A review on closed-loop field development and management

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Abstract

Closed-loop field development and management (CLFDM) is defined as a periodic update of an uncertain field model using the latest measurements (data assimilation), followed by production optimization aiming mainly at maximizing the field economic value. This paper provides a review of the concepts and methodologies in the CLFDM. We first discuss different types of uncertainty encountered in field development and management. Then, concepts, components, and elements of CLFDM are presented. We then discuss and compare different automated methodologies for data assimilation, followed by explaining a hierarchy of different decision variables for production optimization including design variables (G1), life-cycle control rules (G2L), short-term controls (G2S), and revitalization variables (G3). We continue with explanations for the use of closed-loop in both the development and management phases of a field project. We also discuss and compare different methodologies for production optimization. Afterwards, objective functions for production optimization are presented, followed by the description of concepts and different approaches for selecting representative models to speed up solutions. This paper also highlights the necessity of integrated modeling of reservoir and production systems in CLFDM, and also the need for a standardized stepwise approach to apply the CLFDM by discussing one method from the literature. Finally, we summarize all the previous CLFDM studies on the basis of aspects covered in this paper, and suggest open areas for future research to enhance the use of CLFDM.

Key words: uncertainty reduction, field development, field management, closed-loop, data assimilation, production optimization.

Mirzaei-Paiaman, A., Santos, S. M., & Schiozer, D. J. (2021). A review on closed-loop field development and management. *Journal of Petroleum Science and Engineering*, 201, 108457.
https://dx.doi.org/10.1016/j.petrol.2021.108457

1. Introduction

The productive life of oil and gas fields usually spans over several decades, possibly containing several stages of development and management (e.g., Masjed Soleyman oil field in Iran has been on production since 1908). Such a long life is inherently associated with unforeseen economic, operational and technological events. Also, the geological and reservoir engineering characteristics of underground oil and gas bearing formations are initially highly uncertain and their uncertainty decreases over time only when new measurements and data gradually become available. All these factors collectively complicate the process of decision-making for selection of a proper production strategy (sometimes also called exploitation strategy, development plan, production plan, control strategy, or control settings). By production strategy we mean a guide for development or management of a given field, such as drilling sequence of wells, wells opening sequence, production/injection controls (volumes and pressures), position of wells, among others. As a result, it is not feasible to operate a field using a constant production strategy throughout its whole life. Over the field life, as our knowledge of reservoir properties increases through data assimilation processes, and also other influencing economic, operational and technological factors vary, such a strategy (or control) should be repeatedly revised in a closed-loop fashion to obtain an optimized production strategy that fits the operator objectives. As with Schiozer et al. (2019), we adopt the terminology ‘closed-loop field development and management’ (CLFDM) which, as we will present later in Section 6, is a broader category containing closed-loop reservoir management (CLRM) (Jansen et al., 2005, 2009) and closed-loop field development (CLFD) (Shirangi and Durlofsky, 2015; Shirangi, 2019).

Although the petroleum engineering literature associated with individual tasks of data assimilation and production optimization is very extensive (e.g., Zakirov et al., 1996; Floris et al., 2001; Yeten et al., 2002, 2003, 2004; Wen, 2006; Alhuthali et al., 2008; Maschio and Schiozer, 2008, 2015, 2016, 2019; Oliver and Chen, 2010; Glegola et al., 2012; Hanea et al., 2015; Jesmani et al., 2016; Jahandideh and Jafarpour, 2019), the parent class which is CLFDM has received a lesser attention and is the subject of this paper.

To the best of our knowledge, the first publication on life-cycle closed-loop practice was by Brouwer et al. (2004) where they applied a combination of the ensemble Kalman filter technique for data assimilation and an automated adjoint-based optimization algorithm at 10 points in time

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aiming at improving life-cycle net present value (NPV) of a water flooding project in small and simple 2D models with conventional wells. After each data assimilation step, the mean distribution of permeability field of 100 realizations was used in the optimization process, based on which the optimum injection and production strategy was calculated for the entire remaining producing period. The early work of Brouwer et al. (2004) was followed by other studies exercising life-cycle closed-loop with practice of production control in small 2D or 3D synthetic models containing a single or a few wells (conventional or intelligent) with permeability as the sole type of uncertainty and by applying a nominal optimization on a mean of permeability realizations or robust optimization over a limited number of models (Overbeek et al., 2004; Sarma et al., 2005, 2006; Aitokhuehi and Durlofsky, 2005; Nævdal et al., 2006; Chen et al., 2009; Jansen et al., 2009; Wang et al., 2009; Hui et al., 2011). These studies evolved over time to consider a more complex set of problems such as 3D real field/benchmark cases equipped with intelligent wells including diverse types of geological and reservoir engineering uncertainties where optimal robust or specialized solutions for field development and management have been presented by studying an intensive ensemble of models and a various sets of decision variables (Sarma et al., 2008; Lorentzen et al., 2009; Chen and Oliver, 2009; Alhuthali et al., 2009; Chen et al., 2010; Peters et al., 2010; Shirangi, 2013; Bukshtynov et al., 2015; Shirangi and Durlofsky, 2015; Schiozer et al., 2015; Hidalgo et al., 2017; Morosov and Schiozer, 2017; V.L.S. Silva et al., 2017; Elfeel et al., 2018; Jahandideh and Jafarpour, 2018; Hanea et al., 2019; Schiozer et al., 2019; Shirangi, 2019; Jahandideh and Jafarpour, 2020; Barros et al., 2020).

Literature studies have used a vast variety of methodologies and procedures in their closed-loop exercises. This necessitates conducting a comprehensive review of different aspects of closed-loop studies. There are several review papers on this subject (Jansen et al., 2009; Van den Hof et al., 2012; Hou et al., 2015; Benndorf and Jansen, 2017; Udy et al., 2017; Khor et al., 2017), however they mainly address mathematical algorithms of data assimilation and production optimization. This paper emphasizes more on those studies that bring together and apply the aforementioned two tasks of data assimilation and production optimization in closed-loop. Our focus is on concepts, applications, methodologies and procedures within CLFDM. In this regard, this combined overview-review paper is first of its kind as it presents a comprehensive overview of the closed-loop process and review of the previous works.

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2. Uncertainty in field development and management

Decision-making for selection of a proper production strategy in field development and management is a complex task and should include the risk associated to several types of uncertainties (Schiozer et al., 2004, 2017; Santos et al., 2017a,b,c). Disregarding important types of uncertainty in decision-making processes can lead to an apparent optimal production strategy that may be far from the actual optimal solution. It may also cause biased forecasts of performance (Meddaugh and Champenoy, 2012; Meddaugh et al., 2017; Botechia et al., 2018). At the same time, it may not be technically feasible to include all types of uncertainties in the modeling problem as it may become super-complicated. As a result, there should be a compromise between level of uncertainties considered and the reliability (i.e., optimality) of the obtained solution. Generally, the decision of which uncertainties to incorporate in modeling studies may be stage-, field-, country- or company-specific, and different types of uncertainty may have dissimilar impacts on the decision-making outcomes.

In the literature, different terminologies and definitions have been used occasionally for types of uncertainty (e.g., Ligero et al, 2003; Schiozer et al., 2004; Zabalza-Mezghani et al., 2004; Almeida et al., 2010; Correia et al., 2015; M.I.O. Silva et al., 2017; Santos et al. 2018a,b; Schiozer et al., 2015, 2019; Gomes et al., 2019; Mahjour et al., 2019; Jahandideh and Jafarpour, 2020; Santos et al., 2020). In this paper, we present a new classification of uncertainties in field development and management (Figure 1).

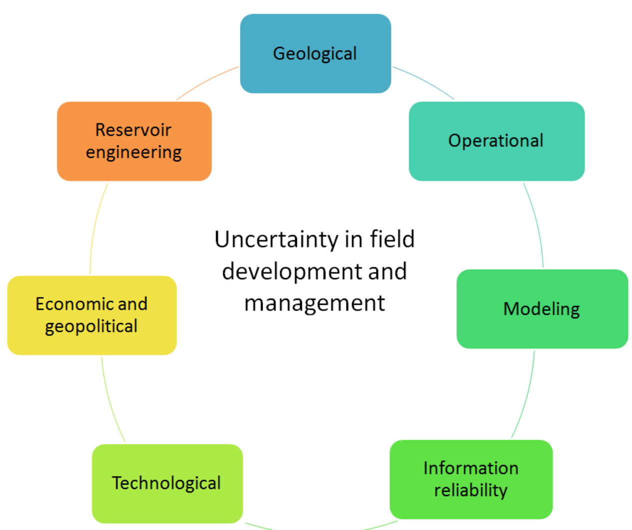

Figure 1: Types of uncertainty in field development and management

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The following definitions may describe each type of uncertainty.

2.1. Reservoir and Fluid

2.1.1. Geological

By geological uncertainty we refer to the lack of knowledge in the properties related to the static model, including petrophysical properties (e.g., facies, permeability, porosity and net to gross (NTG) ratio), structural framework (e.g., reservoir boundaries, layer continuity and thickness), and those associated with discontinuities within a geological formation (e.g., fault and fracture network). The gird properties considered in this definition are represented by spatial distributions and do not include the properties affected by rock and fluid interactions (such as relative permeability, capillary pressure, and wettability). Regarding the geological uncertainties, the literature in closed-loop has only studied petrophysical properties. Such works range from those considering only permeability maps (Brouwer et al., 2004; Overbeek et al., 2004; Aitokhuehi and Durlofsky, 2005; Sarma et al., 2005, 2006, 2008; Nævdal et al., 2006; Jansen et al., 2009; Chen et al., 2009; Wang et al., 2009; Hui et al., 2011; Shirangi, 2013,2019; Shirangi and Durlofsky, 2015) to those considering both permeability and porosity (Aitokhuehi and Durlofsky, 2005; Wang et al., 2009; Hanea et al., 2019; Jahandideh and Jafarpour, 2018, 2020) and to those considering permeability, porosity and NTG (Chen and Oliver, 2009; Lorentzen et al., 2009; Alhuthali et al., 2009; Chen et al., 2010; Peters et al., 2010; Bukshtynov et al., 2015; Hidalgo et al., 2017; Morosov and Schiozer, 2017; V.L.S. Silva et al., 2017).

2.1.2. Reservoir engineering

This type of uncertainty also refers to the lack of knowledge but deals with any reservoir property that is not within the geological uncertainties, for instance, fluid properties and relative permeability. Examples of previous closed-loop studies accounting for reservoir engineering uncertainties are Chen and Oliver (2009), Peters et al. (2010), Hidalgo et al. (2017), Morosov and Schiozer (2017), V.L.S. Silva et al. (2017) and Hanea et al. (2019).

