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(54) Title: METHOD AND SYSTEM FOR EVALUATING VARIABILITY IN SUBSURFACE MODELS TO SUPPORT DECISION MAKING FOR HYDROCARBON OPERATIONS

(57) Abstract: A method and system are described herein for evaluating the intrinsic and extrinsic variability of a decision metric in an ensemble of subsurface models to aid in making a hydrocarbon operation decision.

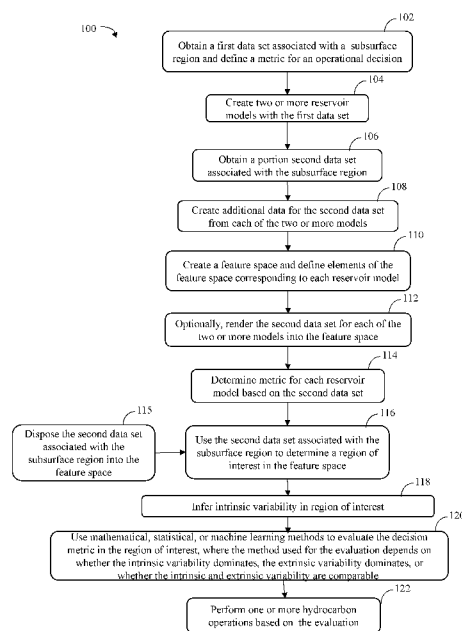


FIGURE 1



Declarations under Rule 4.17:

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- *as to the applicant's entitlement to claim the priority of the earlier application (Rule 4.17(iii))*

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**METHOD AND SYSTEM FOR EVALUATING VARIABILITY IN SUBSURFACE
MODELS TO SUPPORT DECISION MAKING FOR HYDROCARBON
OPERATIONS**

5 **CROSS-REFERENCE TO RELATED APPLICATIONS**

[0001] This application claims the benefit of U.S. Provisional Application No. 62/786,854 filed on December 31, 2018, the disclosure of which is incorporated herein by reference.

[0002] This application is also related to U.S. Patent Application No. 15/851,323 filed on December 21, 2017 which claims the benefit of priority of (i) U.S. Patent Application No. 10 62/440,134 filed on December 29, 2016, and (ii) U.S. Patent Application No. 62/591,576 filed on November 28, 2017, the entirety of which are incorporated by reference herein.

FIELD OF THE INVENTION

[0003] This disclosure relates generally to the field of subsurface modeling, and methods 15 of creating subsurface models for use in hydrocarbon operations, such as hydrocarbon exploration, development, and production operations. Specifically, this disclosure relates to methods and systems that evaluate the intrinsic and extrinsic variability in subsurface models to support decision making for hydrocarbon operations.

20 **BACKGROUND**

[0004] Upstream oil and gas operations require a rich set of decisions on multiple time and spatial scales. These decisions start in the hydrocarbon exploration or acquisition phase of an asset, continue through development planning choices, and persist through the lifetime of an asset. Hydrocarbon exploration, development, and production decision-making always 25 proceeds in the context of considerable uncertainty, both above-ground uncertainties (e.g., facilities performance, markets, commodity prices, etc.) and subsurface uncertainties (e.g., oil in place, effectiveness of recovery mechanisms, key controls on producibility, etc.). For decision-making, operators typically rely on various models, such as subsurface models, to aid in predicting various outcomes.

30 [0005] For example, different types of subsurface models may be used to represent subsurface regions, which may include a description of subsurface structures within the region and material properties for the region. The subsurface model may be a geologic model or a reservoir model. The subsurface model may represent measured data and/or interpreted data for the subsurface region, may be within a physical space or domain, and/or may include

objects (e.g., horizons, faults, surfaces, volumes, and the like). The subsurface model may also be discretized with a mesh or a grid that includes nodes and forms cells (e.g., voxels or elements) within the model. Thus, subsurface properties may be represented as spatially extended, three-dimensional geocellular models, with specific physical and chemical properties associated with each cell of the model. For example, in a reservoir model each cell may be associated with a specific rock permeability and porosity as well as saturations of the three potential phases, oil, gas, and water. Additional information may be incorporated into the reservoir model, such as phase behavior for the hydrocarbon components, aquifer strength, and multiple phase flow parameters such as irreducible saturations. In such a way, the reservoir model can be used to simulate multiphase flow within the subsurface.

[0006] Subsurface modeling is widely utilized in hydrocarbon development and hydrocarbon production phases for hydrocarbon assets. Hydrocarbon development involves determining capital and operating decisions, which relate to the plans for production from an asset. During such stages, one or more subsurface models are created, which are conditioned to seismic data, well logs, well test data, and any other available data to determine the underlying geological and statistical concepts for the subsurface region. In particular, history matching is utilized in conventional approaches to manage production from an asset. History matching utilizes production data, such as flow rates, pressure data and/or temperature data, to condition the reservoir model and determine the reservoir model that matches the measured data. The assimilation of this data is utilized with a reservoir model to provide a more accurate future prediction based on the past production data.

[0007] By way of example, various approaches have been developed to perform this type of modeling. For example, U.S. Patent Application No. 2007/0016389 describes a method for performing history matching using a neural network. The neural network provides a correlation between the calculated history match error and a selected set of parameters that characterize the well bore and/or the reservoir. The neural network iteratively varies the value of the parameters to provide at least one set of history match parameters having a value that provides a minimum for the calculated history matching error. Thus, the method is directed to minimizing the history match error.

[0008] As another example, U.S. Patent No. 7,725,302 describes a method for performing an oilfield operation using a user objective. In the method, a one-dimensional (1D) reservoir model is generated and a three dimensional (3D) reservoir model is generated by distributing properties per unit of depth in the volume. Then, the 3D reservoir model is calibrated using historical response of the reservoir, thereby assisting the forecast of the response of the

reservoir to a set of input data by applying the set of input data to the 3D reservoir model.

[0009] As yet another example, U.S. Patent No. 9,074,454 describes a method for performing reservoir engineering using horizons and positioning wellbore equipment in a well completion design based on an offset. Then, the method further includes calculating an absolute position of the wellbore equipment in the well completion design based on the offset and the location of the geological horizon.

[0010] Further, U.S. Patent No. 9,135,378 describes a method of developing a reservoir traversed using a production indicator. In the method, a position of a well to be drilled is determined by means of a production indicator map. The method involves determining production indicators on a group of cells; determining production indicators on another group of cells; and interpolating production indicators for the other cells of the map. Then, the new well is positioned at the highest production indicator.

[0011] Other references related to history matching include Oliver et al., “Inverse theory for petroleum reservoir characterization and history matching”, Cambridge University Press, 2008. This reference describes the use of inverse theory for estimation and conditional simulation of flow and transport parameters in porous media. Further, the reference describes the use of the theory and practice of estimating properties of underground petroleum reservoirs from measurements of flow in wells.

[0012] Despite these prior art methods, history matching of subsurface models, such as reservoir models, can be problematic. That is, it may be impossible to determine all of the parameters needed for a reservoir model, even with many years of production data, due to the mismatch of the amount of information needed to fully characterize the model and the data available. For example, a typical reservoir model may have 10^7 to 10^9 cells, each with about 10 model parameters to be stipulated. However, daily production rates for ten years across one hundred wells of three phases (oil, gas, and water) may yield, in the best case, only 10^6 independent values with which to condition data. As such, even in the best of cases, it may be impossible to fully history match a subsurface model.

[0013] Further, even if production data is available for conditioning the subsurface model, such data may be unreliable or too “noisy” to provide reliable history matching. That is, the reservoir model optimization approach merely addresses a conditioning problem that determines the reservoir model that best matches the historical production data. Yet, the history matching process has to rely upon noisy production data to determine the model that best matches the historical data. As a result, history matching, which is limited in properly determining the subsurface structures within the reservoir, has evolved to include ensembles

of reservoir models to address this deficiency. The ensemble of models still rely upon the noisy production data to attempt to provide insights on the reservoir model (or models, within the full ensemble). Further, the reservoir model may be underdetermined by the data, and as a result, a unique optimal solution may not exist for the data being used in the history matching approach. Typically, this approach has the goal to select a model or models to use in the performance of further modeling, in support of some business objective. However, this approach may reduce the number or range of the models being reviewed, which may limit the number of models to a narrower or constricted range and/or may not necessarily be suited for assisting in decision making processes. In addition, the process of determining a model that matches the historical production data is time-consuming and cumbersome within the reservoir modeling and software systems currently practiced.

[0014] In many hydrocarbon operations, the ultimate goal of a subsurface model is to aid or support a business decision (e.g., to drill or to not drill), not to create a perfect (physically realistic) subsurface model. As such, it may not be desirable and even may be unnecessary to history match or condition the subsurface model. Instead, it may be desirable to utilize a “goal-oriented inference” type of modeling, which allows the use of uncertain models to optimally determine “quantities of interest” relevant to particular decisions, without necessarily reducing the underlying uncertainty of the full model.

[0015] U.S. Patent Application Publication No. 2018/0188403 describes a regression and classification system for use in subsurface models to support decision making for hydrocarbon systems. In U.S. Patent Application Publication No. 2018/0188403, the method creates multiple reservoir models for a subsurface region using a first data set (e.g., seismic, well log, production data). A second data set (e.g., subsurface measurements) associated with the subsurface region is then obtained. The models are then used to create the remainder of the second data set. A feature space is then created and elements of the feature space corresponding to each reservoir model are defined. Production data is then disposed into the feature space, and a region of interest within the feature space is determined. A metric, such as expected ultimate recovery, is then evaluated for an operation decision (e.g., to drill a well or to not drill a well) in the region of interest in the feature space. However, the method described in U.S. Patent Application Publication No. 2018/0188403 assumes that the decision metric can be viewed as a function in the feature space. As such, the method in U.S. Patent Application Publication No. 2018/0188403 fails to account for instances where the decision metric can take various values at a point, points, or region in the feature space.

[0016] Accordingly, there remains a need in the industry for methods and systems that are

more efficient and may lessen problems associated with using production data in hydrocarbon operations, in particular, to provide support for decision making for hydrocarbon operations, which may be utilized to enhance hydrocarbon operations, such as hydrocarbon exploration, hydrocarbon development and/or hydrocarbon production. The present techniques provide a method and apparatus that overcome one or more of the deficiencies discussed above.

SUMMARY

[0017] Described herein are methods and techniques for evaluating the intrinsic and extrinsic variability of a decision metric in an ensemble of subsurface models to aid in making a hydrocarbon operation decision. The present techniques may provide a method for evaluating and performing a hydrocarbon operation for a subsurface region comprising: obtaining a metric for a hydrocarbon operation decision; obtaining a first data set associated with the subsurface region; creating an ensemble of reservoir models for the subsurface region using the first data set, wherein the ensemble of reservoir models comprises two or more reservoir models; creating a second data set associated with the subsurface region using the ensemble of reservoir models; creating a feature space and defining a plurality of elements of the feature space corresponding to each reservoir model; determining a region of interest within the feature space; inferring an intrinsic variability for the metric in the region of interest within the feature space; comparing the intrinsic variability for the metric with the extrinsic variability for the metric within the ensemble of reservoir models; evaluating the metric for the operational decision at the region of interest in the feature space, wherein the type of evaluation used is determined based on the comparison of the intrinsic variability and the extrinsic variability; and determining whether to perform a hydrocarbon operation based on the evaluation of the metric for the operational decision at the region of interest.

BRIEF DESCRIPTION OF THE FIGURES

[0018] The advantages of the present invention may be better understood by referring to the following detailed description and the attached figures.

[0019] **Figure 1** is an exemplary flow chart in accordance with one or more embodiments of the present techniques.

[0020] **Figure 2** is an exemplary flow chart in accordance with one or more embodiments of the present techniques.

[0021] **Figures 3A, 3B, 3C, 3D, 3E, 3F, 3G, 3H, 3I, 3J, 3K, 3L, and 3M** are exemplary diagrams associated with an embodiment of the present techniques.

[0022] **Figure 4** is a block diagram of a computer system that may be used to perform any of the methods disclosed herein.

[0023] **Figure 5** is an exemplary diagram illustrating the variance in intrinsic and extrinsic variability for a decision metric M.

5 [0024] **Figure 6** is an exemplary diagram illustrating a variogram of a decision metric M.

[0025] **Figure 7** is an exemplary diagram illustrating a distribution of clusters.

NOMENCLATURE

10 [0026] Various terms used throughout this disclosure are defined below. To the extent a term used in a claim is not defined below, it should be given the broadest reasonable definition persons in the pertinent art have given that term as reflected in at least one printed publication or issued patent.

[0027] As used herein, the term “hydrocarbon(s)” refers to molecule(s) formed primarily of carbon and hydrogen atoms. Hydrocarbons may also include other elements or compounds, 15 such as, halogens, metallic elements, nitrogen, oxygen, sulfur, hydrogen sulfide (H₂S), and carbon dioxide (CO₂). Hydrocarbons may be located within or adjacent to mineral matrices, termed reservoirs, within the earth. Matrices may include, but are not limited to sedimentary rock, shales, sands, carbonates, diatomites, and other porous media. Hydrocarbons may be produced from hydrocarbon reservoirs through wells penetrating a hydrocarbon containing 20 formation. Hydrocarbons derived from a hydrocarbon reservoir may include, but are not limited to, oil, natural gas, petroleum, kerogen, bitumen, pyrobitumen, asphaltenes, tars, or combinations thereof.

[0028] As used herein, the term “hydrocarbon exploration” refers to any activity associated with determining the location of hydrocarbons in subsurface regions. Hydrocarbon exploration 25 normally refers to any activity conducted to obtain measurements through acquisition of measured data associated with the subsurface formation and the associated modeling of the data to identify potential locations of hydrocarbon accumulations. Accordingly, hydrocarbon exploration may include acquiring measurement data, modeling of the measurement data to form subsurface models, and determining likely locations for hydrocarbon reservoirs within 30 the subsurface. The measurement data may include seismic data, gravity data, magnetic data, electromagnetic data, and the like.

[0029] As used herein, the term “hydrocarbon development” refers to any activity associated with planning of extraction and/or access to hydrocarbons in subsurface regions. Hydrocarbon development normally refers to any activity conducted to plan for access to

and/or for production of hydrocarbons from the subsurface formation and the associated modeling of data to identify preferred development approaches and methods. Accordingly, hydrocarbon development may include modeling of subsurface formations and extraction planning for periods of production, determining and planning equipment to be utilized and techniques to be utilized in extracting hydrocarbons from the subsurface formation, and the like.

[0030] As used herein, the term “hydrocarbon operations” refers to any activity associated with hydrocarbon exploration, hydrocarbon development, and/or hydrocarbon production.

