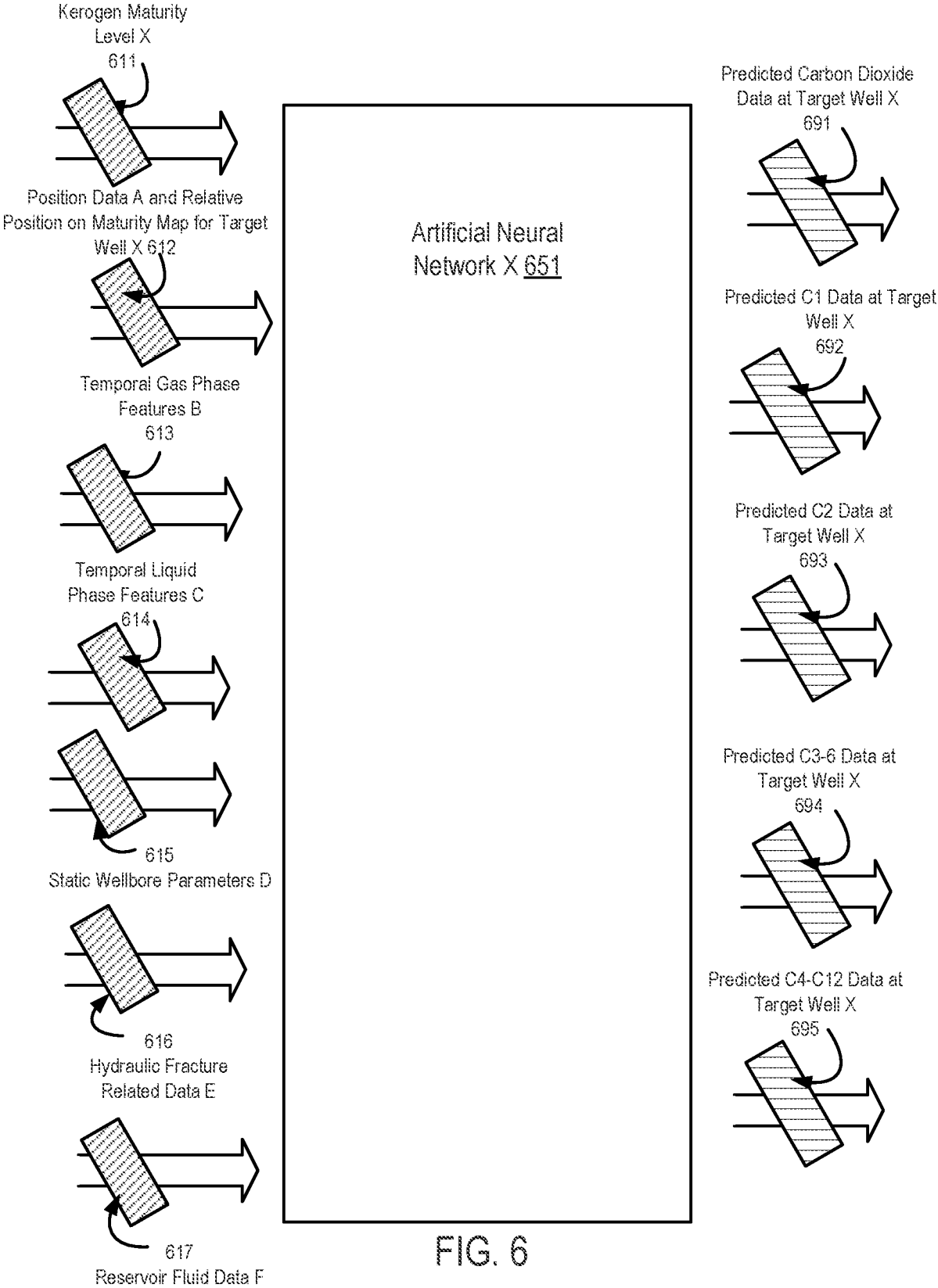


FIG. 5E