2.2. Performance Evaluation

2.2.1. Economic and geopolitical

This kind of uncertainty relates to market variables (e.g., oil price), capital expenditures (e.g., equipment purchasing costs), operational expenditures (e.g., fluids handling costs, operational costs), embargos and sales issue, among others, which are affected by various geopolitical, technological, market, and economic factors.

2.2.2. Technological

This type of uncertainty deals with future potential technological advances that may leverage implementation of new changes (e.g., shorter drilling and completion times), enhance recovery of hydrocarbons (e.g., new materials in enhanced oil recovery projects, new lifting methods, and advanced completions), among others.

2.3. Other uncertainties

2.3.1. Information reliability

This is related to the uncertainty associated with the measurements, which arises from the degree of precision of measurement tools (e.g., seismic data, well logs, well tests, production and pressure measurements). Examples of previous closed-loop papers that have considered uncertainty in the measurement by adding noise to the data during data assimilation are Brouwer et al. (2004), Overbeek et al., (2004), Nævdal et al. (2006), Chen et al. (2009), Chen and Oliver (2009), Jansen et al. (2009), Wang et al. (2009), Lorentzen et al. (2009), Alhuthali et al. (2009), Chen et al. (2010), Peters et al. (2010), Hui et al. (2011), Bukshtynov et al. (2015), Shirangi (2013, 2019), Shirangi and Durlofsky (2015), Hidalgo et al. (2017), Morosov and Schiozer (2017), V.L.S. Silva et al. (2017), Hanea et al. (2019), and Jahandideh and Jafarpour (2018, 2020).

2.3.2. Modeling

This refers to the effect of simplifications or doubt in reliability of any kind of computational method, equation, algorithm, mathematics, among others, that is used in the entire process of production strategy selection based on simulation models (see for example, Mirzaei-Paiaman et al., 2018, 2019a,b,c).

2.3.3. Operational

Operational uncertainty targets the reliability and availability issues and includes a broad range of failures and delays that can halt a continuing production or injection or change the operational conditions. Examples of operational uncertainties are technical or mechanical failures in equipment and facilities (e.g., inflow control valves (ICV) of intelligent wells, downhole/surface pumps, packers, injection pumps, surface separators and production units), well integrity issues (e.g., casing collapse and internal leaks), natural disasters, market availability issues (e.g., inadequate quantities of rigs, pumps, infrastructure, fluids volumes), among others. Examples of accounting for operational uncertainty in closed-loop studies are Jahandideh and Jafarpour (2018, 2020).

Table 1 gives the detailed classification of uncertainties in field development and management and contains more examples for each type of uncertainty.

Table 1: Detailed classification of types of uncertainty in field development and management

Type of uncertainty	Reservoir and fluid		Performance evaluation		Other		
	Geological	Reservoir engineering	Economic and geopolitical	Technological	Information reliability	Modeling	Operational
Examples	•Structural framework and discontinuities (reservoir boundaries, layers top and bottom, faults, fracture network) •Petrophysical properties (facies, permeability, porosity, net-to-gross)	•Fluid properties •Aquifer strength •Rock-fluid properties (e.g., relative permeability and capillary pressure) •Hydraulic communication between layers •Fault transmissibility •Fluids contact levels •Reservoir pressure •Fluids saturation	•Oil price •Operational expenditures (OPEX) •Capital expenditures (CAPEX) •Lack of investment •Embargos and sales issues	•New EOR materials and fluids •New completions •New lifting methods •New fluids separation technologies	•Seismic data •Production volumes •Injection volumes •Bottom hole pressures •Fluid properties •Well logs •Production logs	•Flow equations •Numerical techniques •Upscaling methods •Simulation methodologies •PVT equations	•Well integrity issues •Failure in ICVs •Failure in ESPs •Natural disasters •Market availability (e.g., rig, ESP, ICV) •Injection fluid availability •Gas export infrastructure

3. CLFDM components

Generally, CLFDM takes place over multiple cycles or loops. But basically, exercising at least two cycles names a process as a closed-loop. Usually, the literature describes closed-loop as a two-component process, comprising of a data assimilation task followed by a production optimization part in each cycle (e.g., Jansen et al., 2009; Chen et al., 2012). In some works, cycles within a closed-loop have also been described as a three-component process. Sarma et al. (2008) considered optimization, model updating, and uncertainty propagation as three components of a CLRM approach. Shirangi and Durlofsky (2015) described a CLFD with three components of optimization, execution and measurement, and data assimilation. We describe closed-loop as a four-component process, in which each cycle contains the below actions.

(1) Measurement: acquiring new information (e.g., production/injections volumes, well logs, and seismic data);
(2) Data assimilation: updating uncertain field simulation models;
(3) Production optimization and decision-making: selection of an optimal production strategy through an optimization study (e.g., selection of number, position and type of future wells, and control settings of existing and future equipment);
(4) Implementation (or operation/execution): operating the field with the selected guide production strategy (e.g., drilling new wells, and changing well controls).

The basic concept of closed-loop is shown in Figure 2. In this figure and all other figures presented hereafter, we adopt the color codes that are in accordance with the colors used in the Schiozer et al.'s 12-step methodology for decision analysis in CLFDM (this methodology will be reviewed later in Section 11). As depicted in this figure, we are dealing with two systems: (1) System 1, which comprises a set of fit-for-purpose simulation models (front of the scenes), and (2) System 2, which represents a real field (behind the scenes) sometimes called true model, reference model, or virtual asset model containing one or more reservoirs, wells and surface facilities (Jansen et al., 2005, 2009; Schiozer et al., 2015, 2019). In literature papers, System 2 is normally substituted by synthetic benchmark models to show use of the closed-loop methodology. Usually, the uncertainties in geological and reservoir engineering properties are modeled by generating a collection of reservoir models. Fit-for-purpose models with varying degrees of fidelity are the upscaled version of fine-grid and detailed geological models (Schiozer et al., 2015, 2019). The degrees of fidelity of fit-for-purpose models is case dependent, reflecting the best cost-benefit relation between required precision and available computational infrastructure and time. During the measurement phase, information and data are collected from a real field and then used to revise and also calibrate the fit-for-purpose simulation models in a process called data assimilation with the aim of arriving at more certain simulation models with less geological and reservoir engineering uncertainties. Afterwards, optimization and decision-making process takes place on System 1 to obtain an optimal production strategy. Later, the output production strategy or control will be executed on System 2. This closed-loop process of measurement, data assimilation, optimization and control will then be repeated over the life of a field, creating a cyclic design.

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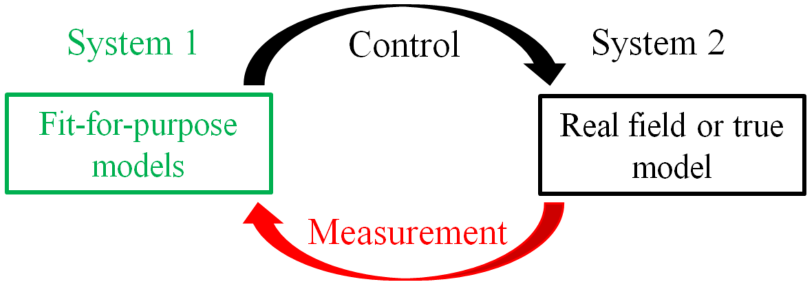

Figure 2: A basic conceptual demonstration of CLFDM

A detailed closed-loop diagram containing multiple cycles and the constituting elements is demonstrated in Figure 3. In cycle one, all available information (called observation) which could be the prior geology knowledge (from exploration and appraisal wells and seismic data) plus the soft (i.e., production and injection data) and hard information (i.e., well logs, coring samples, among others) obtained from the first wells are used to build and calibrate (i.e., data assimilation) the primary fit-for-purpose simulation models. These models are then used to find the best production strategy (i.e., PS1) for the rest of the field life. As such, a production strategy is found by running the optimization problem over the remaining entire life of the field, and we refer to it as life-cycle production strategy. Generally, a production strategy gives information regarding the decision variables in which a field can be operated under, such as number, type and position of future wells, production and injection settings of existing and future wells, among others. The selected production strategy is then executed on the field. Depending on the type of the decision variables considered in the optimization part, such an execution could vary from simple and relatively fast changes in production and/or injection control settings of wells to complex and time consuming changes in infrastructure of a field like platforms and surface facilities, drilling and completion of future wells, etc.

From reservoir engineering point of view, the optimization task in cycles of a closed-loop process may also be designed to obtain an optimal solution for a short-term period, in order of years (e.g., van Essen et al., 2011; Chen et al., 2012; Elfeel et al., 2018). This is different from the previous standard type where field operations were optimized for the rest of the field life (i.e., life-cycle production optimization). The earlier workflow shown for CLFDM can be modified accordingly in the case of sequential short-term production optimization after each data assimilation step (Figure 4). It should be stressed that likewise the life-cycle optimization, the short-term optimization is model-based and different from data-driven practices.

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Throughout the field life, as more information is acquired (i.e., new measurements), like production/injection volumes, well logs, well tests, production logging, seismic, such information could be used to revise the reservoir models and further reduce the uncertainties of the simulation models through a new data assimilation practice. Thus, less uncertain models will provide basis for better field behavior forecasts. At the data assimilation practice, if necessary, one may go to the high fidelity models in a process named Big loop to correct or update those models or the upscaling methods (Hanea et al., 2015; Schiozer et al., 2015, 2019). The above-mentioned process of measurement, data assimilation, production optimization and execution will then be performed at different times within the field life. As this cyclic process continues, our knowledge of field geological and reservoir engineering properties increases, which is normally translated into a continuous reduction in the underlying uncertainties. However, some complex field development cases may be encountered where such an increase in our knowledge may lead to increase in uncertainties in one cycle compared to the previous one.

Within a given cycle, when the field has been decided to be operated under a specific production strategy, depending on the received information (such as sudden changes in oil prices) the production strategy may be altered at any time without performing the so-called data assimilation and production optimization parts. The resulting short-term altered production strategy (i.e., APS) will then govern the field conditions until the next cycle.