[0031] As used herein, the term “hydrocarbon production” refers to any activity associated with extracting hydrocarbons from a subsurface location through a well or other opening. Hydrocarbon production normally refers to any activity conducted to form the wellbore along with any activity in or on the well after the well is completed. Accordingly, hydrocarbon production includes not only primary hydrocarbon extraction, but also secondary and tertiary production techniques, such as injection of gas or liquid for increasing drive pressure or mobilizing the hydrocarbons; treating the well by, for example, chemicals or hydraulic fracturing the wellbore to promote increased flow; well servicing; well logging; and other well and wellbore treatments.

[0032] As used herein, the term “subsurface model” refers to a model of a subsurface region and may include a reservoir model, a geomechanical model, a watertight model, and/or a geologic model. The subsurface model may include subsurface data distributed within the model in two-dimensions (e.g., distributed into a plurality of cells, such as elements or blocks), three-dimensions (e.g., distributed into a plurality of voxels.), or four or more dimensions.

[0033] As used herein, the term “geologic model” refers to a model (e.g., a two-dimensional model or a three dimensional model) of the subsurface region having static properties and includes objects, such as faults and/or horizons, and properties, such as facies, lithology, porosity, permeability, and/or the proportion of sand and shale.

[0034] As used herein, the term “reservoir model” is a model (e.g., a two-dimensional model or a three-dimensional model) of the subsurface that in addition to static properties, such as porosity and/or permeability, also has dynamic properties that vary over the timescale of resource extraction, such as fluid composition, pressure, and/or relative permeability.

[0035] As used herein, the term “extrinsic variability” refers to the variability in the metric of interest, such as expected ultimate recovery or decision-relevant metric, with change in the observed data.

[0036] As used herein, the term “intrinsic variability” refers to the variability in the metric of interest based on the models that are consistent with the observed data (or part of the feature space)

[0037] As used herein, the terms “simulate” or “simulation” refer to the process of
5 performing one or more operations using a subsurface model and any associated properties to create simulation results. For example, a simulation may involve computing a prediction related to the resource extraction based on a reservoir model. A reservoir simulation may involve, by execution of a reservoir-simulator computer program on a processor, computing composition, pressure, and/or movement of fluid as a function of time and space for a specified scenario of
10 injection and production wells by solving a set of reservoir fluid flow equations.

DETAILED DESCRIPTION

[0038] In the following detailed description, specific embodiments of the present disclosure are described in connection with preferred embodiments. However, to the extent
15 that the following disclosure is specific to a particular embodiment or a particular use, this is intended to be for exemplary purposes only and to simply provide a description of the exemplary embodiments. Accordingly, the disclosure is not limited to the specific embodiments described below, but rather, it includes all alternatives, modifications, and equivalents falling within the true spirit and scope of the appended claims.

[0039] In hydrocarbon operations, a subsurface model is created in the physical space or domain to represent the subsurface region. The subsurface model is a computerized representation of a subsurface region based on geophysical and geological observations made of regions on and / or below the surface of the Earth. The subsurface model may be a numerical equivalent of a three-dimensional geological map complemented by a description of physical
25 quantities in the domain of interest. The subsurface model may include multiple dimensions. The subsurface model may include a structural framework of objects, such as faults and horizons, and may include a mesh or grid of nodes to divide the structural framework and/or subsurface model into cells, which may include mesh elements or blocks in two-dimensions, mesh elements or voxels in three-dimensions or other suitable mesh elements in other
30 dimensions. A cell, such as block, mesh element or voxel, is a subvolume of the space, which may be constructed from nodes within the mesh.

[0040] Subsurface modeling is utilized in hydrocarbon development and hydrocarbon production phases for hydrocarbon assets. Hydrocarbon development involves determining capital and operating decisions, which relate to the plans for production from an asset. During

such stages, one or more subsurface models are created, which are conditioned to seismic data, well logs, well test data, and any other available data to determine the underlying geological and statistical concepts for the subsurface region. Accordingly, the subsurface models may be used to determine the fluid flow within the reservoir and from the respective production wells.

5 [0041] Reservoir modeling and simulation are utilized to support particular business decisions. While in the hydrocarbon development phase, the decisions are broad in scope, such as whether to pursue a project, or selections regarding facilities design and constraints, for example. While in the hydrocarbon production phase, the decisions are typically more specific, such as whether to drill a new well or a location for a new well, for example.

10 [0042] The present techniques relate to a system and method that identifies the intrinsic and extrinsic variability in ensemble of subsurface models to support decision making for hydrocarbon operations. As such, the present techniques may be used to address the uncertainty in reservoir properties that determine future production from existing or potential wells. As such, the present techniques do not involve themselves in the inefficiencies of optimizing a
15 reservoir model to match production data, as this effort in determining a large amount of highly granular model information, much of which is irrelevant to the hydrocarbon operations. The resulting enhancements provided by the present techniques may then be used for various hydrocarbon operations, such as hydrocarbon exploration, hydrocarbon development and/or hydrocarbon production operations.

20 [0043] The present techniques utilize an ensemble of models to guide a hydrocarbon operations decision. The hydrocarbon operations decision may be framed as a discrete decision (e.g., yes or no, or a one or zero). For example, a hydrocarbon decision may be whether or not to drill an infill well in a field that is already under production.

[0044] The present techniques involve dividing a data set describing a model and/or the
25 “truth case” (corresponding to actually observed data) into different categories. A first data set, which may be referred to as data set “A”, includes data that is used to condition two or more reservoir models that form the ensemble of reservoir models. This conditioning may be performed using a variety of techniques known in the art. For example, the first data set may include seismic data, well test data, and well log data that is used to generate the reservoir
30 models. For example, the first data set may contain pre-production data such as seismic, well test, and well log data.

[0045] A second data set, which may be referred to as data set “B”, includes data that is not used to condition the reservoir models, but instead defines a feature space (which may ultimately be simplified or reduced in dimension) in which the reservoir model results or

operations data can be represented as points. For example, the second data set may include simulation results, production data, generated or observed seismic data, generated or observed well test data and/or generated or observed well log data. For example, the second data set may correspond to reservoir simulation output for an ensemble of models conditioned of the pre-production data, supplemented by corresponding data for the actual field.

[0046] Finally, a metric, which may be referred to as “**M**”, corresponding to some physical parameter of interest that supports the operations decisions is provided. For example, **M** may denote the decision-relevant metric or the decision itself. Examples of such a metric may include the expected ultimate recovery from a reservoir (“EUR”), which is often used to guide hydrocarbon operation decisions, or expected incremental cumulative oil produced from hydrocarbon operation decision (e.g., as drilling or using an in-fill well). This metric can also be included as a position descriptor for the points in the feature space.

[0047] The present techniques involve analyzing the results of simulations of an ensemble of reservoir models (e.g., two or more reservoir models) to provide information on particular hydrocarbon operations. The method may include various steps, such as assigning particular data to the data set **A** or data set **B**, obtaining or creating two or more reservoir models, using the reservoir models in simulations and analyzing the results in a feature space.

[0048] For example, an ensemble of reservoir models may be created which are conditioned to a first data set (i.e., data set **A**), such as a pre-production data set. Each model of the ensemble of models can be simulated to create a modeled version of data set **B** and the metric **M**. Machine learning methods can then be used to build an approximate for the relationship between **M** and **B**, which can be used with the real-world data sets **B** to estimate the real-world value of the metric **M**. Thus, the present techniques may be used to provide a direct map from the data-space to the metric that drives the decision. While the initial models may be conditioned with the first data set, no actual model purporting to represent the actual field (consistent with its production data) is ever constructed.

[0049] In one example corresponding to hydrocarbon production operations, the reservoir models may be conditioned to an initial data set (e.g., the first data set or data set **A**), which may include seismic data and appraisal well data, but not necessarily production data. The reservoir models should include plausible geological scenarios consistent with the initial data set. The models can be used to generate data set **B**, which define the highest dimensional feature space possible. An example may be production data over a particular time period in the range between 0 less than ($<$) $t < T$, where production may have started at time t equal to ($=$) 0, and the time $t = T$ may be a time at which a particular decision (e.g., such as adding an

infill well to the field development) may be implemented. Then, two simulations may be performed for each of the reservoir models, which involve one using or performing the existing hydrocarbon operations (e.g., using the existing equipment) and the other being the new or updated hydrocarbon operations (e.g., new or updated equipment, well, etc.) subsequent to the time T. From the simulation results, the desirability of the hydrocarbon operation may be determined based on the production differences between the simulations with the respective models, which may be differences in production metrics. A feature space can be defined as a Cartesian space whose axes are the rates at selected times of the phases (oil, gas, water) produced at each well, as well as pressure information corresponding to the wells (e.g. bottom hole pressure). This is an example only; linear or non-linear transformations of these quantities can also be used to define the feature space. Each of the reservoir model results for time in the range between $0 < t < T$ may be embedded into the feature space, which accounts for production information prior to the time of the new or updated hydrocarbon operation. Then, one or more points within the feature space corresponding to the measured or observed production data, possibly with synthetic noise added (e.g., a “truth case” of the measured production data time series over time in the range between $0 < t < T$) can be added to the feature space, where the one or more points may have a spatial relationship within that space. The spatial relationship may be the forming of a region or area that is associated with the results within a distance threshold in the space of the measured or observed production data (e.g., actually observed production data). In the feature space, machine learning classification or regression techniques (e.g., k- means clustering, support vector models, or Kriging) may then be used to establish the preferred decision for a given set of data. This may involve regressing the value of the metric to the point, points, or region that represent the truth case from neighboring reservoir models (e.g., in the feature space or the higher dimensional space), which have been simulated (e.g., both prior to and subsequent to the time T); and/or may involve estimating a probability distribution function of the metric value for the preferred decision or may involve determining clusters from the data corresponding to the reservoir models. The metric may be defined as a function in the feature space, with regression to the value of the function at the point, points, or region corresponding to the truth case, or it is possible to create a larger feature space by including the metric value as an axis, and then determine the metric at the truth case point or points using conventional regression methods, as noted above, in the sub-region occupied by reservoir model data in that larger space. These two approaches are equivalent.

[0050] In another example corresponding to hydrocarbon development operations, data set A may comprise seismic data indicating basic geologic structures, environments of deposition,

and other seismically observable or inferable properties, and data set B may comprise well log and well test data from one or more appraisal wells. Two or more reservoir models may be created from data set A, and synthetic results from examination of these models may be used to create data corresponding to synthetic well log or well test results corresponding to the positions of the appraisal wells, these latter comprising data set B. A feature space can be created by choosing a parameterization of these latter well log or well test results, using methods known to those skilled in the art, and using these parameters to define the axes of a Cartesian space. Linear or non-linear transformations of these parameters may also be used to define the axes. The measured well log or well test results from the appraisal well or wells, possibly with synthetic noise added, may then be placed in the feature space in which data set B is indicated; regression or classification techniques may then be used to characterize the expected value of a metric, such as EUR (Expected Ultimate Recovery), which may be computed from the models, at the point, points or region in feature space corresponding to the measured data (e.g., the truth case).

[0051] In the present techniques, the reservoir models are not conditioned or changed (subsequent to their initial formulation using data set A), as in conventional history matching operations, but are utilized in evaluating the performance of hydrocarbon operations. Also, the reservoir models are not filtered or reviewed to indicate that any particular reservoir model or models is determined to be the closest, in some quantitatively defined sense, to the subsurface region (e.g., actual subsurface region). This is beneficial because the simulation of even a large number of models to determine the parameters that may be used to create data points in the feature space is more computationally efficient and less cumbersome than the “inverse problem” of trying to determine a reservoir model that matches the truth case data. Once the parameters appropriate for the particular hydrocarbon operation decision to be evaluated have been determined, the prediction of the metric describing the outcome of that operation is determined by the evaluated metric of neighboring reservoir models in the feature space, following statistical methods to average over these behaviors to provide a robust solution in that particular feature space. The regression method depends on the metric used, and thus may vary with the business decision being analyzed, even for the same ensemble of models. Thus, the statistical regression techniques may weigh the different reservoir models differently in determining the metric or metrics describing the outcome of the hydrocarbon operations decision at the point or points or region corresponding to the truth case (e.g., within a zone or region near or within a threshold of the truth case). Accordingly, different reservoir models may contribute differently to different decisions, which is not the result if history matching is

performed to identify a preferred, optimal, or best reservoir model.

[0052] Moreover, the present techniques utilize the behavior for the models, which may be computed directly from their properties, such as production for times in the range $0 < t < T$ or $t > T$ (in the production example) or EUR (in the development example). Because any property relevant to hydrocarbon operations of these models for any time may be determined by the simulation, the present techniques provide a mechanism to verify and to test the robustness of the present techniques. One particular model may be chosen as a “synthetic truth case”, and the classification and regression method can be executed on the remaining models within the ensemble. The value computed for the metric at the synthetic truth case may then be compared with the actual value of the metric for the chosen model, which is computable, thereby providing a test of the robustness and accuracy of the procedure for a particular ensemble of models, a particular choice of data sets A and B, and a particular metric used to evaluate an envisioned hydrocarbon operations decision. The data for these model results may also be used to tune the feature determination and regression and/or classification algorithms prior to identification of the predicted behavior for the hydrocarbon operations being evaluated. For example, this may involve using methods, such as, Lasso regression and/or sensitivity analysis, to identify features, which are most informative for the metric of interest.

[0053] Feature space creation is commonly practiced in machine learning applications, and may follow standard supervised or unsupervised machine learning practices. Pre-existing domain knowledge about the subsurface region or its analog(s) in another geospatial area(s) and existing data may be used to assist in defining the feature space. As an example, if data set B includes a set of time series of production data from existing M wells at N time points within the time interval (0, T), data set B may be considered to be embedded in a feature space of dimension greater than or equal to MN, depending on how many data observations are conducted at each well. Then, the dimension of the feature space may be changed by transforming data vectors in data set B into feature vectors via a feature map. A feature map may be based on polynomial combinations of components in a data vector or alternatively functional data analysis (“FDA”) can be used to define a set of basis vectors and coefficients that approximate, within some specified accuracy, the full data set. Further, another alternative configuration may include FDA that may be used to describe the features. FDA involves representing the functional data (e.g., time series corresponding to multiphase flow rates at wells), by coefficients of the smoothing spline or low-dimensional representation of the smoothing spline coefficients. A feature space may be infinite dimensional and a feature map need not be explicitly constructed. Regression or classification in the feature space can be

performed using function kernels representing inner products in the feature space. In this case, choosing a kernel is equivalent to choosing feature map(s) and/or feature space(s). Radial basis functions are often used as kernels in practice.

[0054] There are multiple ways to construct a feature space, including direct use of the original data set B as well as possible linear or non-linear transformations of this data, which may result in an altered (e.g., a lower) dimensionality feature space. In feature space selection, the feature space that provides the most confident and unbiased evaluation of the operations under consideration should be chosen. It follows that the feature space constructed, even for the same ensemble of reservoir or subsurface models, may be different based on the hydrocarbon operations decision to be evaluated. Visual display may be used to assist the selection of the feature space. Dimension reduction methods, such as multi-dimensional scaling or nonlinear dimensionality reduction methods (e.g., manifold learning), such as those described and developed in the machine learning literature, may be used to reduce the dimension of the feature space to two or three-dimensional space for visual inspection. Many such methods are described and known to those skilled in the art. By way of example, such methods may include those discussed in Friedman et al., "The elements of statistical learning", vol. 1, Springer, Berlin: Springer series in statistics, 2001 and Suzuki et al., "Using Association Rule Mining and High-Dimensional Visualization to Explore the Impact of Geological Features on Dynamic Flow Behavior", SPE Annual Technical Conference and Exhibition, Society of Petroleum Engineers, 2015.