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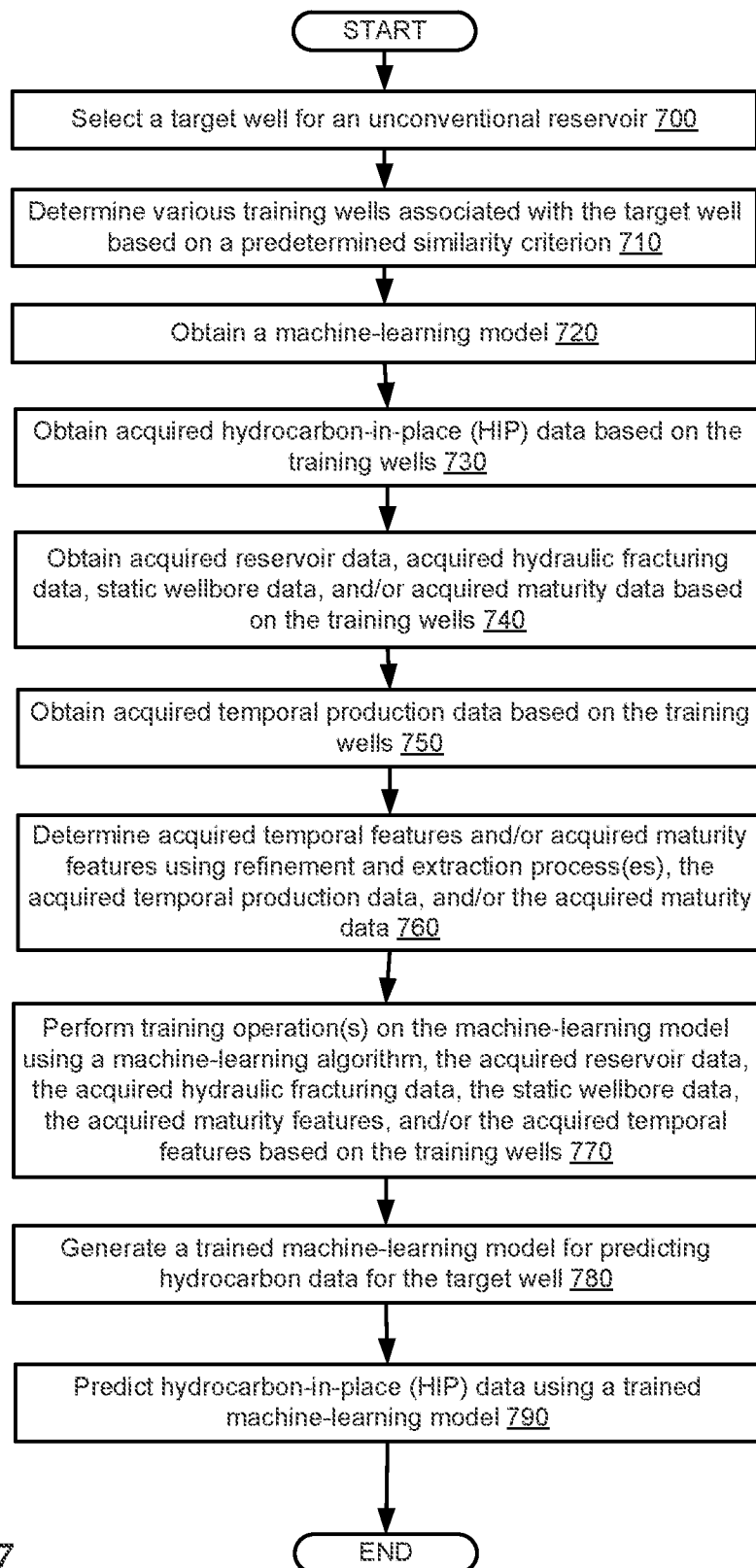
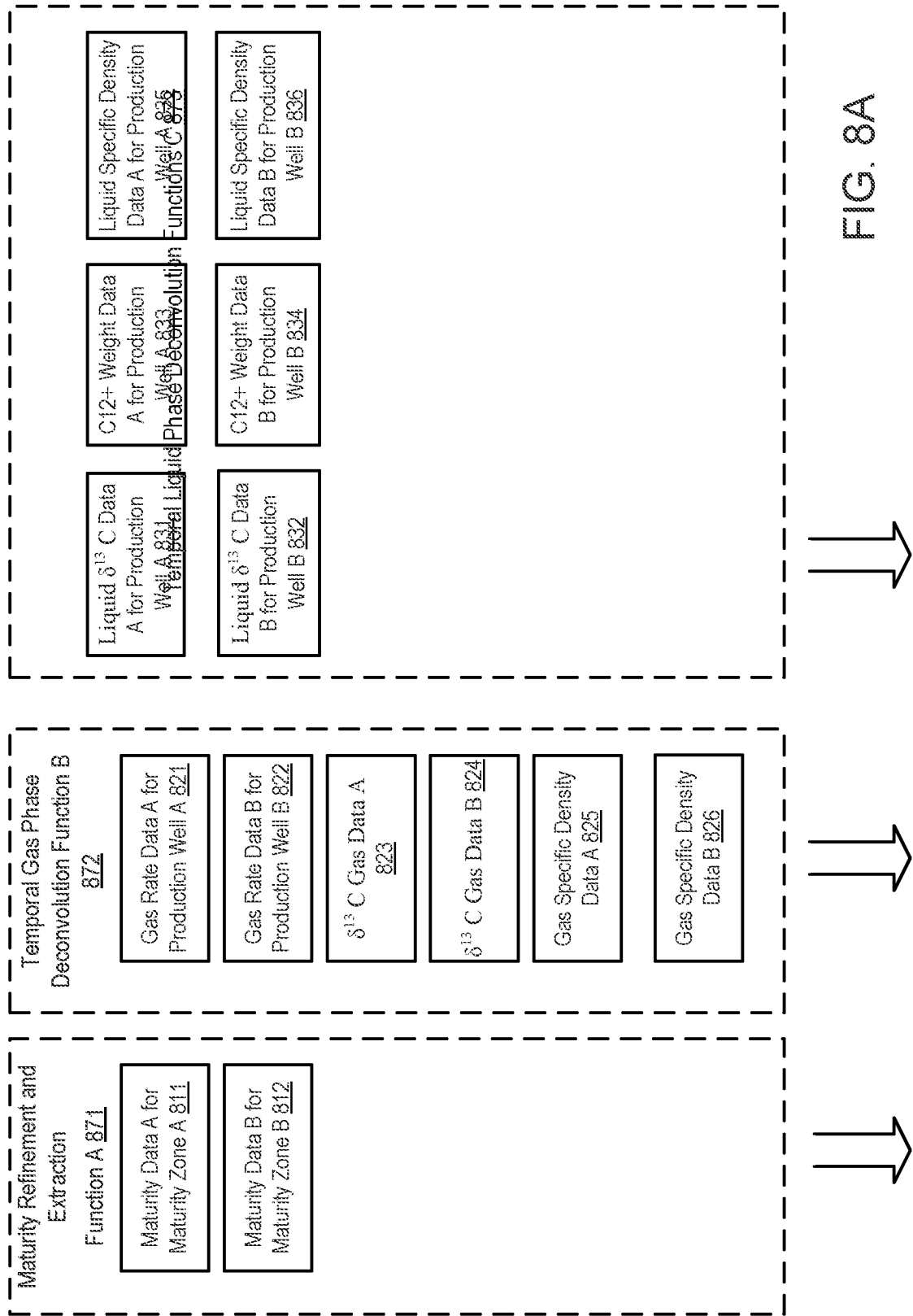