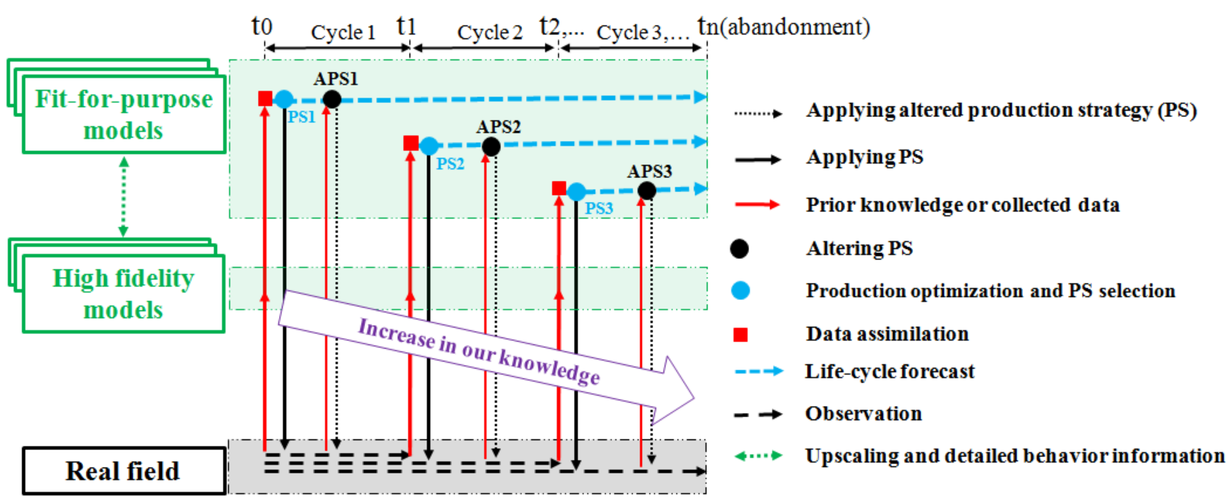

Figure 3: A detailed diagram of CLFDM and its elements where, at each cycle, a life-cycle production strategy is obtained

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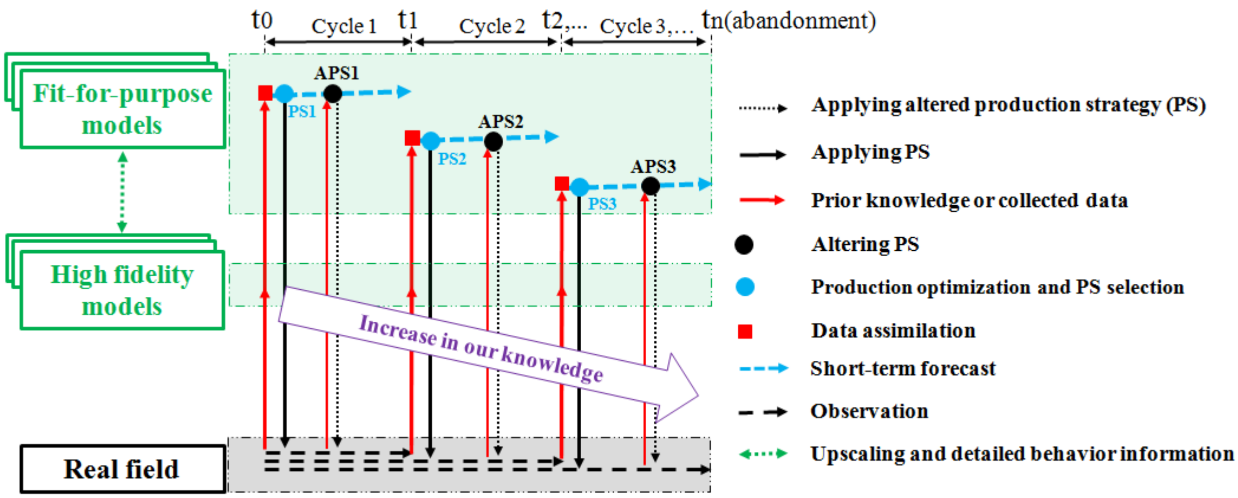

Figure 4: A detailed diagram of CLFDM and its elements where, at each cycle, a short-term production strategy is obtained

3.1. Cycle duration in CLFDM

In real field cases, operators need to collect, check the quality, analyze and interpret necessary measurements for updating reservoir models. While some data may be acquired daily, others may become available monthly or even yearly, depending on the type and nature of measurement. In addition, data assimilation, production optimization and decision-making tasks are usually computationally time consuming and need times in the order of weeks, months or even years, depending on the type, quantity and quality of measured data, type and level of uncertainty, number of the reservoir models, number of the decision variables, computational and simulation hardware, human resources availability, among others.

Generally, implementing the selected production strategy and the corresponding changes in the field settings also need times in the order of months, depending on several factors. As a result, the choice of cycle duration in practical closed-loop processes is affected by many factors and is case-dependent. Thus, the technology available and the infrastructure implemented today in fields do not allow a closed-loop process in real time, but companies seek to attain it aiming to approach to digital field concepts.

However, the detrimental effects that time delays have on attainable performance should be avoided (Foss, 2011). Repeating the process in closed-loop should be performed when all requirements are met, as soon as possible. It should be noted that in situations where simulation model predictions match the real field responses there may be no need to go for a new cycle and it may be wise to continue operating the field under the current production strategy. However, in cases where simulation model predictions are significantly far from the real responses, the production strategy should be revised through performing a new cycle (Abreu et al. 2015; Bertolini et al., 2015; Bertolini and Schiozer, 2016).

Chen and Oliver (2009) in their closed-loop reservoir management on Brugge benchmark case (Peters et al., 2010), where 10 years of initial history data for conventional wells were available and closed-loop was exercised by using intelligent wells at years 10, 11, 12, 13, 14, 16, 18 and 20, noticed that more frequent updating of controls generally did not make a significant difference in the NPV value. In their case study, the NPV value benefitted from a shorter interval after application of initial controls at year 10 where all wells were equipped with ICVs. Thus, it is our impression that a kind of time refinement is needed when deciding the duration of a cycle. In times immediately following a significant change (here installing ICVs), shorter time cycles may be preferred.

In the literature, different choices have been used for cycle durations. Some have used fixed cycle duration, whereas others have preferred variable cycle durations (i.e., different cycles have different durations).

(1) Fixed cycle duration: in Lorentzen et al. (2009), Peters et al. (2010) and Chen et al. (2010) cycle duration of 10 years was used, whereas Bukshtynov et al. (2015) and Jahandideh and Jafarpour (2018, 2020) repeated cycles every 1 year. Hui et al. (2011) used fixed cycle durations of 120 days, while Shirangi (2019) used 180 days, Shirangi (2013) 210 days, Shirangi and Durlofsky (2015) 210 days, and Morosov and Schiozer (2017)4 months. Aitokhuehi and Durlofsky (2005) considered two experiments, where fixed cycle durations of 200 and 240 days were used. Wang et al. (2009) also considered two experiments with fixed cycle durations of 4 and 6 months. Jansen et al. (2009) studied several experiments of fixed cycle duration where cycle durations of 30 days, 1, 2 and 4 years were used. Hanea et al. (2019) performed three experiments each with cycle duration of 6 months, 1 year and 2 years.

(2) Variable cycle duration: Brouwer et al. (2004), Overbeek et al. (2004) and Naevdal et al. (2006) used cycle durations in the order of days, weeks, and months, whereas in Sarma et al. (2005, 2006) and Chen et al. (2009) cycle durations was in the order of months. Cycle

duration in Sarma et al. (2008) and Hidalgo et al. (2017) were in the order of months and years. Furthermore, Chen and Oliver (2009) and V.L.S. Silva et al. (2017) adopted cycle durations in the order of years. It is worth mentioning that some of these studies intentionally used unrealistic very short cycle durations, mainly because of repeatability and computational time aspects.

3.2. True model in closed-loop papers

As described earlier, the measured data collected from a true model are needed in the data assimilation process to reduce the geological and reservoir engineering uncertainties. In a real field case, such a true model is a reservoir with unknown characteristics and the measurements become available gradually over time only at the cost of implementing a production strategy. Also, a real field can undergo only one final production strategy at a given time, and the choice of the production strategy affects the value of measurements.

However, for the sake of research on CLFDM, the literature papers usually assume a synthetic reservoir with known properties as a true model. Such a synthetic true model will be used to evaluate production strategies and also generate the necessary measurements for the purpose of data assimilation. The advantage of this approach is that the components of production strategy execution and measurement are easy to handle, flexible and fast. Furthermore, various production strategies can be implemented at a given time to observe the model response to each of them. Since, in reality, the built simulation models are usually simplified forms of a detailed and complex underground reservoir, a synthetic true model should ideally have a higher fidelity than simulation models, i.e., they should have different flow characteristics. For example, a true case is recommended to use finer grid cells than simulation models.

Review of literature papers on CLFDM shows that the above-mentioned necessary condition for true model has sometimes been overlooked. For example, in Aitokhuehi and Durlofsky (2005), Sarma et al. (2005, 2006, 2008), Bukshtynov et al. (2015), Shirangi and Durlofsky (2015), and Shirangi (2019) one of the multiple generated geological realizations was used as the true model. In these cases, the true model and simulation models have therefore the same characteristics. There are also cases where the true model has not been one of the realizations, but has had the same characteristics as simulation models (e.g., Brouwer et al., 2004; Nævdal et al., 2006; Wang et al., 2009). Overbeek et al. (2004), Chen and Oliver (2009), Lorentzen et al. (2009), Alhuthali et al. (2009), Chen et al. (2010), Peters et al. (2010), Hidalgo et al. (2017), Morosov and Schiozer (2017), and V.L.S. Silva et al. (2017) practiced CLFDM in the systems where the true model was not one of the realizations, and had different characteristics than simulation models (i.e., fine-grid vs. upscaled coarse-grid). These studies have been done usually on realistic synthetic benchmark cases, such as Brugge (Peters et al., 2010, 2013) and UNISIM-I-D (Avansi and Schiozer, 2015; Gaspar et al., 2015, 2016b).

4. Data assimilation

An inherent component in CLFDM is data assimilation, which is performed in order to reduce the geological and reservoir engineering uncertainties in simulation models by tuning them against the available field responses. Other names such as model updating, model conditioning, model adjusting, parameter estimation, history matching, automated history matching, or computer-assisted history matching have also been used in previous publications.

Usually prior to the data assimilation part, uncertainty is characterized in detail and then hundreds of scenarios are generated using an efficient sampling technique, which reduces the number of evaluations and is suitable for use with numerical reservoir simulation. Schiozer et al. (2019) defined a scenario or model as a particular combination of all possible uncertainties and recommended the Discrete Latin Hypercube with Geostatistical Realizations (DLHG) (Schiozer et al., 2017) for sampling. The DLHG applies the Latin Hypercube Sampling (LHS) and integrates all types of uncertainties in the sampling step, so that continuous attributes are discretized, and then combined with discrete attributes and geostatistical realizations. This sampling technique has also been applied to uncertainty quantification (Schiozer et al., 2017), history matching (Maschio and Schiozer, 2016), and production strategy optimization (von Hohendorff Filho et al., 2016). The sampled or generated models then undergo the data assimilation analysis.