[0055] In certain configurations, specific knowledge about the subsurface region may be incorporated into feature space selection. For example, an understanding of the large scale reservoir structure and initial reservoir pressure (e.g., part of data set A) may provide a mechanism to determine that a subset of data set B (e.g., gas production over time at certain wells near the in-fill well) may correlate strongly with the operations being evaluated. This subset of data may be used to build the feature space. Alternatively, certain information in data set B may be of greater physical significance than other information (e.g., the time when water breaks through at certain producers), this understanding might be used to reduce the number of data points that are used in defining the feature space. This selection may lower the dimensionality of the feature space. In another instance, the pressure differences between injector and producer pairs over time or the derivatives of production rates with respect to time may be used to enhance the feature space, which may increase the dimensionality of the feature space. Signal processing tools, which may involve wavelet analysis, may be used to find identifiable or primary characteristics of the time series in the frequency or time domain. These

characteristics (e.g., coefficients of wavelet basis functions) can then be used to construct feature space. Similar procedures can be applied to spatial data along wellbores, for instance in the hydrocarbon development operations example previously discussed.

[0056] Accordingly, in certain configurations, different approaches to feature space
5 construction may be used. The dimensionality of the feature space may decrease or increase through transformation of data vectors. Also, as another example, a tailored principal component analysis (“PCA”) or reduction method may be used, which is related to an objective or goal (e.g., parallel to the metric of interest and/or expanding the divergence of the metric of interest). Further, the method may involve performing machine learning, which may result in
10 a lower dimensional space being used for visualization. In addition, the selection of features that amplify differences may be preferred. Moreover, the method may include using principal component analysis to reduce the feature space, which may be embedded into a higher dimensionality space for certain configurations.

[0057] In certain configurations, the underlying geological drivers for performance of any
15 particular decision relating to hydrocarbon operations may be further evaluated. The present techniques may also involve combining the methods above with regression tree analysis of the underlying geological parameters (especially categorical choices in the construction of the ensemble of subsurface models, such as environment of deposition choices). In such a configuration, the regression tree analysis may be used to identify systematic correlations
20 between particular geological unknowns and characteristics either of data set B or of one or more hydrocarbon operations decision outcomes.

[0058] To enhance hydrocarbon operations, the present techniques provide enhancements for analyzing results of simulations of reservoir models to evaluate particular hydrocarbon operations. For example, in one configuration, a method for evaluating and performing a
25 hydrocarbon operation for a subsurface region is described. The method comprising: obtaining a first data set associated with a subsurface region, wherein the two or more reservoir models are based on a first data set; creating two or more reservoir models for a subsurface region from the first data set; obtaining a second data set associated with a subsurface region and the two or more reservoir models; obtaining production data associated with a subsurface region;
30 disposing the production data and at least a portion of the second data set into a feature space; determining a region of interest within the feature space; evaluating the results of a hydrocarbon operation at the region of interest in the feature space; and determining whether to perform a hydrocarbon operation based on the evaluation of the region of interest.

[0059] The method may include various enhancements. For example, the method may

include performing one or more regression techniques to evaluate the region of interest; wherein the first data set comprises one of seismic data, well log data and any combination thereof; wherein the second data set comprises one of generated or observed seismic data, generated or observed well log data, generated or observed well test data and any combination thereof; wherein the second data set comprises one of well log and well test data from appraisal wells; simulating each of the two or more reservoir models with the hydrocarbon operation being performed to create first simulation results, simulating each of the two or more reservoir models with the hydrocarbon operation not being performed to create second simulation results using the first data set; and wherein the second data set comprises the first simulation results and the second simulation results; simulating each of the two or more reservoir models with the hydrocarbon operation being performed to create simulation results; wherein the second data set comprises the first simulation results and the second simulation results; transforming the second data set to alter dimensionality of at least a portion of the second data set prior to disposing at least a portion of the second data set into the feature space; and/or wherein the hydrocarbon operation may comprise adding a new well to access the subsurface region.

[0060] In much of the discussion above, it has been assumed that the decision metric can be viewed as a function in the feature space. However, there may be instances in which it may be preferable to suppose that the decision metric can take various values at a point, points, or region in the feature space, including but not limited to the point, points, or region corresponding to the truth case corresponding to a subsurface region. This phenomenon can be referred to as the “intrinsic” variability of the decision metric, as contrasted with the “extrinsic” variability corresponding to the differences in the determined decision metric for the two or more reservoir models, which may represent a sampling from the various possible values of the decision metric consistent with the points in the feature space corresponding to the two or more reservoir models.

[0061] Many mathematical, statistical, or machine learning methods may be used to regress to a value of the operational decision metric in the region of interest based on the location in the feature space corresponding to the second data set obtained from the two or more reservoir models can also be used to determine a local variance in the region of interest of the operational decision metric. Examples include model-based regression (such as linear regression), Kriging, and random forest methods. There are a number of ways in which intrinsic or extrinsic variability may be defined, including but not limited to the first (mean) and second moment of the decision metric taken over the multiple reservoir models or using variograms of the decision metric as a function of distance in the feature space

[0062] The intrinsic variability of the decision metric may be smaller, comparable to, or larger than the extrinsic variability. When the intrinsic variability is comparable to or greater than the extrinsic variability, it may be possible to estimate the decision metric at the point, points, or region corresponding to the subsurface region using weighted averages of the decision metric over all of the two or more reservoir models. However, another method of estimating the decision metric at the point, points, or region corresponding to the subsurface region is to use averages of the decision metric over a nearby cluster in the feature space of some subset of the two or more reservoir models. The clustering of the two or more reservoir models into two or more clusters allows identification of regions of the feature space. For example, one may choose to evaluate the average (e.g., mean, median, or other statistical average) and variance cluster by cluster. For example, many clustering methods are known in the art, and an example of clustering methods in the feature space is sometimes referred to as “unsupervised learning”. See e.g., Hastie et al., “The Elements of Statistical Learning”, Springer, Chapter 14 (2001).

[0063] Thus, by comparing the intrinsic and extrinsic variability, the degree to which the decision metric M changes within the region of interest of the feature space can be determined. The intrinsic and extrinsic variability of M within the ensemble of models can then be compared, and this comparison can then be used to specify the mathematical, statistical, or machine learning method used to evaluate the operational decisional metric. For example, if the intrinsic variability (“ I ”) is significantly greater than the extrinsic variability (“ E ”) (i.e., $I \gg E$), then the original ensemble of models can be used for statistical inference of M . However, if the extrinsic variability is greater than the intrinsic variability (i.e., $E > I$), then the various statistical regression techniques described above may be utilized. However, if the intrinsic variability is similar to the extrinsic variability (i.e., $E \approx I$) or if the intrinsic variability is greater than the extrinsic variability (but not significantly greater) (i.e., $I > E$), then the clustering methods described above may be utilized.

[0064] Beneficially, the present techniques provide various enhancements to the hydrocarbon extraction process. The present techniques avoid the slow and cumbersome process of determining the reservoir or subsurface model that preferably matches or assimilates additional data (data set B). In addition, the techniques use information from the full ensemble of two or more reservoir models, and not just from one or more history matched models, to evaluate the results of a hydrocarbon operation, which may improve the accuracy of the determination of the results of a hydrocarbon operation under consideration. Furthermore, the techniques allow two or more reservoir or subsurface models comprising the ensemble to be

used differentially to support different hydrocarbon operations decisions, which may also improve the accuracy of the determination of the results of these different hydrocarbon operations. Additionally, the present techniques allow for a quantification of the variability in the decision metric, thus allowing for improved decision making. The present techniques may be further understood with reference to **Figures 1 to 4**, which are described further below.

[0065] **Figure 1** is an exemplary flow chart **100** in accordance with one or more embodiments of the present techniques. The flow chart **100** includes a method for analyzing the results of simulations of an ensemble of reservoir models to provide information on particular hydrocarbon operations decision in order to enhance hydrocarbon operations. The method may include obtaining data and reservoir models for the subsurface region, as shown in blocks **102** to **104**. Then, second data sets may be created along with an associated metric, as shown in blocks **106** to **110**. Finally, the measured data and computed metrics may be placed into the feature space, as shown in blocks **112** to **115**. Then, a hydrocarbon operation may be evaluated and performed based on the review, as shown in blocks **116** to **122**.

[0066] To begin, the method involves obtaining a first data set (e.g., data set “A”) for a subsurface region, which may include seismic data, well log data, well test data, well appraisal data, or production data, and obtaining two or more reservoir models for the subsurface region conditioned to this data, as shown in blocks **102** to **104**. At block **102**, a first data set (e.g., data set “A”) associated with a subsurface region and a metric (e.g., metric “M”) associated with an operational decision (e.g., potential hydrocarbon operations decision) are obtained. For example, the first data set may include seismic data, well test data and/or well log data, while the metric may be a parameter associated with the results of a hydrocarbon operation. The metric may correspond to a physical parameter of interest in supporting hydrocarbon operations decisions. By way of example, a metric may include the expected ultimate recovery from a reservoir (EUR) and/or expected incremental cumulative oil produced due to a hydrocarbon production decision. At block **104**, two or more reservoir models may be created based on the first data set associated with the subsurface region. The determination of the metric may or may not influence the particular reservoir models chosen and/or constructed. The reservoir models may be stored and obtained from memory or may be created to represent the subsurface region. For example, the reservoir models may be created from seismic data, well test data and/or well data, and may be subsequently conditioned to seismic data, well data, well test data and/or production data. The reservoir models may include a mesh that forms various mesh elements. The mesh elements may have one or more properties assigned to each mesh element. The properties may include transmissibility, rock type, porosity, permeability, rock

compressibility, oil saturation, clay content and/or cementation factors, for example.

[0067] At block **106**, a portion of second data set associated with the subsurface region is obtained. The portion of the second data set corresponding to measurements of the actual subsurface region is obtained. Once created the reservoir models may be used to create the remainder of the second data set at block **108**. At block **108**, a second data set is created from each of the two or more reservoir models. As examples, the second data set may include simulation results, generated or observed seismic data (e.g., generated from the model of the subsurface region combined with seismic forward modeling methods known in the art) and/or generated or observed well log data (e.g., generated from the model of the subsurface region combined with modeling methods known in the art). At block **110**, a feature space and defined elements of the feature space corresponding to each reservoir model is created. The construction of the feature space may be included in which the second data set, or a portion thereof is included in the feature space. The inclusion may involve construction of the feature space and specifying the elements in the feature space corresponding to each reservoir model. Then, the second data set for each reservoir model may be included into feature space, as shown in block **112**. At block **114**, a metric is determined for each reservoir model based on the second data set. The metric may be computed from the reservoir model. As an example, the difference between cumulative oil production corresponding to taking or not taking a particular hydrocarbon operations decision (e.g., introducing an infill well to the field development) is a metric that can be computed using reservoir simulation methods known in the art. Further, the metric may correspond to a physical parameter of interest in supporting a hydrocarbon operations decision. Examples of such a metric may include the expected ultimate recovery from a reservoir (EUR), which is often used to guide hydrocarbon development decisions, or expected incremental cumulative oil produced from hydrocarbon production decisions (e.g., an in-fill well). The hydrocarbon operation may include one or more hydrocarbon exploration operations, one or more hydrocarbon development operations and/or one or more hydrocarbon production operations. For example, the hydrocarbon production operation may involve installing or modifying a well or completion, modifying or adjusting drilling operations, decreasing fracture penetration, and/or to installing or modifying a production facility.

[0068] Once obtained, the measured data and computed metrics may be placed into the feature space, as shown in blocks **115** to **116**. At block **115**, the second data set associated with the subsurface region is disposed into feature space. The measured data may include production data or other measured data from the subsurface region. At block **116**, the second data set associated with the subsurface region may be used to determine a region of interest in

feature space. The measured data, and may be the metric, are used to identify a region of interest. The identification of a region of interest may involve determining a threshold or area surrounding a specific measured data point or points.

5 [0069] At block **118**, the variability of the metric M in the region of interest in the feature space may be inferred or determined. For example, the intrinsic variability of the metric M in the region of interest of a model may be inferred or determined. Additionally, the extrinsic variability of the metric M in two or more of the ensemble of models may be inferred or determined. By inferring the variability, it is meant that the variability is estimated or approximated but is not necessarily exactly determined or measured.

10 [0070] At block **120**, the metric in the region of interest may be evaluated. The type of evaluation used to evaluate the metric in the region of interest, which corresponds to a hydrocarbon operation, may depend on a comparison of the the intrinsic variability (“ I ”) and the extrinsic variability (“ E ”). For example, if E is greater than I (i.e., $E > I$), the evaluation may involve performing regression techniques. These regression techniques may be one of the
15 regression techniques noted above, for example. However, if I is significantly greater than E (i.e., $I \gg E$) simple statistical inference may be used with the original ensemble of models. Additionally, if I is greater than E (i.e., $I > E$), but not significantly greater than E , or if I is similar to E (i.e., $I \approx E$), then the evaluation may involve performing cluster analysis as described above. For example, the clustering may comprise clustering of the data in the feature
20 space to determine an average value of M the cluster.

[0071] Finally, the hydrocarbon operation may be performed or not based on the evaluation, as shown in block **122**. The hydrocarbon operations may include hydrocarbon exploration operations, hydrocarbon development operations and/or hydrocarbon production operations. For example, the hydrocarbon operation may include installing or modifying a well
25 or completion, modifying or adjusting drilling operations, decreasing or increasing fracture penetration, and/or installing or modifying a production facility. The production facility may include one or more units to process and manage the flow of production fluids, such as hydrocarbons and/or water, from the formation.

[0072] Beneficially, this method provides an enhancement in the production, development
30 and/or exploration of hydrocarbons. In particular, the method may be utilized to enhance the decision for a hydrocarbon operation based on the metric being reviewed. Further, this method accounts for variability within and between the models without trying to lessen uncertainty in the reservoir models.

[0073] **Figure 2** is an exemplary flow chart **200** in accordance with one or more

embodiments of the present techniques. The flow chart **200** includes a method for analyzing the results of simulations of an ensemble of reservoir models to provide information on particular hydrocarbon operations to enhance operations. The method may include obtaining data and reservoir models for the subsurface region, as shown in blocks **202** to **204**. Then, a hydrocarbon operation may be evaluated through simulations of the reservoir models, as shown in blocks **205** to **210**, and then a feature space is used with mathematical techniques to evaluate the hydrocarbon operation, as shown in blocks **212** to **220**. Finally, the hydrocarbon operation may be performed, as shown in block **222**.