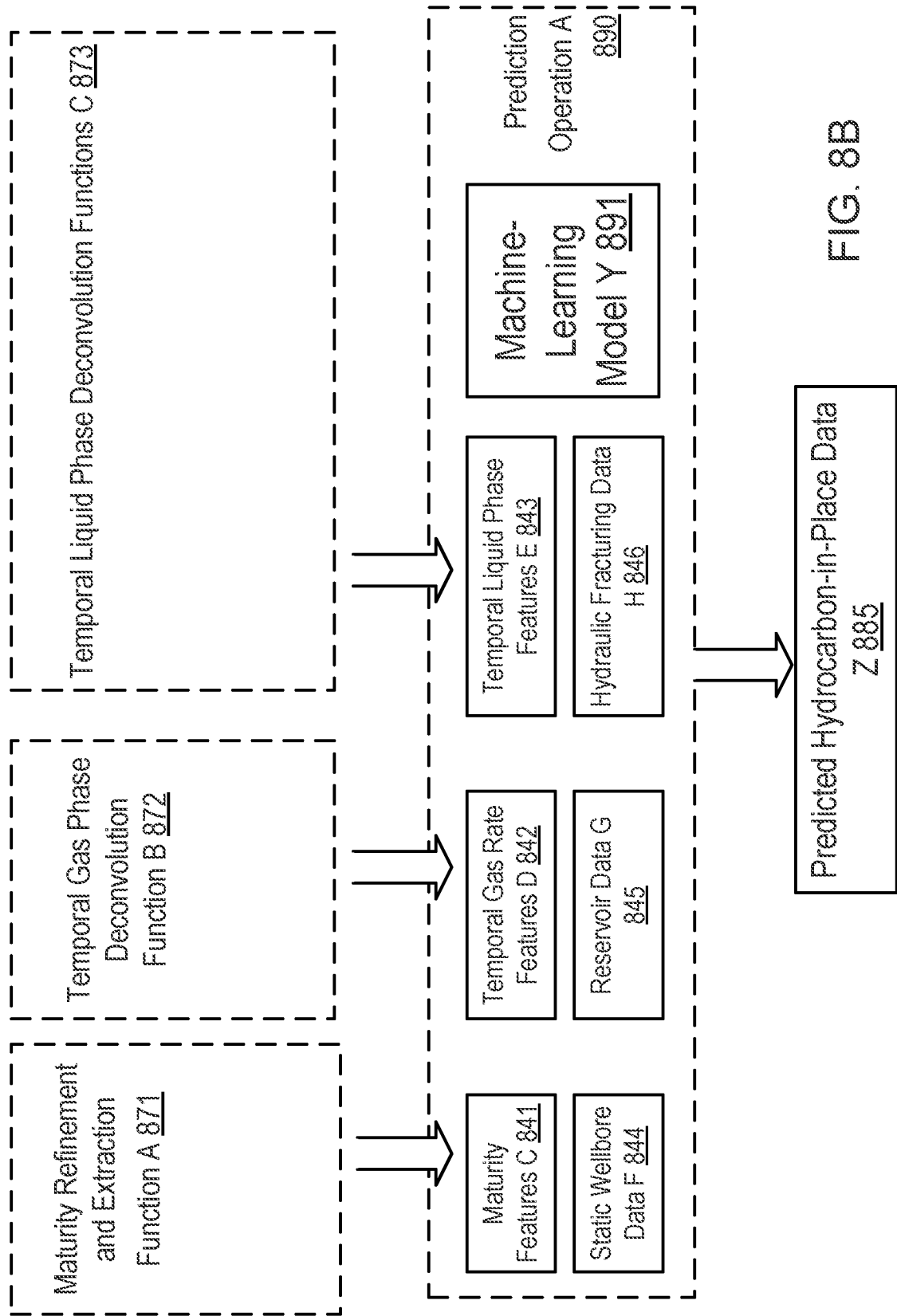