In data assimilation, the collected field data (e.g., well production/injection and pressure data) are used to reduce geological and reservoir engineering uncertainties and thus provide a set of matched models for the production optimization study. In the literature of closed-loop, different approaches have been used for data assimilation, as follows:

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(1) Starting with an ensemble of models but updating the parameters of only a single model to match the field responses (Figure 5B). This single model could be the best fitted model (see e.g., Halliburton approach in Peters et al. (2010)), or simply one of the models of an ensemble (see e.g., Bukshtynov et al. (2015) and Stanford/Chevron approach in Peters et al. (2010)). This single matched model then will be used in the production optimization part.

(2) Adjusting and updating parameters of all models to match the history data (Figure 5C). This is the method that has been widely used in the previous closed-loop studies (Brouwer et al., 2004; Overbeek et al., 2004; Aitokhuehi and Durlofsky, 2005; Sarma et al., 2005, 2006, 2008; Nævdal et al., 2006; Chen and Oliver, 2009; Chen et al., 2009; Jansen et al., 2009; Wang et al., 2009; Lorentzen et al., 2009; Alhuthali et al., 2009; Chen et al., 2010; Roxar, SIEP and TAMU approaches in Peters et al. (2010); Hui et al., 2011; Shirangi, 2013, 2019; Shirangi and Durlofsky, 2015; Hidalgo et al., 2017; V.L.S. Silva et al., 2017; Hanea et al., 2019; Jahandideh and Jafarpour, 2018, 2020). In this approach, the problem is formulated in the form of a minimization problem where the misfit between measurements and model forecast should be minimized. Some studies have then proceeded with the mean of the updated models for the production optimization, such as Brouwer et al. (2004), Overbeek et al. (2004), Nævdal et al. (2006), Jansen et al. (2009), Chen et al. (2010), SIEP approach in Peters et al. (2010), and V.L.S. Silva et al. (2017), whereas some other researchers have preferred using the central model (Wang et al. 2009) or the maximum likelihood estimate of the parameter (Sarma et al. 2006), or the best updated model (Roxar approach in Peters et al. (2010)), or one of the updated models (Hui et al., 2011). To reduce the computational efforts, some studies have proceeded with a set of representative models instead of the all updated models, selected either randomly (Lorentzen et al., 2009; Alhuthali et al., 2009; TAMU approach in Peters et al. (2010); Shirangi, 2013), or based on other measures for the production optimization such as Shirangi and Durlofsky (2015), Hidalgo et al. (2017), V.L.S. Silva et al. (2017) and Shirangi (2019). Aitokhuehi and Durlofsky (2005), Sarma et al. (2005, 2008), Chen and Oliver (2009), Chen et al. (2009), Hanea et al. (2019) and Jahandideh and Jafarpour (2018, 2020) used all of the updated models for the production optimization.

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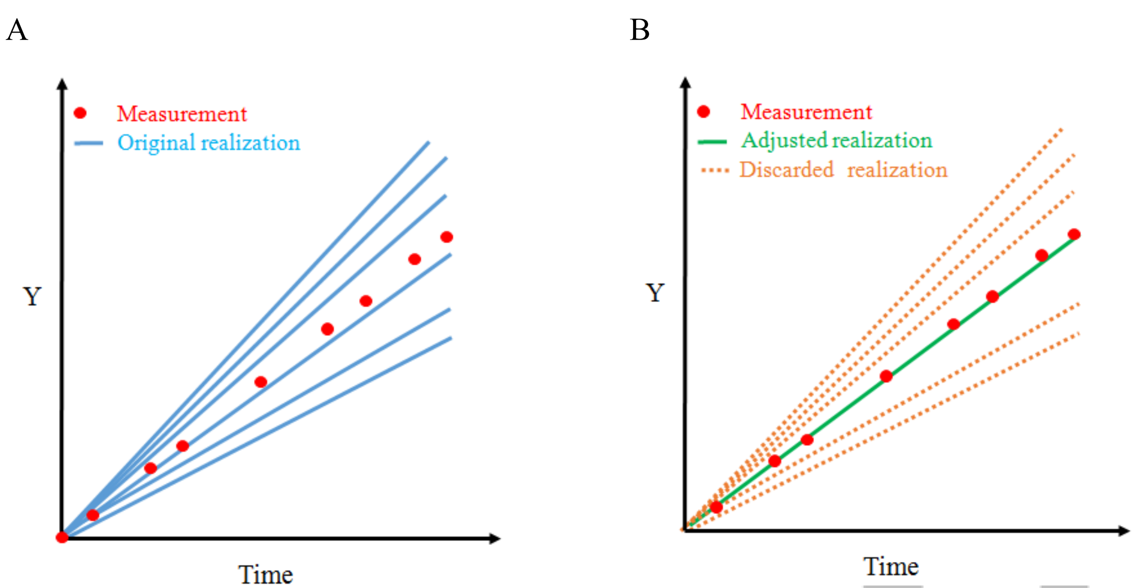
(3) Iterative procedures of uncertainty reduction to find the best fitting models (Figure 5D). In this case, usually a filtering technique is performed to select those models that match the field measurements, and others are discarded (Avansi and Schiozer, 2015). In this approach, some studies have proceeded with the best fitted model for the next step (e.g., Schlumberger approach in Peters et al. (2010)). Another choice is to proceed with a set of representative models (Morosov and Schiozer, 2017) instead of the all fitted models. Another possible choice could be continuing with the mean of the fitted models.

During data assimilation, and to account for the uncertainty related to information reliability, one should consider a tolerance for each kind of data by adding a realistic noise to the measured data. Also, overfitting of models to the measurements should be avoided, as it may ignore the uncertainty in the measured data. As stated by Brouwer et al. (2004), the overfitted models may reproduce the history data perfectly, but have no predictive power because they have been obtained by adjusting a large number of unknown parameters using a too small number of field measurements.

In the above discussions, in each cycle within a closed-loop process, data assimilation is followed by an optimization part. Alhuthali et al. (2008) discussed another approach, named measurement-based-optimization (MBO), where the history data were incorporated in the optimization process by giving different weight to multiple models.



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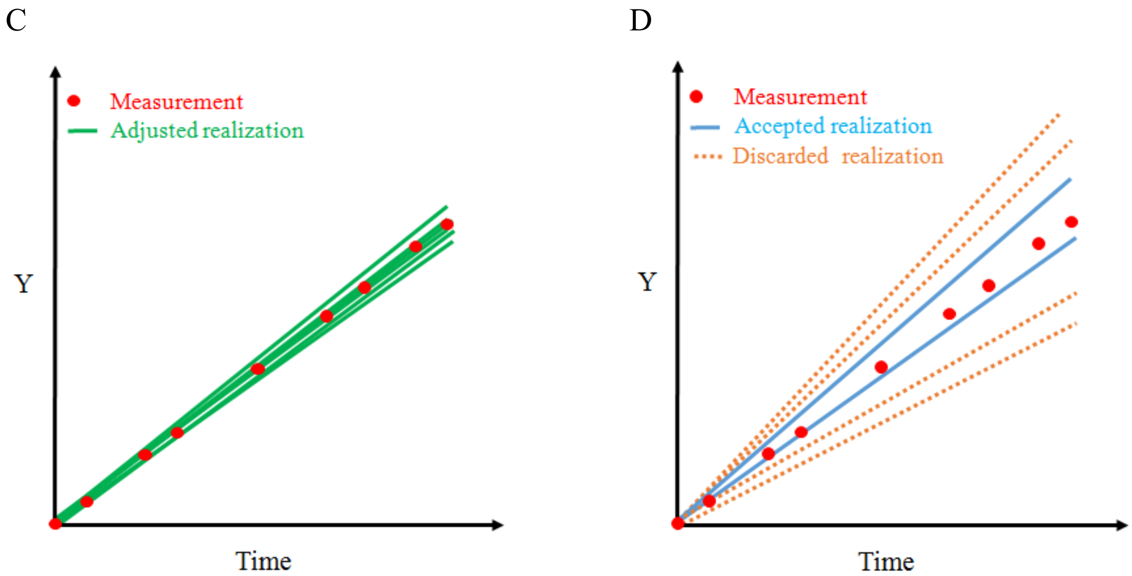

Figure 5: Illustration of the different approaches for data assimilation used in the literature of closed-loop studies. A: an original ensemble, B: finding the best fitting model to the history measurements followed by updating its parameters, C: Adjusting parameters of all models, and D: finding the best fitting models and discarding the remaining models. In this figure, Y is an example for dynamic performance indicators

5. Decision variables in production optimization

Production optimization is an inherent component in each cycle of a closed-loop process, where a set of decision variables (other names include optimization variables, control decisions, control variables) is optimized with the goal of maximizing or minimizing an objective function(s) over a specific time horizon (either life-cycle or short-term). The choice of decision variables used for the production optimization depends on several factors such as the phase of field project (i.e., development or management), recovery mechanisms, field location (i.e., onshore or offshore), well completion complexity (i.e., conventional or intelligent), among other factors.

Gaspar et al. (2016a) provided a comprehensive and detailed definition and classification of different decision variables in the production optimization. A shorter and different classification of decision variables, mainly based on occurrence at different project stages, was also presented by Benndorf and Jansen (2017). The classification and definitions made by Gaspar et al. (2016a) are preferred because of their generality and comprehensiveness. Gaspar et al. (2016a) proposed engineering analyses to hierarchically order variables and organize the optimization steps based on the impact of the parameters on the objective function(s). They defined three groups for decision variables as:

(1) Group 1 (G1): design variables

(2) Group 2 (G2): operation/control variables
(3) Group 3 (G3): revitalization (or future design) variables

Later, Schiozer et al. (2019) outlined the short-term and life-cycle production optimization in a general workflow for closed-loop applications. As a result, G2 category may be further divided into two subclasses of:

(1) Life-cycle control operation rules (G2L) for life-cycle optimization
(2) Short-term controls (G2S) for short-term optimization

Erro! Fonte de referência não encontrada. summarizes a classification of these decision variables and their examples. The definition of each decision variable category is as follows.

5.1. Design variables, Group 1 (G1)

These variables represent the specification of the infrastructure of a field (i.e., the choice of configuration and equipment) before starting field development and have a significant impact on the economic expectation of the field. They need to be defined in order to avoid project delay. These variables normally involve significant investments and can be hardly revised (Gaspar et al., 2016a). Examples of design variables are recovery methods (e.g., water flooding and WAG), size, location and arrangement of surface facilities, number, type (producer or injector) and position of wells, drilling sequence, number, type and position (installation location) of ICVs (Barreto and Schiozer, 2015; Barreto et al., 2016; Morais et al., 2017).