[0074] To begin, the method involves obtaining data for a subsurface region, and obtaining two or more reservoir models for the subsurface region, as shown in blocks **202** to **204**. At block **202**, production data is obtained for the subsurface region of interest. The production data may include measured data from wells or other measured data. At block **203**, two or more reservoir models may be created from other data associated with the subsurface region. The other data used to create the reservoir models may include seismic data, well test data and/or well data (e.g., a first data set). Then, two or more reservoir models associated with the subsurface region are obtained, as shown in block **204**. The reservoir models may be obtained from memory, may have been used previously for other hydrocarbon operations decisions, or may be created to represent the subsurface region. For example, the reservoir models may be created from seismic data, well test data and/or well data, and may be subsequently conditioned to seismic data, well test data, well data and/or production data. The reservoir models may include a mesh that forms various mesh elements. The mesh elements may have one or more properties assigned to each mesh element. The properties may include transmissibility, rock type, porosity, permeability, rock compressibility, oil saturation, clay content and/or cementation factors, for example.

[0075] Then, the present techniques may evaluate a hydrocarbon operation through simulations of the reservoir models, as shown in blocks **205** to **210**. At block **205**, a metric for a hydrocarbon operation is determined. The metric may correspond to a physical parameter of interest in supporting hydrocarbon operation decisions. By way of example, a metric may include the expected ultimate recovery from a reservoir (EUR) and/or expected incremental cumulative oil produced corresponding to a particular hydrocarbon operation. At block **206**, a hydrocarbon operation is determined for evaluation.

[0076] The hydrocarbon operation may include one or more hydrocarbon exploration operations, one or more hydrocarbon development operations and/or one or more hydrocarbon production operations. For example, the hydrocarbon production operation may involve

installing or modifying a well or completion, modifying or adjusting drilling operations, decreasing or increasing fracture penetration, and/or to installing or modifying a production facility. Once the hydrocarbon operation is determined, each of the two or more reservoir models are simulated with the hydrocarbon operation and without the hydrocarbon operation, as shown in block **208**. The hydrocarbon operation may include large scale decisions, such as whether or not to develop a field at all, in which latter case the simulation without the hydrocarbon operation may essentially consist of not developing the field at all. The performance of the simulation may include modeling fluid flow based on the reservoir model and the associated properties stored within the mesh elements (e.g., cells or voxels) of the respective reservoir model. The simulation results may include the computation of time-varying fluid pressure and fluid compositions (e.g., oil, water, and gas saturation) and the prediction of fluid volumes produced or injected at wells. The simulation results and/or the respective reservoir model may be outputted. The outputting of the simulation results and/or the subsurface model may include displaying the simulation results and/or the reservoir model on a monitor and/or storing the simulation results and/or the reservoir model in memory of a computer system. The simulations are performed once with the hydrocarbon operation being performed and once without the hydrocarbon operation being performed for each of the respective reservoir models. Once the simulations are performed, a metric for the hydrocarbon operation is determined based on a comparison of the simulation results, as shown in block **210**.

[0077] Once the simulations are performed, a feature space is used with mathematical techniques to evaluate the hydrocarbon operation, as shown in blocks **212** to **220**. The mathematical techniques may include estimate of the model form error or bias along with estimate of measurement noise. At block **212**, a feature space is determined. As noted above, the feature space may be a higher dimensional space or may be a lower dimensional space with respect to some reference, e.g. that created by raw, unfit or unapproximated data alone. The feature space may be used to highlight differences and to assist in evaluating the metric and/or hydrocarbon operations. Then, the simulation results or a portion of the simulation results are optionally transformed into the feature space, as shown in block **214**. This transformation may involve a mathematical representation or a graphical representation, which may depend on the size of the dimensionality. Then, at block **216**, a region of interest in the feature space is identified. The region of interest may be identified by setting a threshold that defines the region as compared with a truth point or actual production data. The region of interest may be extended or altered to account for noise. At block **218**, the intrinsic variability of the decision metric in

the region of interest in the feature space is inferred or determined. The extrinsic variability of the decision metric in the region of interest in the feature space may also be inferred or determined. The intrinsic and extrinsic variability may be compared, and this comparison may be used to choose the type of mathematical techniques, such as the type of regression technique, that is used to evaluate the decision metric and/or to evaluate the outcome of the hydrocarbon operation at the point, points or region corresponding to the region of interest. The mathematical techniques may be similar to those noted above.

[0078] Finally, the hydrocarbon operation may be performed based on the evaluation, as shown in block **220**. The hydrocarbon operations may include hydrocarbon exploration operations, hydrocarbon development operations and/or hydrocarbon production operations. For example, the hydrocarbon operation may include installing or modifying a well or completion, modifying or adjusting drilling operations, decreasing fracture penetration, and/or to installing or modifying a production facility. The production facility may include one or more units to process and manage the flow of production fluids, such as hydrocarbons and/or water, from the formation.

[0079] Beneficially, this method provides an enhancement in the production, development and/or exploration of hydrocarbons. In particular, the method may be utilized to enhance the evaluation of the hydrocarbon operation by providing a region of interest that does not involve refining the reservoir models, but is directed to evaluating the hydrocarbon operations.

[0080] By way of example, the present techniques may be utilized for evaluating drilling a new well. In the present techniques, the reservoir models and production data are obtained, as shown in blocks **202** and **204** of **Figure 2**, and used in the analysis for a determined hydrocarbon operation, such as drilling a new well, as shown in block **206**. In particular, the production data may be accumulated from an initial time T_0 until time T (or T_{drill}) that involves a decision to place a new well or to not place a new well. The workflow to support the drill a new well decision may include various steps. The reservoir models may be a suite of reservoir models used during the development phase as part of a scenario generation or scenario discovery process. It may be useful that the reservoir models span all plausible geological scenarios consistent with the development-phase data.

[0081] Then, as shown in block **208**, two simulations of each reservoir model may be performed. In a first simulation, a first reservoir model is simulated with existing wells and facilities through a target time T_{max} , but without the new well being reviewed. In a second simulation, the first reservoir model is simulated through target time T_{max} with the new well inserted at decision time T_{drill} . Similar simulations are also performed for the second reservoir

model, and any other reservoir models being utilized in the evaluation.

[0082] As shown in block **210**, the desirability of the decision to drill the new well is based on the production differences or comparisons between simulations with the new well and simulations without the new well for the respective models. The production differences may be a production metric, such as differences in oil produced for a time in the range between $T_{\text{drill}} < t < T_{\text{max}}$ (where t is time for the respective time step), an absolute production metric, or water breakthrough time or other facilities-related metric. Based on the production metric, each reservoir model is tagged with a parameter related to the difference observed between simulations with the new well and simulations without the new well.

[0083] Then, the feature space is determined and the simulation results are transformed into the feature space, based on the simulated production data for a time in the range between $0 < t < T_{\text{drill}}$, as shown in blocks **212** and **214**. The feature space accounts for production data prior to the time of the insertion (or non-insertion) of the well at change time T_{drill} . This feature space is one whose axes are a summary of all of the information in the various time series of production information; numerous technologies such as multidimensional scaling or principal component analysis exist to project the information embedded in the time series into a tractable and relatively low dimensional feature space.

[0084] Once the data is in the feature space, machine learning classification and regression techniques are utilized to determine the optimal solution, as shown in blocks **216** to **220**. The identification of the point, points, or region in the feature space corresponds to the “truth case” of the actual production data time series over the range $0 < t < T_{\text{drill}}$. The intrinsic variability of the decision metric within the “truth case” may be inferred or determined, and the extrinsic variability of the decision metric within the ensemble of models may be inferred or determined. The intrinsic and extrinsic variabilities may be compared, and the comparison may be used to choose the standard machine learning classification or regression techniques (e.g. k-means clustering, support vector models, kriging) that are used to establish the optimal decision given the truth case data. For example, where $E > I$, this may be determined by regression of the value of the metric at the truth case point from neighboring simulation results from the respective reservoir models which have been simulated. Alternatively, an estimate of a probability distribution function of the metric value for the truth case may also be utilized. Another approach may be to use classification algorithms known in the statistical learning or machine learning art to determine if the point, points, or region corresponding to the truth case clusters or classifies with those reservoir models for which with the decision to add the well was successful or unsuccessful based on pre-determined economic and/or physical criteria. For

example, where $I > E$ or where $I \approx E$, it may be desirable to perform clustering within the data space, and then use the cluster that contains the truth space to average the values of the decision metric.

[0085] The method does not change or condition any reservoir model, nor does it identify
5 any particular reservoir model as corresponding to the truth case. The prediction of behavior at the truth case point is determined by the behaviors of neighboring reservoir models, following a statistical method to average over the behaviors to find a robust regression in that particular feature space. Further, the behavior for the time period in the range of $0 < t < T_{\text{drill}}$ of the production data for any reservoir model may be used as a synthetic truth case, which
10 provides a mechanism to test the robustness of the workflow, and tune both the feature determination and regression and/or classification algorithms prior to identification of the predicted behavior for the actual truth case. The approach is summarized in Figure 3 below.

[0086] **Figure 3A** is an exemplary diagram **300** of a feature space determined by production data. In the diagram **300**, the data points, such as data points **306**, **308**, **310** and
15 **312**, are represented along a first axis **302** of three phase flow rate and a second axis **304** of three phase flow rate. Each reservoir model, as well as the truth case, corresponds to a point in the feature space determined by production data for time $t < T_{\text{drill}}$. For example, the circle points, such as points **306**, represent simulation results that provide acceptable performance with respect to some decision metric corresponding to a hydrocarbon operation, the triangle
20 points, such as points **308**, represent simulation results that provide unacceptable performance with respect to the same decision metric, the square points, such as points **310**, represent simulation results that provide marginal performance and the diamond point **312** represents the actual flow rates. In this example, the reservoir models are characterized by the performance of the well added at a decision time T_{drill} , evaluated for times in the range between $T_{\text{drill}} < t <$
25 T_{max} . The analysis estimates that the truth case exhibits acceptable performance, notwithstanding the fact that the apparently closest reservoir model in the feature space exhibits unacceptable performance.

[0087] In one example, the method and system may involve a modeling a hydrocarbon operation. A first data set may include pre-production data, which is used to create the ensemble
30 of reservoir models. Then, a second data set may include production history data for time less than the performance of the hydrocarbon operation. Then, the metric may be the total production for the time period after the hydrocarbon operation being performed compared to that without the hydrocarbon operation having been performed.

[0088] In another example, the first data set may include seismic data, while the second

data set may include appraisal well logs, which may be associated with various wells. Then, the metric may be the expected ultimate recovery from a reservoir (EUR). Implicitly, the hydrocarbon operation in this case is the decision to develop the field, possibly in more than one manner, or with more than one set of facility choices; versus the decision not to develop
5 the field.

[0089] By way of example, **Figure 3B** is an exemplary diagram **320**, that shows the permeability K_x of a sample realization of the subsurface region, which contains various wellbores that are configured to operate as producers or injectors. This sample realization is a part of an ensemble of two hundred eighty-five reservoir models, which are generated by
10 conditioning the reservoir models to pre-production data. The ensemble of realizations represents uncertainty in the earth parameters, such as the porosity, the proximal/distal/medial grain size, the net-to-gross ratio (NTG) and the stacking pattern. **Figure 3E** is an exemplary diagram **346** of the ensemble of the 285 models, which represent different clusters associated with different scenarios. In **Figure 3E**, the x-axis indicate observed historical data (d_H) while
15 the y-axis indicate quantity of interest (QoI).

[0090] The subsurface region is assumed to contain ten producer wells and three injector wells. In this example, the metric for hydrocarbon operation, which is denoted by Z , corresponds to an infill drilling decision (e.g., a categorical variable (e.g., 0 or 1)). Further, it is assumed that this infill well (e.g., if drilled) may be brought online (e.g., start producing
20 hydrocarbons) at a time six years from the beginning of the time steps. All the wells are assumed to be bottom hole pressure-controlled. **Figure 3B** shows the location of the six (e.g., out of thirteen) wells **322**, **323**, **324**, **325** and the infill well **326** in the hydrocarbon system. **Figure 3C** is an exemplary diagram **330**, which shows the oil production rate for well **325** in **Figure 3B** in the units of barrels per day (bbl/d). In **Figure 3C**, the oil production rate during
25 the history corresponds to the time period from the beginning of the hydrocarbon production to six years, which is shown as the history from zero years to six years (noted by the vertical dashed line), which is also plotted separately in exemplary diagram **340** of **Figure 3D**. In **Figure 3D**, the oil production forecast corresponds to the time period from six years to twenty seven years, which is shown as the oil production rate from six years to twenty-seven years.
30 Further, in **Figure 3C**, the oil production rate from different realizations in the ensemble are indicated by curves and the oil production rate for the specific realization shown in **Figure 3B** is highlighted by the darker curve. The unit of the oil production rate in axis **332** and **342** is bbl/d, while the unit of time in axis **334** and **344** is years. To predict the metric Z , a comparison of the existing history-matching-based approach with the approach in the present disclosure

may be performed.

[0091] In a traditional history matching approach, given prior assumption about the earth parameters, denoted by \mathbf{m} , and vector of observables, such as the rates (q) and the bottom-hole pressure (BHP) during the history, denoted by \mathbf{d}_H^{obs} , the posterior distribution of the earth parameters $p(\mathbf{m} | \mathbf{d}_H^{obs})$ may be computed as shown in equation (e1) below:

$$\mathbf{d}_{Full} = g(\mathbf{m})$$

$$\mathbf{d}_{Full} = \left[\overbrace{\mathbf{d}_{f_1}, \mathbf{d}_{f_2}, \dots, \mathbf{d}_{f_{HM}}}^{\text{History } \mathbf{d}_H}, \underbrace{\mathbf{d}_{f_{HM+1}}, \dots, \mathbf{d}_{f_N}}_{\text{Forecast } \mathbf{d}_F} \right]^T$$

$$p(\mathbf{m} | \mathbf{d}_H^{Obs.}) \propto p(\mathbf{d}_H^{Obs.} | \mathbf{m}) p(\mathbf{m})$$

10 (e1)

[0092] Here, \mathbf{d}_{t_j} denotes the data vector of the observables, such as the rates (q) and the bottom-hole pressure (BHP) at time t_j , \mathbf{d}_H denotes the observables during the history, \mathbf{d}_F denotes the observables during the forecasting period, and $g(\mathbf{m})$ denotes the forward simulator. Next, given samples from the posterior distribution $p(\mathbf{m} | \mathbf{d}_H^{obs.})$, denoted by $\mathbf{m}^{posterior}$, the vector of observables may be predicted (including the flow rates) and the associated uncertainty during the forecast time window. The forecasted rates (and the associated uncertainty) may then be used to compute the metric \mathcal{Z} as shown in equation (e2) below:

$$\mathcal{Z} = P(\mathbf{d}_F)$$

20 (e2)

Here, P denotes a mathematical operator which acts on the vector of observables during the forecast time window. However, history matching is an ill-posed problem and is computationally intensive. Further, to make business decisions, it is the flow predictions and the corresponding uncertainty rather than the posterior geological models ($\mathbf{m}^{posterior}$) that are of primary interest. Therefore, in contrast to the history matching approach, here, the present techniques may be used to directly map the latent features (e.g., defined as the data-space of observables in the history and denoted by \mathbf{d}_H) to the metric (\mathcal{Z}). Such a mapping, denoted by J , is shown by equation (e3) below:

$$\mathcal{Z}(\mathbf{x}) = P(\mathbf{d}_F(\mathbf{x})) = P(F(\mathbf{x}, \mathbf{d}_H)) = J(\mathbf{x}, \mathbf{d}_H) + \epsilon$$

30 (e3)

The mapping J is based on the fact that geological models with similar well connectivity have similar time series, and hence, similar metric (\mathcal{Z}).