FIG. 7





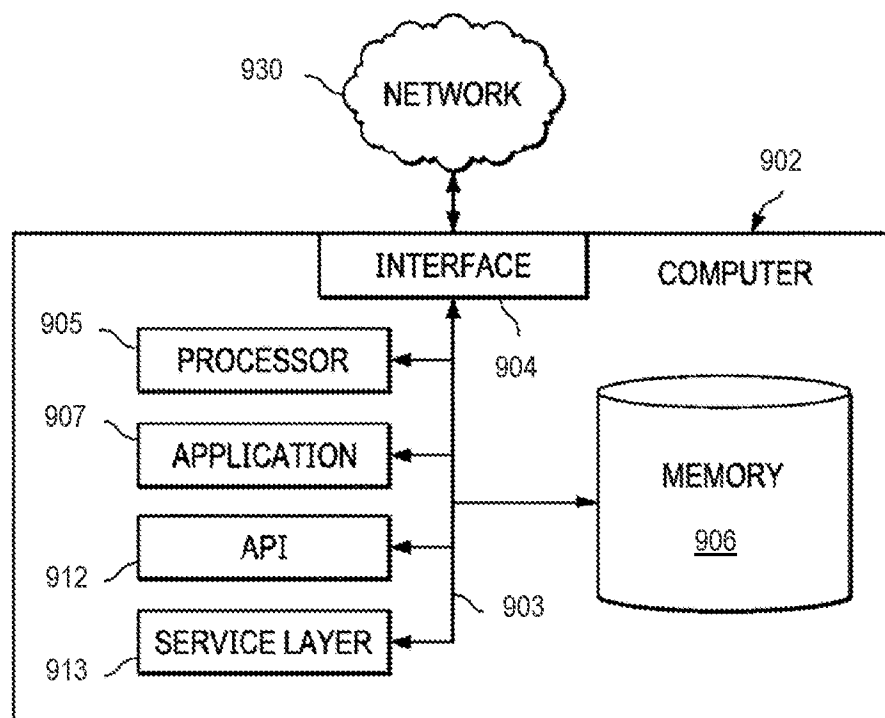


FIG. 9

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2024/035042

A. CLASSIFICATION OF SUBJECT MATTER INV. E21B41/00 E21B49/00 ADD.		
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		
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) EPO - Internal		
C. DOCUMENTS CONSIDERED TO BE RELEVANT		
Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	DOIG MARSHALL ET AL: "Understanding Unconventional Reservoirs With an Integrated Physics and Machine Learning Based Methods - Case Studies and Novel Approaches From Tight Gas and Tight Oil Reservoir", PROCEEDINGS OF THE 11TH UNCONVENTIONAL RESOURCES TECHNOLOGY CONFERENCE, 13 June 2023 (2023-06-13), pages 2669-2682, XP093211504, Denver DOI: 10.15530/urtec-2023-3863143 ISBN: 978-1-7361922-1-4 Retrieved from the Internet: URL:https://library.seg.org/doi/10.15530/urtec-2023-3863143> figures 2a,2b,2c, 2d ----- -/-	1 - 20
☒ Further documents are listed in the continuation of Box C. ☒ See patent family annex.		
* Special categories of cited documents : "A" document defining the general state of the art which is not considered to be of particular relevance "E" earlier application or patent but published on or after the international filing date "L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified) "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 4 October 2024		Date of mailing of the international search report 14/10/2024
Name and mailing address of the ISA/ European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016		Authorized officer Dantinne, Patrick

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2024/035042

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT		
Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	IBRAHIM AHMED FARID ET AL: "Application of Machine Learning to Predict Estimated Ultimate Recovery for Multistage Hydraulically Fractured Wells in Niobrara Shale Formation - PMC", COMPUTATIONAL INTELLIGENCE AND NEUROSCIENCE, vol. 2022, 21 June 2022 (2022-06-21), pages 1-18, XP093211543, US ISSN: 1687-5265, DOI: 10.1155/2022/7084514 Retrieved from the Internet: URL:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9239790/> figures 3,6 -----	1-20
A	CHENET P. ET AL: "Prospective Resources Evaluation Offshore Newfoundland and Labrador -Uncertainty and Risk Assessment Using Machine Learning Processes", FIRST EAGE WORKSHOP ON EAST CANADA OFFSHORE EXPLORATION, 15 November 2021 (2021-11-15), pages 1-5, XP093211525, Online DOI: 10.3997/2214-4609.202186031 Retrieved from the Internet: URL:https://www.researchgate.net/publication/356560502_Prospective_Resources_Evaluation_Offshore_Newfoundland_and_Labrador_Uncertainty_and_Risk_Assessment_Using_Machine_Learning_Processes> page 3; figures 2,4,5 -----	1-20
A	WO 2021/086902 A1 (SAUDI ARABIAN OIL CO [SA]; ARAMCO AMERICAS [US]) 6 May 2021 (2021-05-06) paragraph [0008] paragraph [0034]; claims 1,5; figures 2,3,4 -----	1-20

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Information on patent family members

International application No

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		US 2021124087 A1	29-04-2021
		WO 2021086902 A1	06-05-2021