Table 2: Classification of different decision variables in production optimization (Gaspar et al., 2016a; Schiozer et al., 2019)

Decision variable	Group1 (G1) Design variables	Group 2 (G2L and G2S) Operation/control rule and variables	Group 3 (G3) Revitalization variables
Examples	• Recovery method • Number, size, capacity, location and arrangement of surface facilities and production units • Number, type, position, trajectory, completion and pattern of wells • Number, type, position and trajectory of laterals in multi-lateral wells • Number, type and position (installation locations) of ICVs in intelligent wells • Type of artificial lift methods • Well opening schedule • Drilling sequence	• Control valve choke in platform level • Control valve choke in well region level • Control valve choke in well level • ICV control • WAG cycles	• Infill drilling • Well conversion (from producer to injector) • Well stimulation • Well workover and recompletions

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	• Specifications of pipelines, manifolds, and risers		

5.2. Operation/control rules and variables, Group 2 (G2L and G2S)

This category of decision variables represents the operational specifications of hardware over time, and can be flexibly changed at any moment over the field's lifetime without significant costs. They have less, but still significant, impact than design variables (G1) on the expected financial returns of the production strategy. A given infrastructure can only be properly evaluated if an optimized operation of hardware is set up. Contrary to design variables, the definition of G2 variables will not be used to control any equipment immediately, but will be used to properly evaluate the system, representing future conditions (Gaspar et al., 2016a). While G2L variables aim to represent future control operations to allow an adequate evaluation of the life-cycle production strategy, G2S variables refer to control of equipment in short-term and their immediate/real time control in the field (Schiozer et al. 2019). Examples of G2 variables are injection and production rates and pressures, ICV operation and WAG cycles.

5.3. Revitalization variables, Group 3 (G3)

Revitalization variables represent possible future alternatives for fields in the management phase, where a production strategy is implemented. Accommodating future alternatives may minimize the effects of development uncertainties. G3 decision variables, applicable at later stages, may be considered from early stages because they may affect current project design. The variables of this group involve additional investments (Gaspar et al., 2016a). Examples are infill drilling, recompletion and well conversion (producers into injectors).

6. Closed-loop in different phases of a field project

Operating an oilfield, as a physical asset, usually is achieved through several stages or waves in which each stage spans over a certain period of time, normally in the order of years or decades. A given stage usually starts with a development phase with those activities that define infrastructure of a field, such as drilling and completion of new wells, installing production and injection facilities, well connections, among others. Development phase is then followed by a management (or operation) phase. In the management phase, injection and production wells are already drilled and operating (i.e., normally, it does not involve drilling new wells) and no more development activities take place.

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In the literature, the terms CLFD (Shirangi and Durlofsky, 2015; Shirangi, 2019) and CLRM (Jansen et al., 2009) have been widely used to represent closed-loop processes corresponding to the development and management phase, respectively. In these acronyms, 'F' stands for the field, 'R' reservoir, 'D' development, and 'M' management. In this paper, we attempt to standardize such notations. As field is a general name containing all components of a production system including reservoir(s), wellbores, surface gathering/injection networks, and surface facilities (von Hohendorff Filho and Schiozer, 2018), it should be distinguished from reservoir. Thus, the terms CLRD and CLRM may better suite when a reservoir is not integrated with wells and surface facilities in modeling studies. In this context, a more general term CLRDM can account for both these terms. Once such integrated modeling is performed, then the terms CLFD and CLFM may fit the problem statement better. Accordingly, the general term CLFDM can be regarded as a broader category containing closed-loop activities in both development and management phases of a field (Figure 6). Furthermore, as field is more general than reservoir, CLFD, CLFM and CLFDM may describe CLRD, CLRM and CLRDM, as well. For this reason, throughout this paper we use the term CLFDM, in accordance with Schiozer et al. (2019).

The main distinction between production optimizations in CLFD and CLFM phases is that, in the latter, the G1 variables are fixed and only the G2 and G3 variables are considered as decision variables (Jansen et al., 2009; Jahandideh and Jafarpour, 2018), whereas in the former, the G1 decision variables are the focus of optimization despite G2L and G3 decision variables can also be included in the optimization process (Gaspar et al., 2016a; Morosov and Schiozer, 2017; Schiozer et al., 2019).

CLFD and CLFM also differ from data assimilation and uncertainty standpoints. While in CLFM generally only soft and temporal data (such as production and injection volumes, 4D seismic-derived saturations, and well testing parameters) are used for data assimilation and reduction of uncertainties, in CLFD in addition to soft data, hard and spatial data (e.g., well logs and coring information) are also utilized for preparing more certain simulation models. Furthermore, in a given stage/wave, as the field development phase precedes the management phase, the former is dealing with a higher level of uncertainty in geological and reservoir engineering properties than the latter.

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While CLRM has been performed and investigated extensively (Brouwer et al., 2004; Overbeek et al., 2004; Aitokhuehi and Durlofsky, 2005; Sarma et al., 2005, 2006, 2008; Nævdal et al. 2006; Chen and Oliver, 2009; Chen et al., 2009; Jansen et al., 2009; Wang et al., 2009; Lorentzen et al., 2009; Alhuthali et al., 2009; Chen et al., 2010; Peters et al., 2010; Hui et al. 2011; Bukshtynov et al., 2015; V.L.S. Silva et al., 2017; Barros et al., 2020), CLRD has received less attention (Shirangi, 2013, 2019; Shirangi and Durlofsky, 2015; Hidalgo et al., 2017; Morosov and Schiozer, 2017; Hanea et al., 2019; Jahandideh and Jafarpour, 2018,2020).

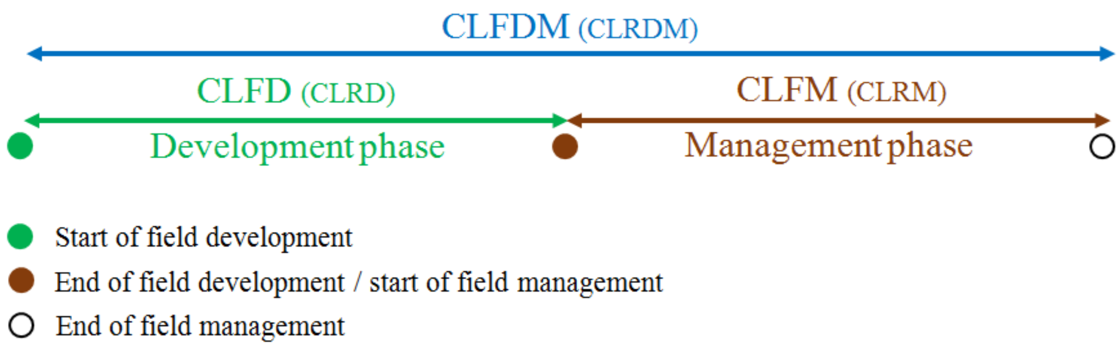

Figure 6: Closed-loop terms for different phases of a field project

7. Production optimization and decision-making

An optimized production strategy is selected through optimizing a set of decision variables by maximizing or minimizing an objective function(s). As discussed earlier, depending on the approach used in data assimilation, the outcome of this process is either a single model, a limited number of models (i.e., representative models), or a vast number of models. In this context, depending on the outcome of data assimilation (i.e., the number of models for further analysis) and treating the uncertainty, several types of optimization can be used as shown in Figure 7, and described as follows.

(1) Nominal (or deterministic) optimization on a single model
(2) Ensemble nominal optimization on an entire ensemble of models
(3) RM nominal optimization (or extended nominal optimization) on a set of representative models (RM stands for representative model)
(4) Robust optimization on an entire ensemble of models
(5) RM robust optimization on a set of representative models

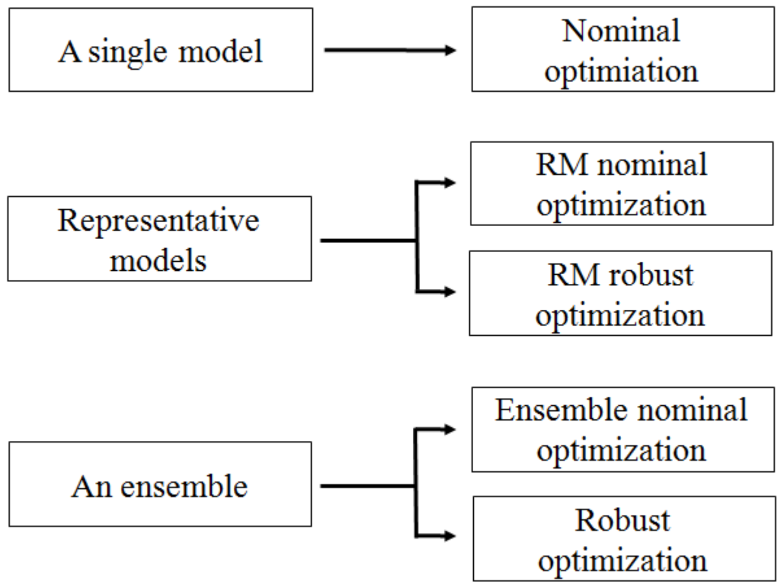

Figure 7: Different types of production optimization based the on number of models and treating the uncertainty

7.1. Nominal optimization

In this approach, the optimization problem is formulated deterministically to maximize or minimize an objective function(s) for one model only. The output of this process is a solution or a production strategy for a single model (Yeten et al., 2002). Since such a single model may not truly represent the unknown true model, applying this set of optimal decision variables to the real field may not yield the anticipated returns (Hanssen and Foss, 2016).

The workflow for nominal optimization is shown in Figure 8. Initially, a sampling technique is used to build *Ns* number of scenarios out of the uncertain attributes (pdf and range of values). They are reduced to *Nd* number (which could be different than *Ns*, depending on the type of data assimilation approach) by data assimilation. Then, a scenario is selected (e.g., central model) or generated (e.g., mean model) to undergo a nominal optimization to find an optimal solution. The optimal solution is afterwards applied to the ensemble of *Nd* scenarios to produce the associated risk curves or other measures for different performance metrics. Brouwer et al. (2004), Overbeek et al. (2004), Sarma et al. (2006), Naevdal et al. (2006), Jansen et al. (2009), Wang et al. (2009), Chen et al. (2010), Roxar, SIEP, Halliburton, Stanford/Chevron and Schlumberger approaches in

Peters et al. (2010), Hui et al. (2011), Bukshtynov et al. (2015) and V.L.S. Silva et al. (2017) used nominal optimization in their closed-loop works.