[0093] To construct the mapping, J , a four step procedure may be used. In the first step, the reservoir simulation is performed for all 285 realizations in the ensemble. While performing the reservoir simulation, it is assumed that the infill well was drilled and comes online at six years. Second, the entire reservoir simulation is performed again for all 285 realizations in the ensemble. However, this time, it is assumed that infill drilling was not performed. As a result, for each realization in the ensemble, incremental hydrocarbon production may be computed (e.g., due to infill drilling) and the associated economic impact. Based on the economic impact, for each realization in the ensemble, the metric of interest Z is computed (e.g., whether it is economically viable to drill infill well ($Z = 1$) or not ($Z = 0$)). The reservoir simulations may be performed by one or more reservoir simulator, as is known in the art. Based on the above two steps, a dataset may be constructed by described by a tuple $\{\mathbf{d}_H, Z\}_i$, where i denotes the realization number. In this example, $i = 1, 2, \dots, 285$. References to the concept of data-space \mathbf{d}_H include C. *See, e.g.,* Scheidt et al., “Prediction-focused subsurface modeling: Investigating the need for accuracy in flow-based inverse modeling”, *Mathematical Geosciences*, 2015, and W. Sun et al., “A new data-space inversion procedure for efficient uncertainty quantification in subsurface flow problems”, *Mathematical Geosciences*, (2017). In the third step, dimensionality reduction is performed on the latent feature space (or the data-space of observables in the history), denoted by \mathbf{d}_H . In this example, the dimensionality reduction is performed using Functional Data Analysis (FDA). For more details on FDA, refer to the following reference: Ramsay, J. O. (2006), “Functional data analysis. John Wiley & Sons, Inc.”. Performing dimensionality reduction using FDA involves the following steps:

1. For each realization, describe the latent features (e.g., the observables during the history, which are denoted by \mathbf{d}_H). \mathbf{d}_H is shown in equation (e1) above.
2. Represent the latent features \mathbf{d}_H for i^{th} realization as shown in equation (e4) below:

25

$$\mathbf{d}_{H_i} = \mathbf{x}(t_i) + \epsilon_i^{\text{FDA}}$$

where $\mathbf{x} = \sum_{k=1}^K \Phi_k(t) c_k$

(e4)

Here, ϵ_i^{FDA} is noise and Φ_k represents the basis, such as cubic B-spline basis.

30 3. Find the coefficients c_k by minimizing equation (e5):

$$\sum_i (\mathbf{d}_{H_i} - \mathbf{x}(t_i))^2 + \lambda J[\mathbf{x}]$$

(e5)

4. For each well, project the coefficients c_k to a low-dimensional space using principal component analysis (PCA) and denote the low-dimensional representation of the coefficients by $(\mathbf{y}_H^{o,w,g})$. Here, “o” denotes the oil phase, “w” denotes the water phase, and “g” denotes the gas phase.
5. Low-dimensional representation of the latent features is now shown in equation (e6).

$$\mathbf{y}_H = [(\mathbf{y}_H^o)_{P_1}, (\mathbf{y}_H^w)_{P_1}, (\mathbf{y}_H^g)_{P_1}, \dots, (\mathbf{y}_H^o)_{P_{10}}, (\mathbf{y}_H^w)_{I_1}, \dots, (\mathbf{y}_H^w)_{I_3}] \in \mathbb{R}^{10-50} \quad (\text{e6}),$$

where P_j denotes j^{th} producer and I_j denotes j^{th} injector. Thus, a dataset that contains tuples $\{\mathbf{y}_H, \mathbf{Z}\}_i, i = 1, 2, \dots, 285$ is the result.

[0094] The results from functional PCA technique are shown in exemplary diagram **350** in **Figure 3F**, diagram **352** in **Figure 3G** and diagram **354** in **Figure 3H**, where the x-axis show the time in years, while the y-axis show the oil production rate during the history (with shutin removed) in bbl/d. **Figure 3G** shows the oil production rate for well **325** of **Figure 3B**. **Figure 3G** shows the reconstructed oil production rate for well **325** in **Figure 3B** after representing \mathbf{d}_H (for each realization in the ensemble) using the approximation shown in equation (e5). Similarly, **Figure 3H** shows the reconstructed oil rate (for well **325** in **Figure 3B**) after representing \mathbf{d}_H (for each realization in the ensemble) using functional PCA approximations shown in equation (e6).

[0095] In the fourth step, the above dataset is used to learn the mapping J . The technique may be used in this example to learn the form of the mapping J is random forest. See, e.g., Breiman, L. (2001), “Random forests”, Machine learning, 45(1), 5-32. This reference provides more details on random forest. Random forest is a (e.g., non-parameteric) decision-tree-based supervised learning technique. It involves segmenting the feature-space into multiple homogenous regions. The segmentation is determined by minimizing the following equation (e7) in a top-down greedy approach:

$$\sum_{n,k: \mathbf{y}_H^n \in \mathbb{R}_1(j,s)} (\mathbf{Z}^n - \hat{\mathbf{Z}}_{R_1})^2 + \sum_{n,k: \mathbf{y}_H^n \in \mathbb{R}_2(j,s)} (\mathbf{Z}^n - \hat{\mathbf{Z}}_{R_2})^2 \quad (\text{e7})$$

[0096] In equation (e7), $\hat{\mathbf{Z}}^n$ denote average value of metric \mathbf{Z} in a given region, such as R_1 or R_2 or R_3 . The recursive segmentation provides a mechanism to capture the nonlinear interactions between the features. The segmentation concept is shown in **Figure 3I** that

includes the exemplary diagram 360. **Figure 3I** shows different realizations (of the ensemble) in two-dimensional representation of \mathbf{y}_H . In **Figure 3I**, the realizations represent drill or do not drill decisions. The darker points denote the realizations for which the metric Z suggests to drill the infill well, while the lighter points denote the realizations for which the metric Z suggests not to drill the infill well. In **Figure 3I**, the domain (of \mathbf{y}_H) is divided into regions R1, R2 and R3 as indicated by the lines dividing the points.

[0097] Finally, to construct the random-forest-based binary classifier (J) for the metric Z (e.g., drill or do not drill) as a function of low-dimensional features \mathbf{y}_H , it is possible to use the dataset for the previously constructed (e.g., tuple $\{\mathbf{y}_H, Z\}_i$). However, to validate the quality of predictions from the random-forest-based binary classifier (J), the original dataset is split into two (unequal) parts. The first part is referred to as the training set, while the second part is referred to as the test set.

[0098] The training set (shown in equation e8 below) contains 255 randomly selected realizations from the ensemble. The training set is used to construct the random-forest-based binary classifier J .

$$\Gamma_{tr.} = \{\mathbf{y}_{H_1}, Z_1, \mathbf{y}_{H_2}, Z_2, \dots, \mathbf{y}_{H_n}, Z_n\}, n = 255 \tag{e8}$$

[0099] **Figure 3J** is an exemplary diagram 370, which shows the oil production rate for well 325 of **Figure 3B** for all the realizations in the training set. In this exemplary diagram, the oil production rate (on the y-axis) is shown in bbl/d and the time (on x-axis) is shown in years. **Figure 3K** is an exemplary diagram 372, which shows a histogram of the metric Z for all the realizations in the training set. In **Figure 3K**, the y-axis denotes the frequency of the metric Z (0 on the x-axis denotes the decision to not drill the infill well, and 1 denotes the decision to drill the infill well).

[0100] The second part is called the test set (shown in equation e9 below).

$$\Gamma_{test} = \{\mathbf{y}_{H_1}^{Obs.*}, Z_1^*, \mathbf{y}_{H_2}^{Obs.*}, Z_2^*, \dots, \mathbf{y}_{H_m}^{Obs.*}, Z_m^*\}$$

$$Z_{Pred}^* = J(\mathbf{y}_{H_1}^{Obs.*}), m = 30. \tag{e9}$$

[0101] This second part contains the remaining 30 realizations from the ensemble. **Figure 3L** is an exemplary diagram 374, shows the oil production rate for well 325 of **Figure 3B** for all the realizations in the test set. In this exemplary diagram, the oil production rate (on the y-axis) is shown in bbl/d, and time (on the x-axis) is shown in years. **Figure 3M** is an exemplary

diagram 376, which shows the histogram of the metric Z for all the realizations in the test set. In Figure 3K, the y-axis denotes the frequency of the metric Z (e.g., 0 on the x-axis denotes the decision to not drill the infill well, and 1 denotes the decision to drill the infill well).

[0102] The binary classifier J , by construction, has no information about the feature-space y_H or the metric Z for the realizations in the test set. Thus, the test set acts as a blind test to validate the prediction quality of the random-forest-based binary classifier J . The value of the metric Z , predicted by J on the test set, is denoted by $Z^*_{Pred.}$. Thus, for all realizations in the test set, the prediction quality of J is measured by comparing $Z^*_{Pred.}$ with the actual metric Z as shown by the confusion matrix in Table 1 below:

10

Table 1

		<i>Reference</i>	
	<i>Prediction</i>	Do not drill	Drill
Do not drill		11	2
Drill		0	17

15

[0103] Finally, in the above (detailed) example, random forest is used as a technique to construct the binary classifier J . In other hydrocarbon applications, the metric Z can be a categorical variable (with multiple classes) or a real-valued variable such as EUR or NPV. In such cases, different machine learning algorithms for classification (such as the neural networks, support vector machines) or regression techniques (such as neural networks or Gaussian Process) can be used.

20

[0104] Alternatively, a Bayesian calibration approach in the data-space \mathbf{d}_H or a low-dimensional representation of the data-space y_H can be used. Such a Bayesian calibration approach may involve expressing the binary/multiclass classifier or regression function (in case the metric Z is a real-valued variable) as shown in equation (e10) below:

$$Z(\mathbf{x}) = P(\mathbf{d}_F(\mathbf{x})) = P(F(\mathbf{x}, \mathbf{d}_H)) = J(\mathbf{x}, \mathbf{d}_H) + \delta(\mathbf{d}_H) + \epsilon \tag{e10}$$

25

Here, J is the mapping from the data-space to the QoI-space, \mathbf{x} denotes calibration inputs to the mapping J , δ is the bias/model-form error, and ϵ denotes the residual uncertainty. The form of the mapping J and δ can be defined using machine-learning-based algorithms. Let θ denote the array of hyper-parameters corresponding to J and δ . Then, given the historical production rates $\mathbf{d}_H^{obs.}$, the posterior distribution of θ can be found as shown in equation (e11) below.

$$p(\theta | \mathbf{d}_H^{obs.}) \propto p(\mathbf{d}_H^{obs.} | \theta) p(\theta). \tag{e11}$$

30

Using $p(\theta | \mathbf{d}_H^{\text{obs}})$, the posterior mean μ_Z and variance σ_Z can be computed.

[0105] As noted above, a notable feature of the decision process is the large differences between the dimensionalities of the relevant spaces in which the evaluation of the decision metric is being conducted. The largest dimensionality space, the model space, may include values of 10^7 to 10^{10} different geological parameters, such as permeability in a reservoir model cell, or the transmissibility of a particular fault. The data space (from the first data set, data set A), by contrast, may only include 10^5 to 10^6 parameters. Thus, even if the model space is conditioned by the first data set, data set A, (e.g., seismic data), the dimension of the model space is expected to be substantially greater than the dimension of the data space. Thus, each manifold in the model space of models consistent with a particular data set B (or a point in the data space) will have its own value of M . The variation of the decision metric, M , over the manifold of the model space (i.e., the intrinsic variability) is a variability that cannot be resolved from the data set B. If the intrinsic variability is large, then its existence casts into question the validity of any attempt to infer M , and thus the ability to make a correct decision from the ensemble of models. Moreover, the intrinsic variability can be contrasted with the extrinsic variability, that is the variability of M corresponding to the full range of dataset B values as seen in **Figure 5**. As seen in **Figure 5**, the intrinsic variability captures that portion of the variability in the decision metric, M , as a function of the second data set, data set B, that is irreducible, and arises from the high dimensionality of the model space. The extrinsic variability corresponds to the variability in M that is observable across values of dataset B.

[0106] Intrinsic variability may be difficult to measure, as it may require a large number of samples (generated using unbiased sample) such that each sample has an identical (or almost-identical) data vector but different reservoir model parameters. Thus, as it is difficult to generate samples that are located at identical, or extremely close, locations in the data space, it may be difficult to directly determine the intrinsic variability. Most machine learning methods (including random forest methods) can provide an estimate and a variability at each location at which regression is conducted; however, variability for an inference method includes all statistical sources of variability arising from the intrinsic inaccuracy of the regression method. Thus, such statistical variances will, at best, be upper bounds on the intrinsic variability. An alternate method is to use a variogram of the metrics M , i.e., the low-dimensional representation of observables in the history match period and the output. By looking at the variance in M with distance in the data space, insight can be obtained into the extent to which such variations decline with distance, which can give an estimate of the intrinsic variability, provided that the intrinsic variability is significantly less than the extrinsic variability. This approach is based

only on the results from simulating the ensemble of reservoir models, and is thus independent of the statistical method used to build inferences for a particular element of a test set.

[0107] The results of such an analysis is shown in **Figure 6**. In **Figure 6**, the x-axis shows the normalized distance in data space between ensemble elements q, r, defined by equation
 5 (e12):

$$d_{qr} = \frac{\| (y_q)^* - (y_r)^* \|_1}{\| d \|_\infty} \tag{e12}$$

while the y-axis displays the difference $2\gamma(q,r) = (M_q - M_r)^2$. As described above, most pairs of ensemble elements are not particularly close, and have appreciable values of d_{qr} , which is to be expected in a high-dimensional space.

10 [0108] If the intrinsic variability is comparable to the extrinsic variability, then relatively simple clustering approaches can be used to estimate $p(Z;m)$, as in such cases, $p(Z;m)$ varies weakly with the full data set B.