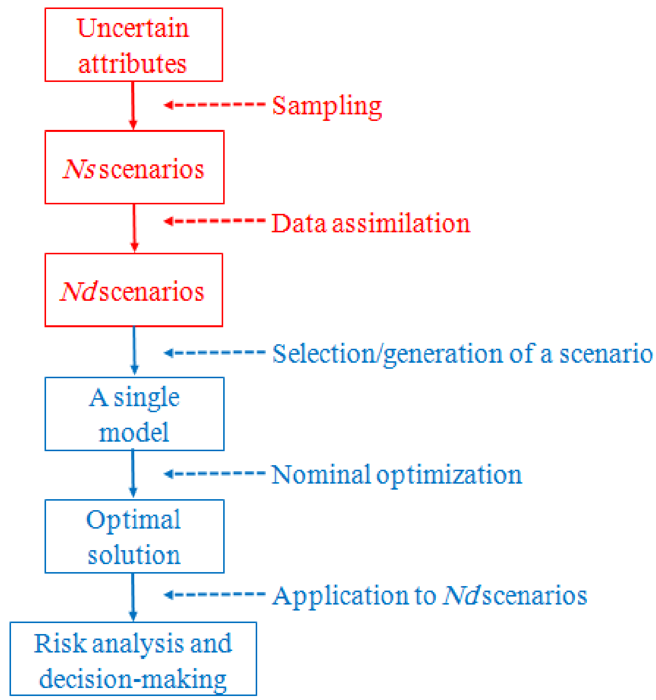

Figure 8: A flowchart for nominal optimization in a cycle of a closed-loop process

7.2. Ensemble nominal optimization

In ensemble nominal optimization, the optimization problem is formulated to maximize or minimize an objective function(s) for each model belonging to an ensemble of models, separately. This differs from nominal optimization in the way that it is performed for a set of individual models, and not only one model. The output of this optimization process is a set of optimal solutions or production strategies, where each solution is optimal for one model (Ligero et al., 2003).

One of the challenges in the nominal optimization applied to multiple models is that the resulting optimal solutions are not always the same across different models (Meira et al., 2016; Hutahaean et al, 2019). However, these solutions provide objective and quantitative evaluation of how different (and similar) these alternatives are, yielding valuable insights for uncertainty management and decision risk analysis (Schiozer et al., 2019). Furthermore, ensemble nominal optimization can be advantageous in decision and risk analyses, provided that it is part of a probabilistic process, in other words, it is not limited to the most likely models. Several

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techniques exist for risk-return analyses to select one of a set of optimal solutions. Santos et al. (2017a) combined the expected monetary value (EMV), downside risk, and upside potential to determine the economic value of a production strategy adjusted to the decision maker's attitude, while maintaining the same units and dimension as the NPV. Santos et al. (2018a) proposed a decision structure to objectively define a flexible production strategy from a set of rigid candidate production strategies to manage geological and reservoir uncertainties. For different risk curves, each corresponding to a production strategy, Morosov and Schiozer (2017) plotted EMV against a value that quantified the dispersion of the risk curve. This value was calculated by the standard deviation of curve divided by its EMV. In each cycle within closed-loop, the best production strategy was selected based on the highest EMV, if the risk was equal to or lower than to that of strategy from the previous cycle.

The workflow for ensemble nominal optimization is shown in Figure 9. Each model of the *Nd* ensemble undergoes a separate nominal optimization to find an optimal solution. The overall outcome will be a set of *Nd* specialized solutions. Each optimal solution is subsequently applied to the *Nd* scenarios to produce risk curves for risk analysis and decision-making.

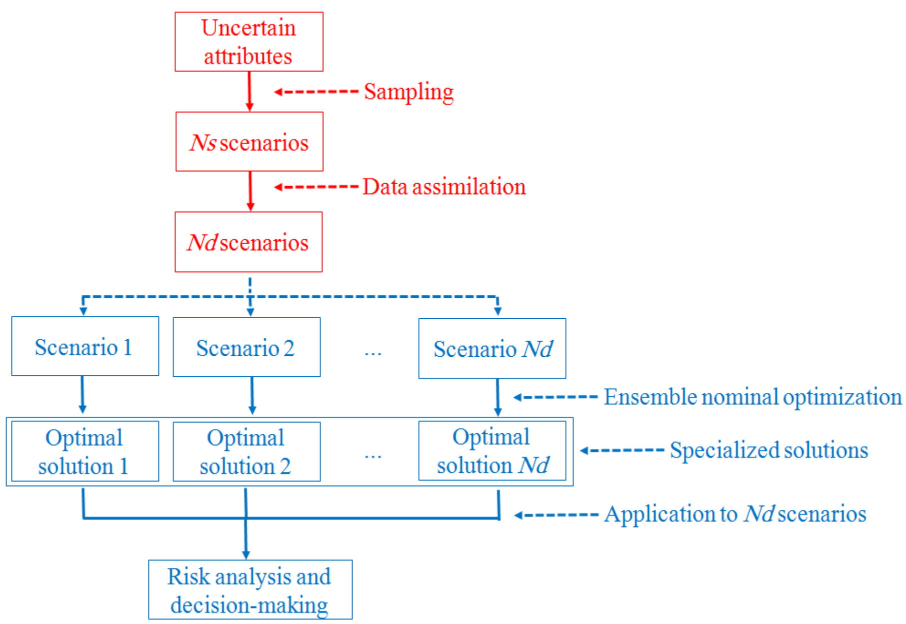

Figure 9: A flowchart for ensemble nominal optimization in a cycle of a closed-loop

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7.3. RM nominal optimization

In RM nominal optimization, the optimization problem is formulated to maximize or minimize an objective function(s) for each model of a set of models, separately. Similar to the ensemble nominal optimization, the RM nominal optimization differs from nominal optimization in the way that it is performed for a set of models, and not only one model. RM nominal optimization differs from the ensemble nominal optimization because it uses a subset of models from the entire ensemble (i.e., representative models), while ensemble nominal optimization uses the entire ensemble. The output of this optimization process is a set of optimal solutions or production strategies, where each solution is optimal for one model. However, an adequate representative models selection must be guaranteed (Schiozer et al., 2019).

The workflow for RM nominal optimization is shown in Figure 10. A set of *Nr* representative models is selected out of *Nd* ensemble. Then, each representative model undergoes a separate nominal optimization process to find an optimal solution. The overall result will be a set of specialized solutions. Each specialized solution can then be applied to either *Nd* or *Nr* models for risk analysis; however application to *Nd* models is suggested. The closed-loop papers by Morosov and Schiozer (2017) and V.L.S. Silva et al. (2017) are examples of applying RM nominal optimization.

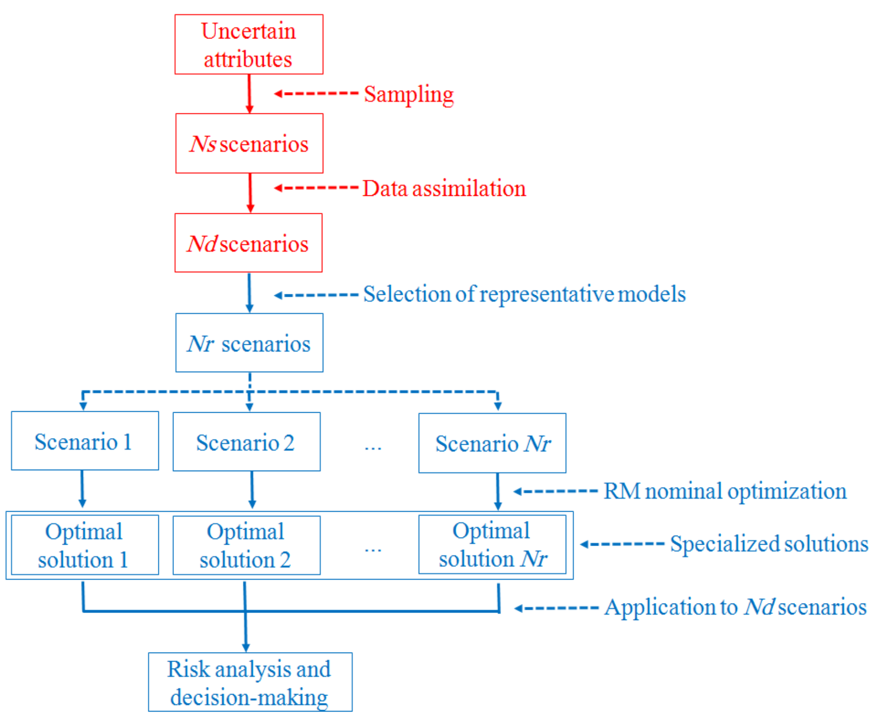

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Figure 10: A flowchart for RM nominal optimization in a cycle of a closed-loop

7.4. Robust optimization

In robust optimization, the optimization problem is formulated to maximize or minimize a probabilistic objective function(s) over a set of models within an entire ensemble, simultaneously (Yeten et al., 2003). The output of this process is one production strategy with the best performance on average for the subject models under uncertainty, but suboptimal for each model individually. The general goal of robust optimization is to obtain an optimal solution which is the least sensitive to the uncertainty (van Essen et al., 2009; Yang et al., 2011; Yasari and Pisvaie, 2015; Bagherinezhad et al., 2017). In other words, we seek an optimal solution that is most likely to give good performance for any model of the uncertainty in a given population (Yang et al., 2011). Thus, the objective of robust optimization should ideally consist of two components of expected value and variability of the desired objective function over the subject models (Yang et al., 2011; Yasari et al., 2013). These two objectives are the main goals of robust optimization problems that apply a trade-off between performance and robustness (Yasari and Pisvaie, 2015). Generally, robust optimization gives not only a higher expected NPV but also a significantly smaller NPV standard deviation than is obtained from nominal optimization (van Essen et al., 2009; Yang et al., 2011; Yasari et al., 2013; V.L.S. Silva et al., 2017). However, cases may be found where the opposite may happen, so that a nominal optimization production strategy gives a higher expected NPV with a lower NPV standard deviation than the robust optimization strategy (Capolei et al., 2013).

Robust optimization is strong in robustness as it is insensitive to uncertainty and ensures good performance across multiple scenarios without requiring system modifications after production has started (de Neufville, 2004). However, the output single production strategy gives little information on the different possibilities of field development (Schiozer et al., 2019). Contrary to the cases of ensemble nominal optimization and RM nominal optimization, where an additional task is needed to account for different optimal solutions found by each optimization model, in robust optimization this task is not required because the attained optimal solution is common to all models (Hutahaean et al., 2019). Furthermore, the output constraints make the robust optimization approach overly conservative, as all constraints must be satisfied for all models (Hanssen et al., 2017).

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Figure 11 demonstrates the workflow for robust optimization. In robust optimization, *Nd* models are used to find an optimal solution. The solution is eventually applied to the *Nd* models to prepare the risk curves or other statistical measures of performance metrics. Examples of closed-loop studies applying robust optimization are Aitokhuehi and Durlofsky (2005), Sarma et al. (2005, 2008), Chen et al. (2009), Chen and Oliver (2009), Hanea et al. (2019) and Jahandideh and Jafarpour (2018,2020).