[0109] If the intrinsic variability is too large for such an approach to work, then other clustering approaches may be used. The method would be to characterize clusters within the
 15 space spanned by the low-dimensional representation of the data vector, and ascribe the best decision based on the majority result within that cluster. An example of such clusters are shown in **Figure 7**. This involves clustering (or classifying) the ensemble of realizations based on the low-dimensional representation of the data vector in the history match period. The number of clusters can be identified using techniques such as elbow method or silhouette score. As seen
 20 in **Figure 7B**, $E[Z]=1$ (proceed with infill drilling) for all realizations in the second cluster, while for realizations in the **Figure 7A, 7C, and 7D**, $E[Z] = 0$ (i.e., do not proceed with infill drilling). Thus, an estimate of the correct decision based on the field data can be made by identifying the cluster which the actual production history (in its low-dimensional form) most closely resembles.

25 [0110] Persons skilled in the technical field will readily recognize that in practical applications of the disclosed methodology, it is partially performed on a computer, typically a suitably programmed digital computer. Further, some portions of the detailed descriptions which follow are presented in terms of procedures, steps, logic blocks, processing and other symbolic representations of operations on data bits within a computer memory. These
 30 descriptions and representations are the means used by those skilled in the data processing arts to most effectively convey the substance of their work to others skilled in the art. In the present application, a procedure, step, logic block, process, or the like, is conceived to be a self-consistent sequence of steps or instructions leading to a desired result. The steps are those

requiring physical manipulations of physical quantities. Usually, although not necessarily, these quantities take the form of electrical or magnetic signals capable of being stored, transferred, combined, compared, and otherwise manipulated in a computer system.

[0111] It should be borne in mind, however, that all of these and similar terms are to be associated with the appropriate physical quantities and are merely convenient labels applied to these quantities. Unless specifically stated otherwise as apparent from the following discussions, it is appreciated that throughout the present application, discussions utilizing the terms such as “processing” or “computing”, “calculating”, “comparing”, “determining”, “displaying”, “copying,” “producing,” “storing,” “adding,” “applying,” “executing,” “maintaining,” “updating,” “creating,” “constructing” “generating” or the like, refer to the action and processes of a computer system, or similar electronic computing device, that manipulates and transforms data represented as physical (electronic) quantities within the computer system's registers and memories into other data similarly represented as physical quantities within the computer system memories or registers or other such information storage, transmission or display devices.

[0112] Embodiments of the present techniques also relate to an apparatus for performing the operations herein. This apparatus may be specially constructed for the required purposes, or it may comprise a general-purpose computer selectively activated or reconfigured by a computer program stored in the computer (e.g., one or more sets of instructions). Such a computer program may be stored in a computer readable medium. A computer-readable medium includes any mechanism for storing or transmitting information in a form readable by a machine (e.g., a computer). For example, but not limited to, a computer-readable (e.g., machine-readable) medium includes a machine (e.g., a computer) readable storage medium (e.g., read only memory (“ROM”), random access memory (“RAM”), magnetic disk storage media, optical storage media, flash memory devices, etc.), and a machine (e.g., computer) readable transmission medium (electrical, optical, acoustical or other form of propagated signals (e.g., carrier waves, infrared signals, digital signals, etc.)).

[0113] Furthermore, as will be apparent to one of ordinary skill in the relevant art, the modules, features, attributes, methodologies, and other aspects of the invention can be implemented as software, hardware, firmware or any combination of the three. Of course, wherever a component of the present invention is implemented as software, the component can be implemented as a standalone program, as part of a larger program, as a plurality of separate programs, as a statically or dynamically linked library, as a kernel loadable module, as a device driver, and/or in every and any other way known now or in the future to those of skill in the art

of computer programming. Additionally, the present invention is in no way limited to implementation in any specific operating system or environment.

[0114] As an example, **Figure 4** is a block diagram of a computer system **400** that may be used to perform any of the methods disclosed herein. A central processing unit (CPU) **402** is coupled to system bus **404**. The CPU **402** may be any general-purpose CPU, although other types of architectures of CPU **402** (or other components of exemplary system **400**) may be used as long as CPU **402** (and other components of system **400**) supports the inventive operations as described herein. The CPU **402** may execute the various logical instructions according to disclosed aspects and methodologies. For example, the CPU **402** may execute machine-level instructions for performing processing according to aspects and methodologies disclosed herein. In addition, a computer system **400** may also include a graphical processing unit(s) (GPU(s)) **414**.

[0115] The computer system **400** may also include computer components such as a random access memory (RAM) **406**, which may be SRAM, DRAM, SDRAM, or the like. The computer system **400** may also include read-only memory (ROM) **308**, which may be PROM, EPROM, EEPROM, or the like. RAM **406** and ROM **308** hold user and system data and programs, as is known in the art. The computer system **400** may also include an input/output (I/O) adapter **410**, a communications adapter **422**, a user interface adapter **424**, and a display adapter **418**. The I/O adapter **410**, the user interface adapter **424**, and/or communications adapter **422** may, in certain aspects and techniques, enable a user to interact with computer system **400** to input information.

[0116] The I/O adapter **410** preferably connects a storage device(s) **412**, such as one or more of hard drive, compact disc (CD) drive, floppy disk drive, tape drive, etc. to computer system **400**. The storage device(s) may be used when RAM **406** is insufficient for the memory requirements associated with storing data for operations of embodiments of the present techniques. The data storage of the computer system **400** may be used for storing information and/or other data used or generated as disclosed herein. The communications adapter **422** may couple the computer system **400** to a network (not shown), which may enable information to be input to and/or output from system **400** via the network (for example, a wide-area network, a local-area network, a wireless network, any combination of the foregoing). User interface adapter **424** couples user input devices, such as a keyboard **428**, a pointing device **426**, and the like, to computer system **400**. The display adapter **418** is driven by the CPU **402** to control, through a display driver **416**, the display on a display device **420**.

[0117] The architecture of system **400** may be varied as desired. For example, any suitable processor-based device may be used, including without limitation personal computers, laptop

computers, computer workstations, and multi-processor servers. Moreover, embodiments may be implemented on application specific integrated circuits (ASICs) or very large scale integrated (VLSI) circuits. In fact, persons of ordinary skill in the art may use any number of suitable structures capable of executing logical operations according to the embodiments.

5 [0118] As may be appreciated, the method may be implemented in machine-readable logic, such as a set of instructions or code that, when executed, performs the instructions or operations from memory. By way of example, the computer system includes a processor; an input device and memory. The input device is in communication with the processor and is configured to receive input data associated with a subsurface region. The memory is in communication with
10 the processor and the memory has a set of instructions, wherein the set of instructions, when executed, are configured to: obtain a first data set associated with a subsurface region, wherein the two or more reservoir models are based on a first data set; create two or more reservoir models for a subsurface region from the first data set; obtain a second data set associated with a subsurface region and the two or more reservoir models; obtain production data associated
15 with a subsurface region; dispose the production data and at least a portion of the second data set into a feature space; determine a region of interest within the feature space; evaluate the region of interest or a business-relevant metric in the feature space; and determine whether to perform a hydrocarbon operation based on the evaluation of the region of interest or of the business-relevant metric.

20 [0119] The system may include various enhancements. For example, the system may include the set of instructions, when executed by the processor, configured to: perform one or more regression techniques to evaluate the region of interest; wherein the first data set may comprise one of seismic data, well test data, well log data, production data, and any combination thereof; wherein the second data set may comprise one of generated or observed seismic data,
25 generated or observed well log data, generated or observed well test data, generated or observed production data and any combination thereof; may simulate each of the two or more reservoir models with the hydrocarbon operation being performed to create first simulation results, may simulate each of the two or more reservoir models with the hydrocarbon operation not being performed to create second simulation results, wherein the second data set may comprise the
30 first simulation results and the second simulation results; transform the second data set to alter dimensionality of the second data set, or portion of the second data set, prior to disposing the second data set, or a portion of the second data set, into the feature space; wherein the hydrocarbon operation may comprise adding a new well to access the subsurface region.

[0120] Further in other configurations, while the second data set (e.g., data set B) may

contain production data (for instance in the hydrocarbon production applications), it does not need to contain production data. Thus, in the hydrocarbon development application, the second data set (e.g., data set B) may be limited to well log and well test data from appraisal wells, because in this example there is no production data. Alternatively, certain examples may
5 involve using production data in the first data set (e.g., data set A), such as production data up to a certain time that is used to condition the initial ensemble of reservoir models, for example.

[0121] It should be understood that the preceding is merely a detailed description of specific embodiments of the invention and that numerous changes, modifications, and alternatives to the disclosed embodiments can be made in accordance with the disclosure here
10 without departing from the scope of the invention. The preceding description, therefore, is not meant to limit the scope of the invention. Rather, the scope of the invention is to be determined only by the appended claims and their equivalents. It is also contemplated that structures and features embodied in the present examples can be altered, rearranged, substituted, deleted, duplicated, combined, or added to each other. As such, it will be apparent, however, to one
15 skilled in the art, that many modifications and variations to the embodiments described herein are possible. All such modifications and variations are intended to be within the scope of the present invention, as defined by the appended claims.

CLAIMS

1. A method for evaluating and performing a hydrocarbon operation for a subsurface region comprising:

obtaining a metric for a hydrocarbon operation decision;

obtaining a first data set associated with the subsurface region;

creating an ensemble of reservoir models for the subsurface region using the first data set, wherein the ensemble of reservoir models comprises two or more reservoir models;

creating a second data set associated with the subsurface region using the ensemble of reservoir models;

creating a feature space and defining a plurality of elements of the feature space corresponding to each reservoir model;

determining a region of interest within the feature space;

inferring an intrinsic variability for the metric in the region of interest within the feature space;

comparing the intrinsic variability for the metric with the extrinsic variability for the metric within the ensemble of reservoir models;

evaluating the metric for the operational decision at the region of interest in the feature space, wherein the type of evaluation used is determined based on the comparison of the intrinsic variability and the extrinsic variability; and

determining whether to perform a hydrocarbon operation based on the evaluation of the metric for the operational decision at the region of interest.

2. The method of claim 1, wherein the first data set comprises one of seismic data, well log data, well test data production data and any combination thereof.

3. The method of claim 1 or 2, wherein creating the second data comprises:

simulating at least two of the models in the ensemble of models to create simulation results;

wherein the second data set comprises the simulation results.

4. The method of any one of claims 1 to 3, further comprising transforming the second data set to alter the dimensionality of at least a portion of the second data set prior to disposing at least a portion of the second data set into the feature space.

5. The method of any one of claims 1 to 4, wherein if the extrinsic variability is greater than the intrinsic variability, the evaluation comprises performing one or more mathematical, statistical, or machine learning techniques combined with reservoir model simulation data, model-form error and metrics to evaluate metric at the region of interest.

6. The method of any one of claims 1 to 4, wherein if the intrinsic variability is comparable to the extrinsic variability, the evaluation comprises performing clustering to evaluate metric at the region of interest.

7. The method of any one of claims 1 to 4, wherein if the intrinsic variability is greater than the extrinsic variability, the evaluation comprises performing clustering to evaluate metric at the region of interest.

8. The method of any one of claims 1 to 4, wherein if the intrinsic variability is significantly greater than the extrinsic variability, the evaluation comprises using statistical techniques to evaluate metric at the region of interest.

9. The method of any one of claims 1 to 8, wherein the hydrocarbon operation comprises adding a new well to access the subsurface region.

10. A system for evaluating and performing a hydrocarbon operation for a subsurface region, comprising:

a processor;

an input device in communication with the processor and configured to receive input data

associated with a subsurface region;

memory in communication with the processor, the memory having a set of instructions,

wherein the set of instructions, when executed by the processor, are configured to:

obtaining a metric for a hydrocarbon operation decision;

obtaining a first data set associated with the subsurface region;

creating an ensemble of reservoir models for the subsurface region using the first data set, wherein the ensemble of reservoir models comprises two or more reservoir models;

creating a second data set associated with the subsurface region using the ensemble of reservoir models;

creating a feature space and defining a plurality of elements of the feature space corresponding to each reservoir model;

determining a region of interest within the feature space;

inferring an intrinsic variability for the metric in the region of interest within the feature space;

comparing the intrinsic variability for the metric with the extrinsic variability for the metric within the ensemble of reservoir models;

evaluating the metric for the operational decision at the region of interest in the feature space, wherein the type of evaluation used is determined based on the comparison of the intrinsic variability and the extrinsic variability; and

determining whether to perform a hydrocarbon operation based on the evaluation of the metric for the operational decision at the region of interest.

11. The system of claim 10, wherein the set of instructions, when executed by the processor, are further configured to: perform one or more regression techniques to evaluate the decision metric or any other quantity of interest.

12. The system of claim 10 or 11, wherein the first data set comprises one of seismic data, well log data, well test data, production data and any combination thereof.

13. The system of any one of claims 10 to 12, wherein the second data set comprises one of generated or observed seismic data, generated or observed well log, generated or observed well test data, generated or observed production data and any combination thereof.

14. The system of any one of claims 10 to 13, wherein the set of instructions, when executed by the processor, are further configured to

simulate each of the two or more reservoir models to create simulation results;

wherein the second data set comprises the simulation results.

15. The system of any one of claims 10 to 14, wherein the set of instructions, when executed by the processor, are further configured to

simulate each of the two or more reservoir models with the hydrocarbon operation being performed to create first simulation results;

simulate each of the two or more reservoir models with the hydrocarbon operation not being performed to create second simulation results;

wherein the decision metric is determined from the first simulation results and the second simulation results.

16. The system of any one of claims 10 to 15, further comprising transforming the second data set to alter dimensionality of the at least a portion of the second data set prior to disposing the at least a portion of the second data set into the feature space.

17. The system of any one of claims 10 to 16, further comprising transforming the second data set to incorporate additional information corresponding to later times prior to disposing the at least a portion of the second data set into the feature space.

18. The system of any one of claims 10 to 17, wherein the hydrocarbon operation comprises adding a new well to access the subsurface region.