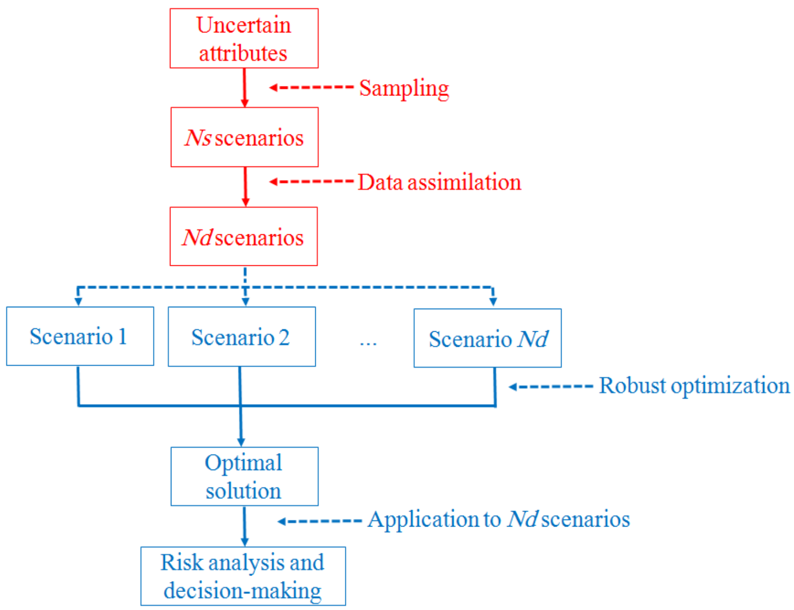

Figure 11: A flowchart for robust optimization in a cycle of a closed-loop

7.5. RM robust optimization

In the case of RM robust optimization, the optimization is performed on a subset of models instead of an entire ensemble (i.e., representative models). Compared to robust optimization, RM robust optimization gives an approximate solution since fewer models undergo the optimization process.

The workflow for RM robust optimization is shown in Figure 12, where a set of *Nr* representative models, selected from the *Nd* models, undergo a common optimization. The output optimal solution can then be applied to either *Nd* or *Nr* models for risk analysis; however application to *Nd* models is suggested. Examples of closed-loop studies applying RM robust optimization are Lorentzen et al. (2009), Alhuthali et al. (2009), TAMU approach in Peters et al. (2010), Shirangi (2013, 2019), Shirangi and Durlofsky (2015), Hidalgo et al. (2017) and V.L.S.

Silva et al. (2017). These studies have selected representative models either randomly or based on other measures for the production optimization.

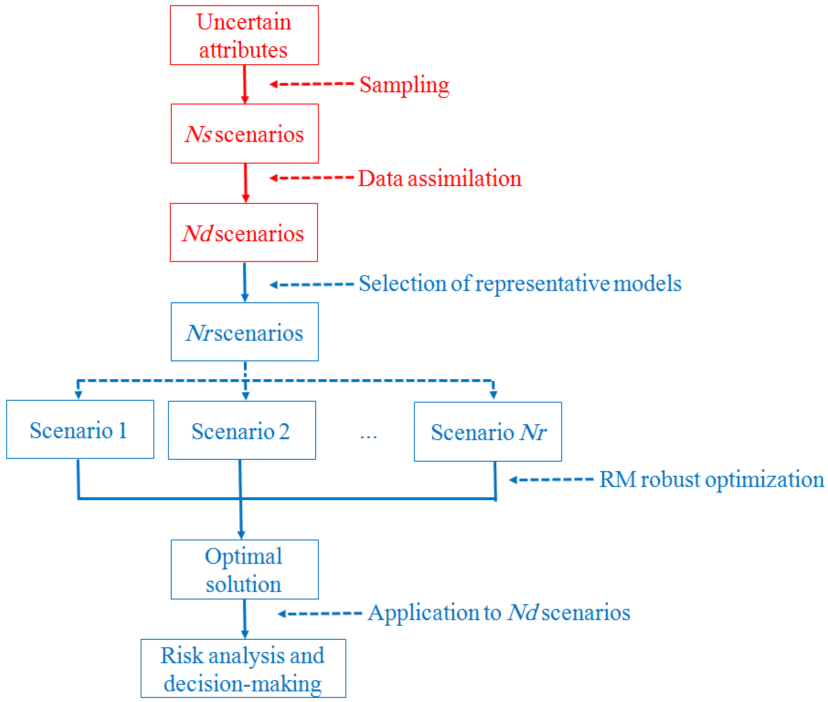

Figure 12: A flowchart for RM robust optimization in a cycle of a closed-loop

8. Production optimization objective functions

Based on the type of optimization (i.e., nominal vs. robust), the objective function can accordingly be either deterministic or probabilistic. While deterministic objective functions are evaluated for a single model only, probabilistic objective functions are evaluated across multiple models.

8.1. Deterministic objective functions

These can be financial or production/injection parameters such as NPV, revenue, recovery factor, cumulative fluid production (oil, gas or water), cumulative fluid injection (water, gas, solvent or CO2), displacement efficiency at water breakthrough (Sudaryanto and Yortsos, 2011), sweep efficiency through equalizing the arrival times of water/gas front at all producers (Alhuthali et al., 2007, 2008, 2009; Elfeel et al., 2018), and water breakthrough time (Bagherinezhad et al., 2017).

8.2. Probabilistic objective functions

These are usually described as expected parameters such as EMV, expected recovery factor, expected cumulative fluid production (oil, gas or water), and expected cumulative fluid injection (water, gas, solvent or CO_2); sometimes combined with a risk measure.

Those previously described closed-loop studies that have used nominal optimization, RM nominal optimization or ensemble nominal optimization, represent the cases of using deterministic objective functions (with discounted or undiscounted NPV as a widely used objective function). Furthermore, those working with RM robust optimization or robust optimization have used probabilistic objective functions (with expected discounted or undiscounted NPV as a widely used objective function). Alhuthali et al. (2009) and TAMU in Peters et al. (2010) used expected arrival time of water fronts as the objective function in their water-flooding RM robust optimization problems.

Furthermore, regardless of deterministic or probabilistic optimization, the optimization problem could be either single or multi-objective, depending on the number of objective functions considered.

8.3. Single-objective optimization

This aims to maximize or minimize a certain objective function (measures of production, injection, economic, risk, etc). Another form of single-objective optimization also exists in which optimization is performed by lumping several objective functions into a single general balanced objective function, each objective function having its own weight (Marler and Arora, 2004). Nevertheless, the difficulty is finding the suitable weighting factor corresponding to each objective function. As the weighting factors strongly govern the characteristics of the optimal solution, a vast number of trial and error runs with different weighting factors may be required to obtain a satisfactory solution (van Essen et al., 2011).

8.4. Multi-objective optimization (or multi-criterion optimization)

The practical optimization problems should normally consider multiple, possibly competitive and conflicting, objectives (Yasari et al., 2013; Moradi and Rasaei, 2017). The multi-objective optimization overcomes the difficulty of the single-objective optimization to address objectives with differing data types, to accommodate multiple objectives, and to handle the possible conflicts between objectives (Isebor and Durlofsky, 2014; Hutahaean et al., 2019). For instance,

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in a water flood project, one may be interested in maximizing oil recovery while minimizing water injection, or maximizing produced oil while minimizing produced water.

8.4.1. Simultaneous multi-objective optimization

In this form of multi-objective optimization, several objective functions are optimized simultaneously. Usually, the final optimal solution set (Pareto front) provides different solutions for decision-makers to select the production strategy by trade-off between objectives (Bagherinezhad et al., 2017; Hutahaean et al., 2019). Yasari et al. (2013) performed a multi-objective robust optimization to optimize the different components of NPV under economical and geological uncertainty with the aim of omitting the relevancy of the optimization problem to the prices. They documented a well placement optimization problem where multi-objective approach allowed to maximize recovery and to minimize cost, or to maximize the expected oil recovery over multiple models and to minimize its variance. Liu and Reynolds (2015, 2016), Isebor and Durlofsky (2014), Yasari and Pisvaie (2015) and Hutahaean et al. (2019) documented cases where the optimization objectives were to maximize the expected NPV while minimizing its associated uncertainty (standard deviation) over a set of models. Liu and Reynolds (2016) studied an optimization case where the objective was to maximize life-cycle NPV and to maximize the short-term NPV of production. In a work by Bagherinezhad et al. (2017), a procedure was applied for reservoir development optimization subject to maximization of the cumulative oil production and minimization of water front velocity (or respectively maximization of water breakthrough time). Hasan et al. (2013) documented a case where short-term and life-cycle objective functions were optimized simultaneously.

8.4.2. Hierarchical multi-objective optimization

Although production optimization studies normally focus on a life-cycle window, in practice short-term objectives usually dictate the course of the production strategy, especially in view of geological and economic uncertainties (van Essen et al., 2011; Chen et al., 2012). Therefore, short-term objectives should also be incorporated into the life-cycle optimization problem (Pinto et al., 2015). Following Jansen et al. (2009), who showed that a life-cycle performance could be optimized while maintaining freedom to perform short-term production optimization, van Essen et al. (2011), Chen et al. (2012) and Fonseca et al. (2014) utilized hierarchical optimization processes where maximization of the life-cycle NPV served as the primary objective and maximization of the short-term operational performance was the secondary objective (short-term in the context of reservoir engineering, in contrast to production engineering). In their approach, optimality of the primary objective function constrains the secondary optimization problem. In other words, optimization of the second objection function is constrained by the requirement that the primary objective function must remain close to its optimal value.

To the best of our knowledge, all of the previous closed-loop studies have been based on optimization of a single-objective function, and multi-objective optimization has been the center of attention only in purely optimization studies.

9. Representative models to speed up production optimization

For practical cases where the output of data assimilation is a large number of models, performing either ensemble nominal optimization or robust optimization on all the models is computationally expensive. An alternative option could be reducing a large number of models to a small manageable subset of models, called representative models, to speed up the optimization process while not risking its performance accuracy (Ligero et al., 2003; Schiozer et al., 2004; Morais et al., 2017). This process is usually referred to as scenario reduction or selection of representative models (Meira et al., 2016; V.L.S. Silva et al., 2017; Schiozer et al., 2019). Such a subset of representative models should be selected in the way that it represents the uncertain characteristics of the original large population of models and also be free of optimistic and pessimistic bias (Meira et al., 2016). As uncertain attributes affect the outcome of production optimization (i.e., a set of optimal decision variables), they influence a field's performance metrics, too. Thus, it could be alternatively said that a subset of representative models should be selected in the way that it represents the performance metrics of the original large ensemble. In some studies, representative models have been selected randomly out of the original ensemble of models (Lorentzen et al., 2009; Alhuthali et al., 2009; TAMU approach in Peters et al. (2010); Shirangi, 2013). However, randomly choosing a small set of models may represent inaccurately the uncertainty in a population (Yang et al., 2011; Yasari et al., 2013).