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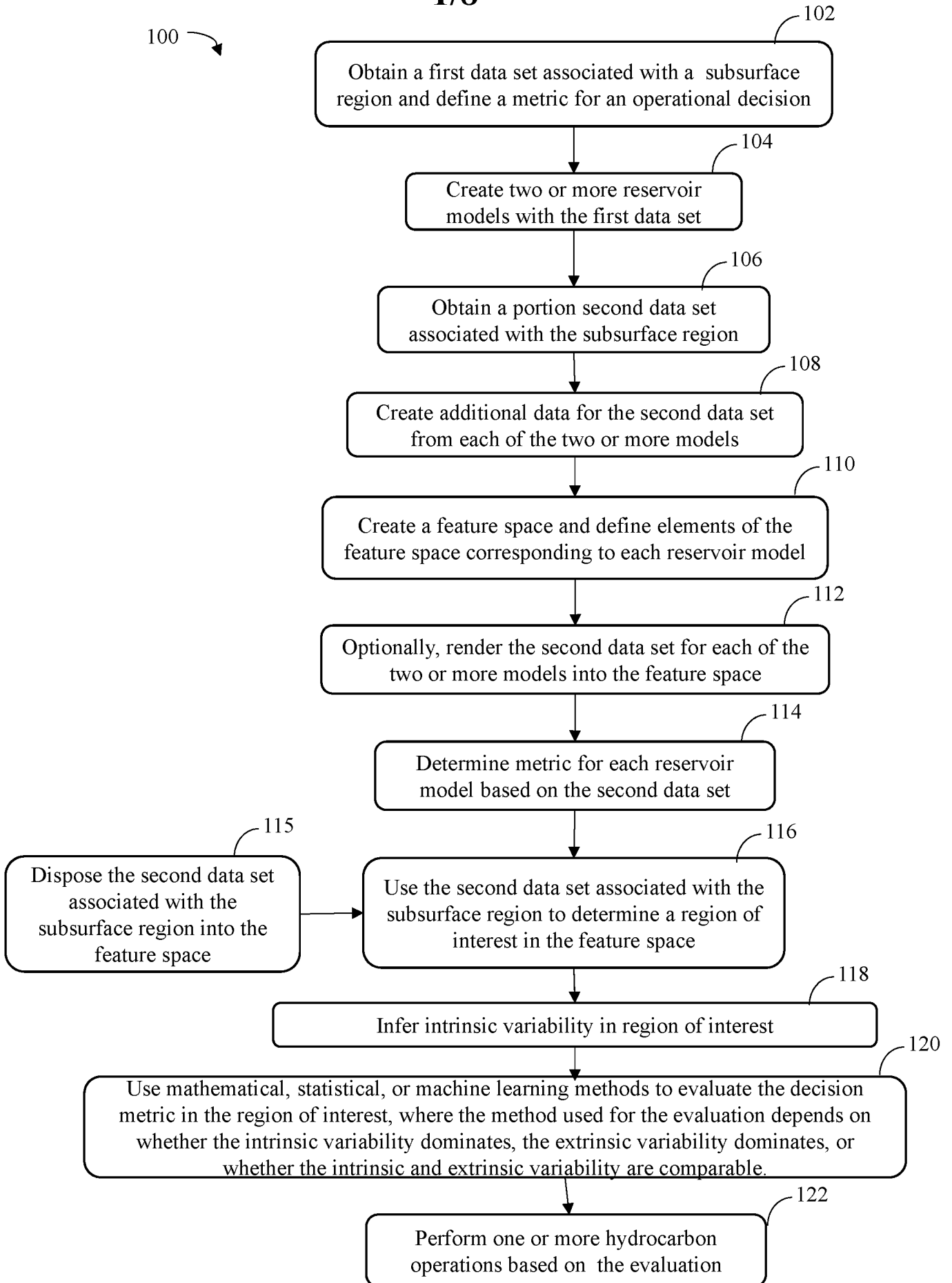


FIGURE 1

2/8

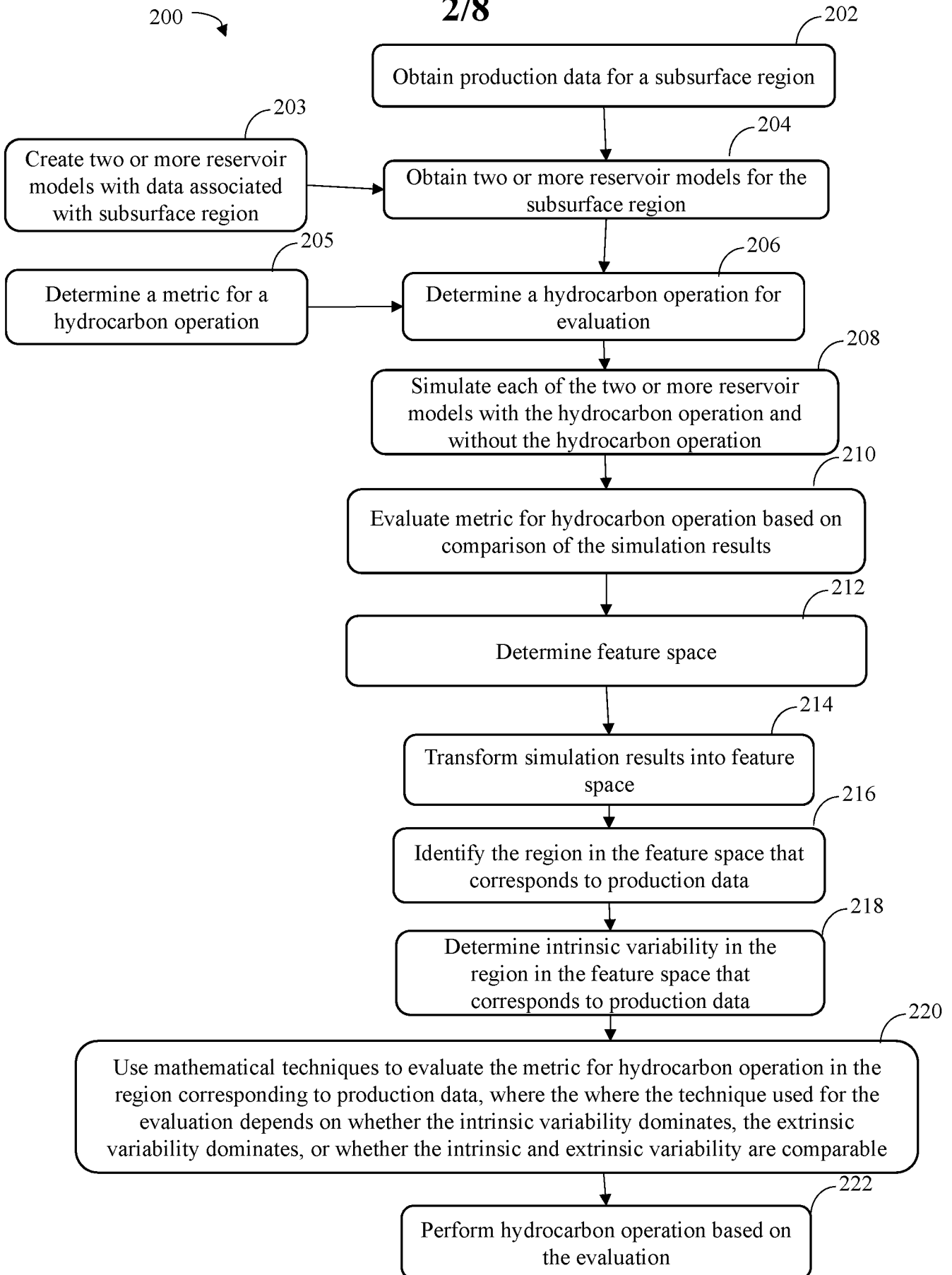


FIGURE 2

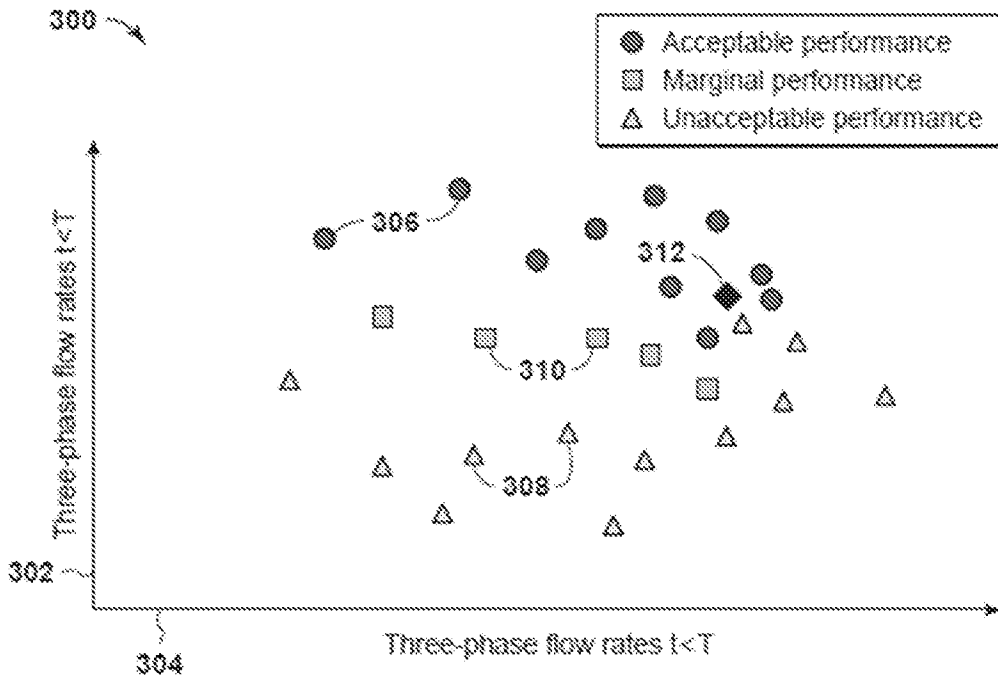


Figure 3A

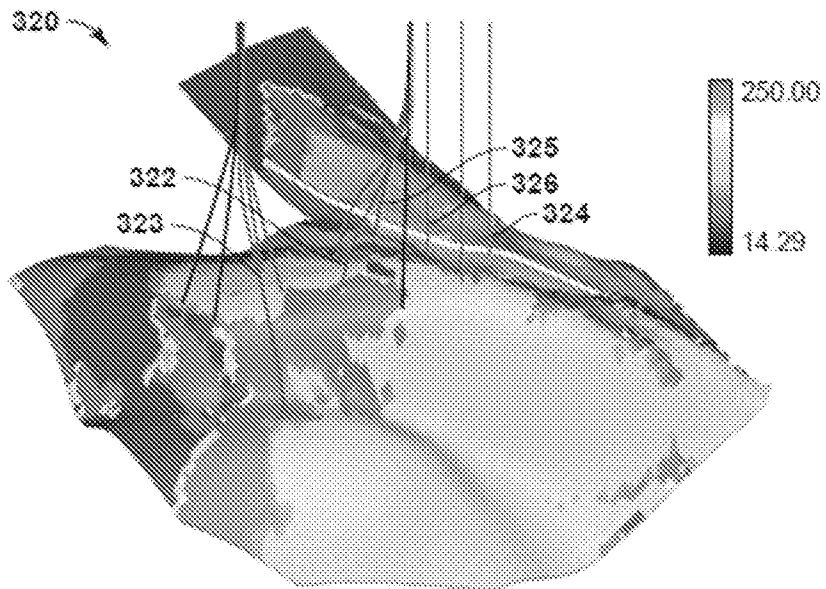


Figure 3B

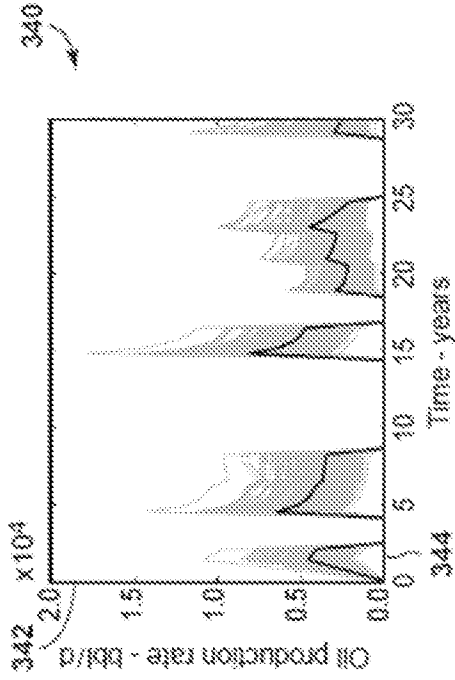


Figure 3D

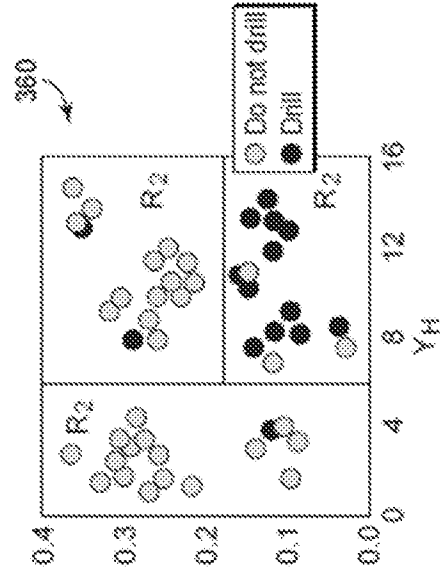


Figure 3I

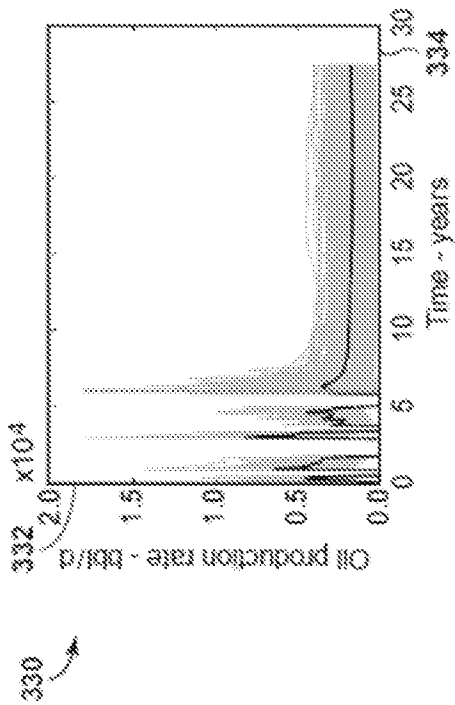


Figure 3C

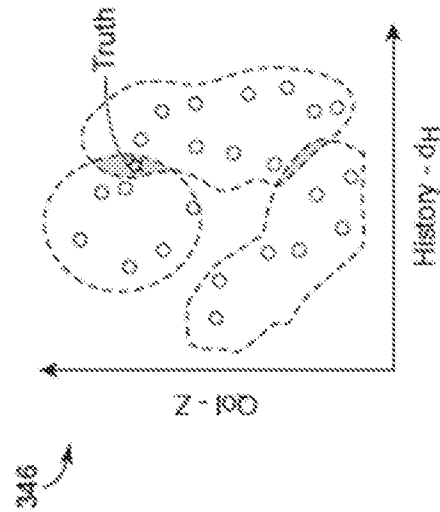


Figure 3E

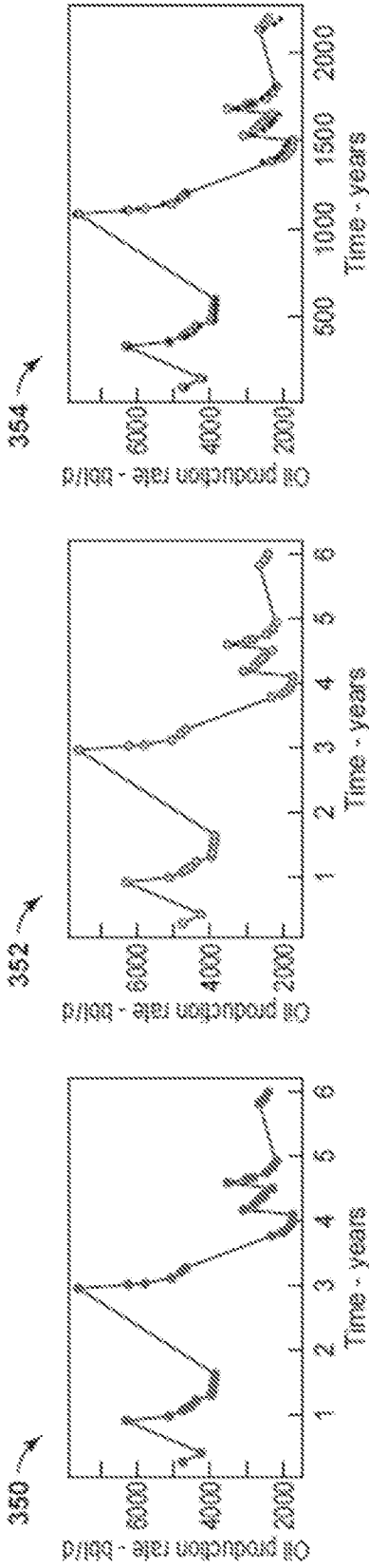


Figure 3H

Figure 3G

Figure 3F

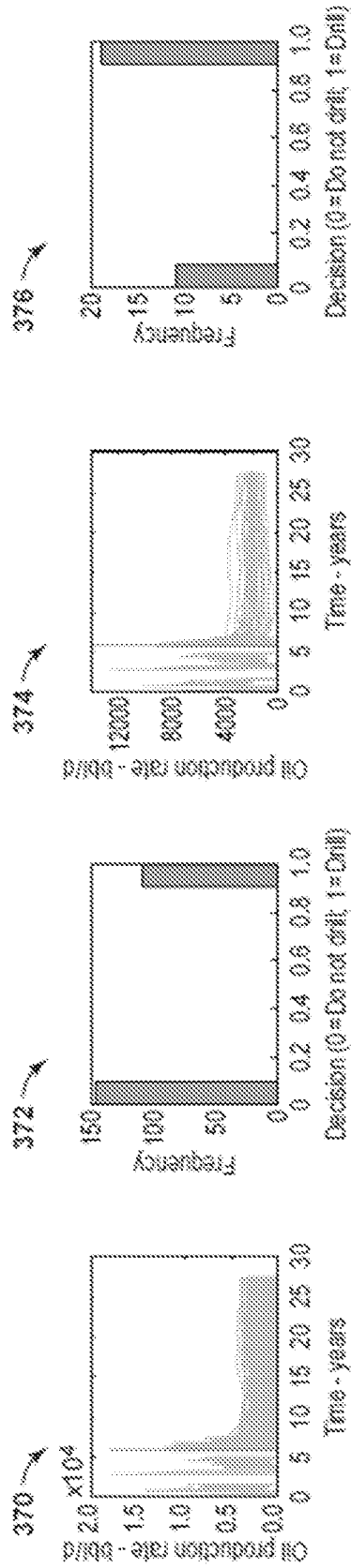


Figure 3M

Figure 3L

Figure 3K

Figure 3J

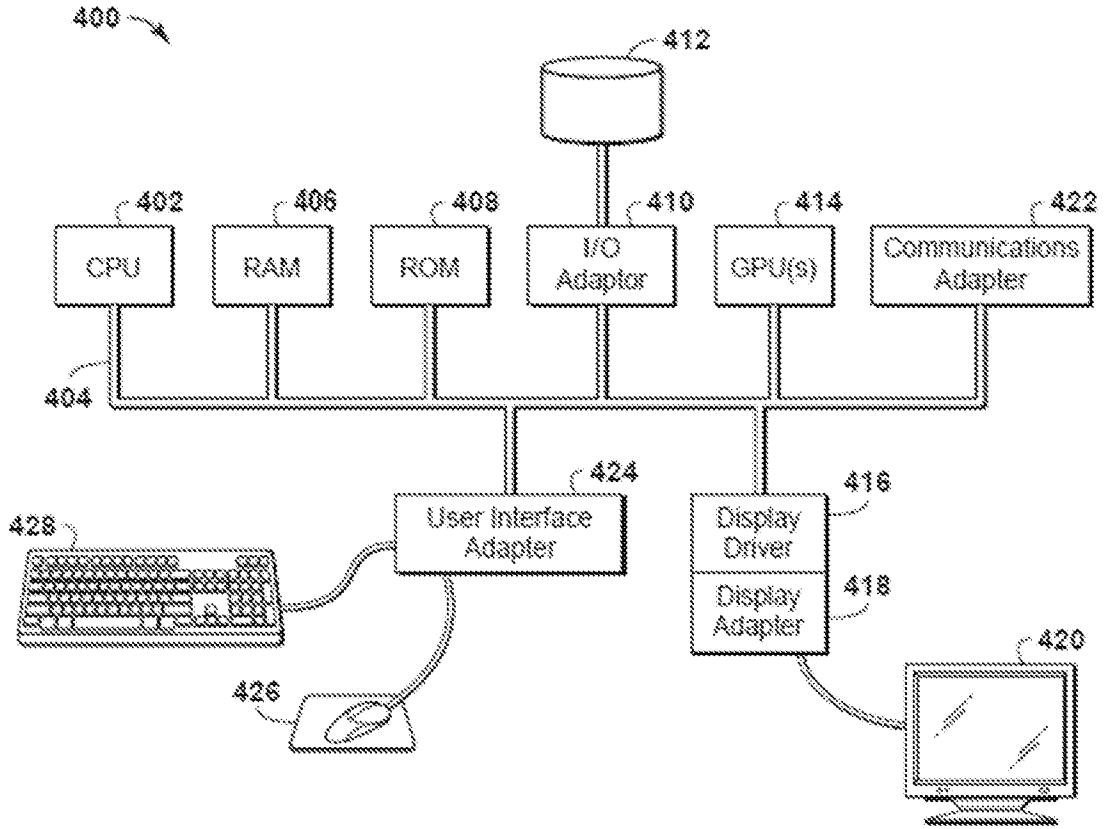


Figure 4

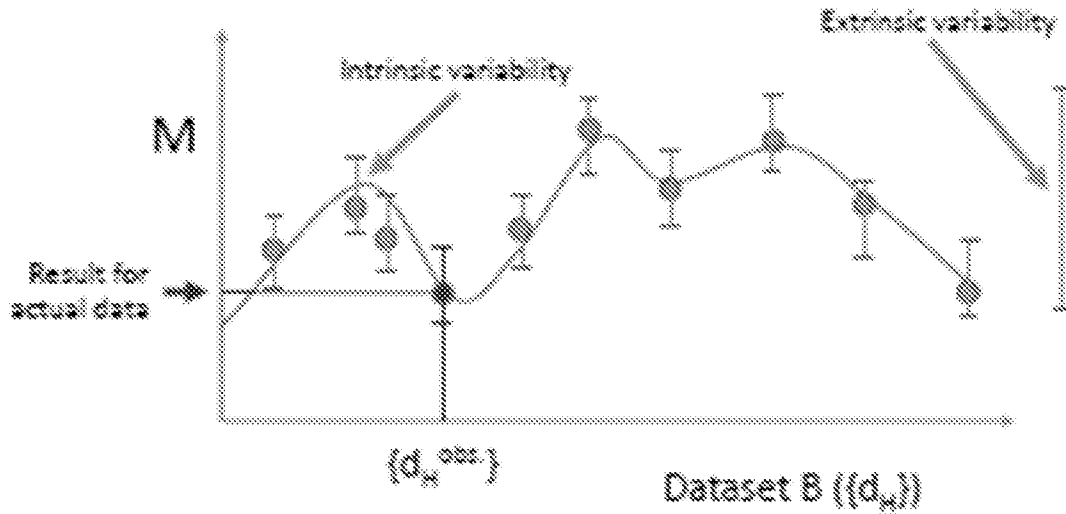


FIGURE 5

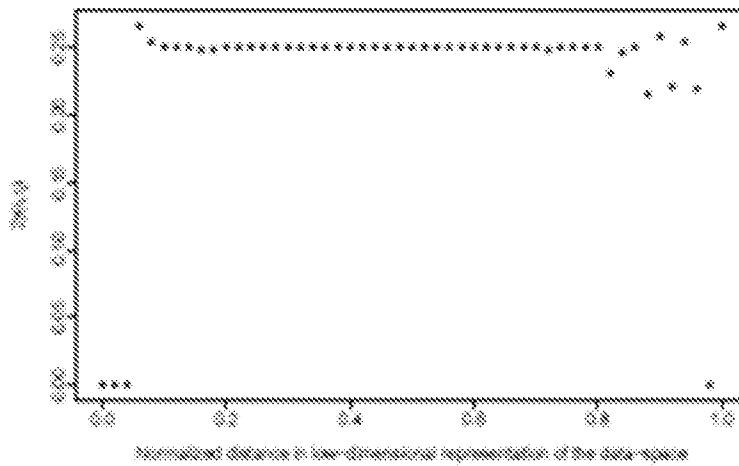
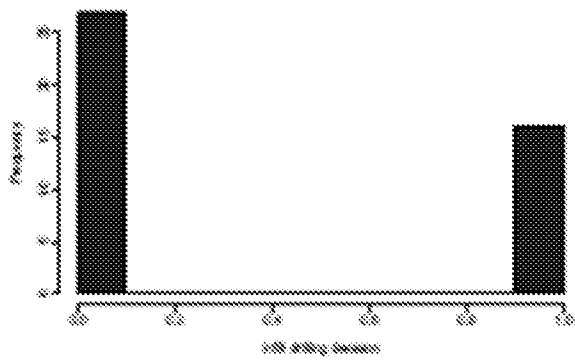
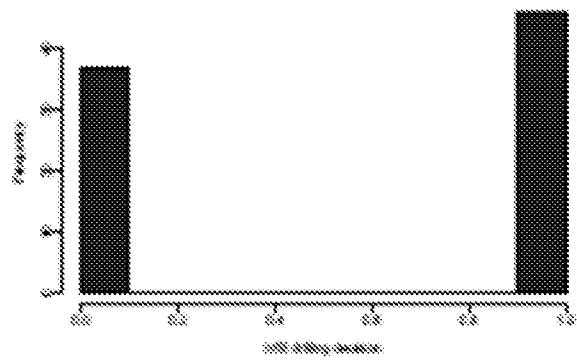


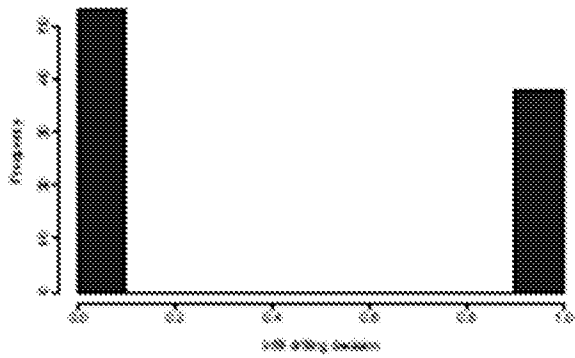
FIGURE 6



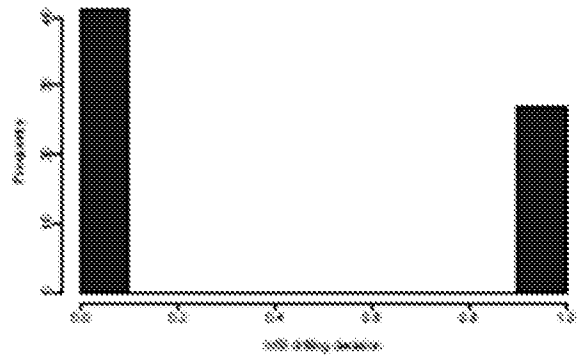
(a) Distribution within cluster #1



(b) Distribution within cluster #2



(c) Distribution within cluster #3



(d) Distribution within cluster #4

FIGURE 7

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2019/067764

A. CLASSIFICATION OF SUBJECT MATTER
INV. E21B41/00
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, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	WO 2018/125760 A1 (EXXONMOBIL UPSTREAM RES CO [US]; HALSEY THOMAS C [US] ET AL.) 5 July 2018 (2018-07-05) page 1 - page 38; figures 1-4 -----	10-18

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 7 April 2020	Date of mailing of the international search report 20/04/2020
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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 Hennion, Dmitri
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INTERNATIONAL SEARCH REPORT

International application No.
PCT/US2019/067764

Box No. II Observations where certain claims were found unsearchable (Continuation of item 2 of first sheet)

This international search report has not been established in respect of certain claims under Article 17(2)(a) for the following reasons:

1. Claims Nos.: 1-9
because they relate to subject matter not required to be searched by this Authority, namely:
see FURTHER INFORMATION sheet PCT/ISA/210
2. Claims Nos.:
because they relate to parts of the international application that do not comply with the prescribed requirements to such an extent that no meaningful international search can be carried out, specifically:
3. Claims Nos.:
because they are dependent claims and are not drafted in accordance with the second and third sentences of Rule 6.4(a).

Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

1. As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.
2. As all searchable claims could be searched without effort justifying an additional fees, this Authority did not invite payment of additional fees.
3. As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos.:
4. No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims; it is covered by claims Nos.:

Remark on Protest

- The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.
- The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.
- No protest accompanied the payment of additional search fees.

FURTHER INFORMATION CONTINUED FROM PCT/ISA/ 210

Continuation of Box II.1

Claims Nos.: 1-9

1.1 The subject-matter of claims 1-9 is such that the International Searching Authority is not required, under the Regulations, to establish a written opinion concerning novelty, inventive step and industrial applicability (Article 34(4)(a)(i)). 1.2 Although independent claim 1 relates to a method for evaluating and performing a hydrocarbon operation for a subsurface region, the method does not disclose any step related to the hydrocarbon operation itself nor does it disclose any other step comprising technical character. The subject-matter of claim 1 therefore relates to a purely mental act and falls under Rule 67.1(iii) PCT. 1.3 It is reminded that the International Search Authorities have divergent practice concerning the examination of such claims. Under the Agreement between the EPO and WIPO (PCT-EPO Guidelines G-II.3), claims concerning mathematical theories or purely mental acts fall within the EPO's discretion to exclude matter which would be excluded under Art. 52(2)(c) and Art.52(3) EPC. Sections G-II.3.3 and G-II.3.5 in the Guidelines for Examination in the EPO apply *mutatis mutandis*.

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No

PCT/US2019/067764

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
WO 2018125760 A1	05-07-2018	CA 3043756 A1	05-07-2018
		EP 3563030 A1	06-11-2019
		US 2018188403 A1	05-07-2018
		WO 2018125760 A1	05-07-2018