9.1. Representative models for RM nominal optimization

To illustrate the concept of representativeness and representative models, suppose that the output of data assimilation is an ensemble of *Nd* models. If nominal optimization is performed only on one model and the attained set of optimal decision variables (i.e., a production strategy) is implemented on all models, then we will have a set of performance metrics that can be displayed in several ways. One popular way is using risk curve which is a plot of complementary cumulative distribution function (CCDF) for a given performance metric (e.g., NPV, recovery factor, and produced oil/gas/water). The use of cross-plots (or scatter plots) is also common, in which different performance metrics are evaluated against each other (Ligero et al., 2003; Schiozer et al., 2004; Meira et al., 2016; Schiozer et al., 2019). If we continue and perform nominal optimization on each of the other models, and apply each obtained optimal solution on the *Nd* ensemble, we will have *Nd* sets of optimal decision variables or performance metrics, each set corresponding to a specific optimal solution. If by any computationally inexpensive means and without performing nominal optimization on all models, one could select a small manageable subset of models (i.e., *Nr*<*Nd)* such that the *Nr* sets of optimal decision variables or performance metrics can represent the *Nd* models, then such a subset will be representative for an entire ensemble.

For the sake of demonstration, a schematic example of the above-mentioned representativeness is shown in Figure 13 for one performance metric only, where the NPV risk curves of a few selected models cover fairly well the wide distribution of NPV risk curves of an ensemble. If such representativeness is also seen for risk curves of other performance metrics (e.g., produced water), then the selected models can be regarded as representative models for the problem. In this figure, a set of bad representative models is also shown. As stated before, cross-plots of performance metrics can also be included in this workflow. Cross-plots belonging to *Nr* models should cover reasonably well the wide scatter seen in cross-plots of *Nd* models. Eventually, only these representative models will undergo nominal optimization (i.e., RM nominal optimization), instead of a whole set of models, which is computationally more efficient. In the closed-loop works by Morosov and Schiozer (2017) and V.L.S. Silva et al. (2017) representative models have been used for RM nominal optimization.

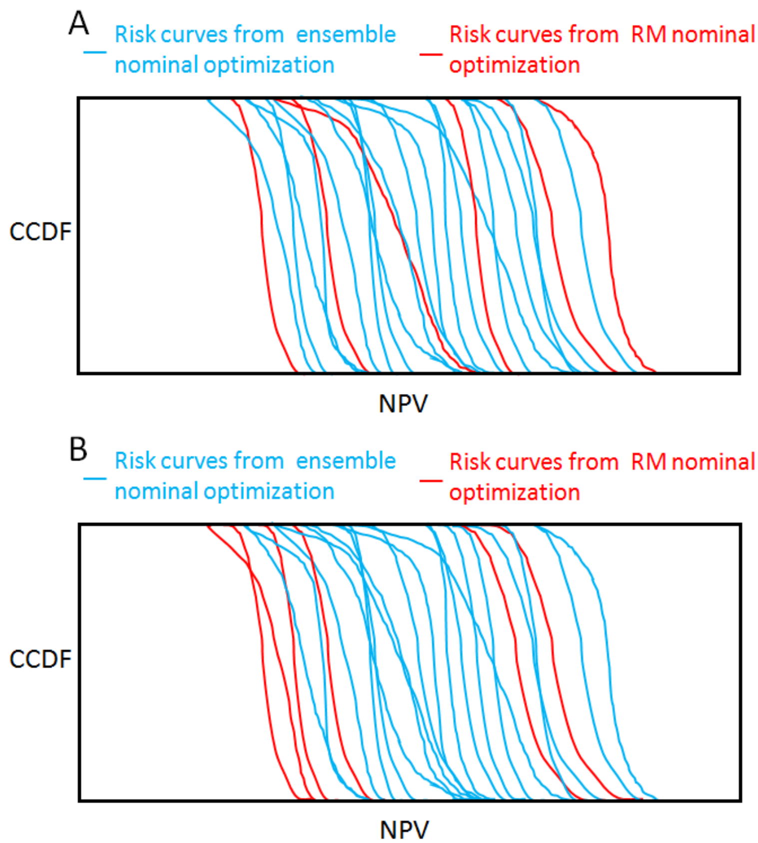

Figure 13: A schematic example of the concept of representative models for RM nominal optimization: (A) a good set of representative models vs. (B) a bad set of representative models

9.2. Representative models for RM robust optimization

We consider the previous illustration where the output of data assimilation was *Nd* models. If robust optimization is exercised on all models and the obtained robust production strategy is tested on the entire ensemble, then we will have a set of performance metrics that can be displayed using risk curves or cross-plots. If by any inexpensive means, one could select a small set of models such that when undergoing RM robust optimization yields an optimal solution similar to the optimal solution obtained from the robust optimization of the original ensemble, then models of this set will be representative models for the problem. In this context, by similar optimal solutions we mean similarity and closeness in the optimal values of decision variables, or, alternatively speaking, performance metrics (in the form of risk curves and cross-plots) (see e.g., Meira et al. (2017, 2020). It is noteworthy mentioning that compared to robust optimization, RM roust optimization gives an approximate solution. A schematic example is depicted in Figure 14 where NPV risk curves originating from robust optimization and RM robust optimization are

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very close. In this figure, the results from a set of bad representative models are also shown. Lorentzen et al. (2009), Alhuthali et al. (2009), TAMU approach in Peters et al. (2010), Shirangi (2013, 2019), Shirangi and Durlofsky (2015), Hidalgo et al. (2017) and V.L.S. Silva et al. (2017) used representative models to conduct RM robust optimization in closed-loop studies.

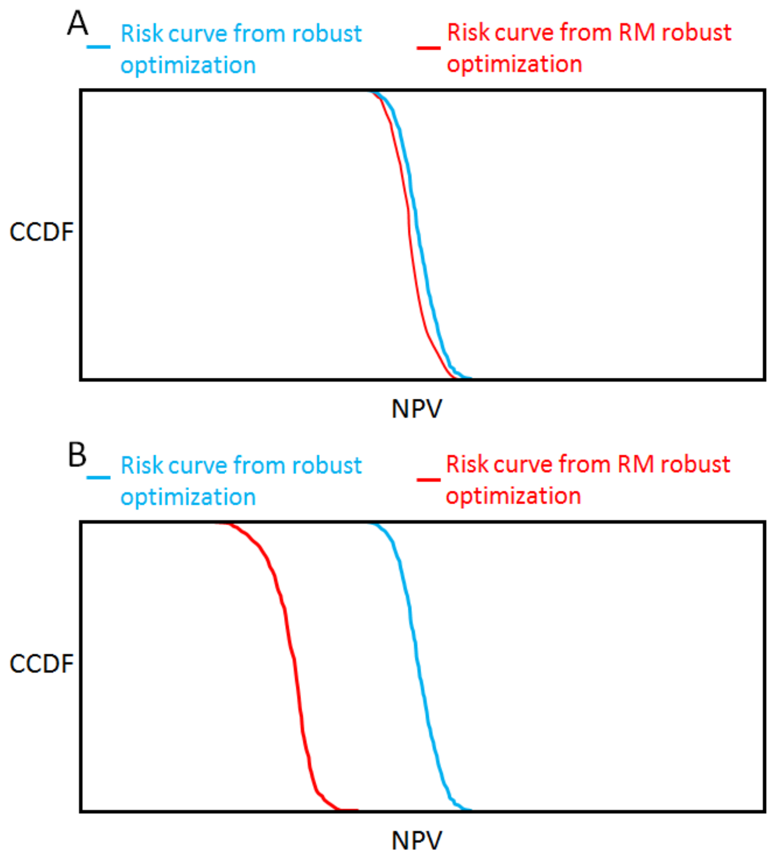

Figure 14: A schematic example of the concept of representative models for RM robust optimization: (A) a good set of representative models vs. (B) a bad set of representative models

9.3. Selection of representative models

Literature hosts many techniques for selection of representative models. Generally these techniques can be divided into three categories, as follows.

9.3.1. Clustering-based techniques

Techniques of this category try to find representative models by clustering continuous uncertain properties of an available ensemble. Several clusters are built, from which representative models will be selected (Kang et al., 2019). As an example, Rahim and Li (2015) used mixed integer

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linear optimization (MILP) technique to select representative models. Their algorithm used geological properties and static measures to quantify the dissimilarity between models, and used Kantorovich distance to quantify the probability distance between the whole ensemble of models and the representative models. The main limitation of this category is that clustering techniques are mainly suited for continues parameters and may not apply to discrete properties (Liu and Forouzanfar, 2018; Mahjour et al., 2020a). Another difficulty with this category is that, without performing any simulation, one may not be sure that the selected models are truly representative of flow performance indicators of an original ensemble.

9.3.2. Simulation-based techniques

This category introduces techniques that are based on flow performance metrics of all models generated via simulation of a base-case production strategy. The performance metrics corresponding to the selected models should represent the entire ensemble. These techniques are advantageous as they are applicable to every kind of property (i.e., continuous and discrete) and can give us confidence whether the resulting representative models truly represent the performance metrics of an original ensemble. However, the choice of the base-case production strategy may affect the resulting representative models. Liu and Forouzanfar (2018) have called these methods as response-based clustering techniques. They also introduced a state-based clustering technique which is based on the reservoir grid state parameters, such as water saturation snapshot. Steagall and Schiozer (2001) proposed a ranking-based technique that used three classes of pessimistic, probable and optimistic models with respect to the NPV (i.e., P_{90}, P_{50} and P_{10}) to select representative models. According to Schiozer et al. (2004), models close to P_{10}, P_{50} and P_{90} of NPV and of oil recovery factor should be selected, but such selection should be made in a way that these models are also representative in cumulative oil production and cumulative water production. Meira et al. (2016) developed a relevant optimization-based mathematical tool named RMFinder to automatically identify the representative models considering not only the cross-plots of the flow performance metrics, but also the risk curves and the probability distribution of the uncertain attributes. This technique was later improved by Meira et al. (2017, 2020) to increase the number of variables considered by RMFinder and also enhance the representativeness of selected models. RMFinder has been used in many studies such as Morosov and Schiozer (2017) and Schiozer et al. (2019). A different approach was shown by Yang et al. (2011), who obtained representative models by ranking 100 models based on performance of each model in terms of its NPV under a base-case production strategy. Afterwards, nine realizations ranked based on their percentiles were selected as representative models. They also compared the whole 100 models and the selected nine representative models in terms of the mean and standard deviation of NPV, and used these criteria to judge the adequacy of the selected models for representing an original set. Chen et al. (2012), Yasari et al. (2013), Yasari and Pisvaie (2015) and Pinto et al. (2019) used a similar approach. Shirangi and Durlofsky (2015) introduced a technique for selection of representative models, called optimization with sample validation (OSV), in which the number of models for optimization is increased if an appropriate validation criterion is not satisfied.

9.3.3. Combination techniques

The third category contains techniques that try to combine the two above approaches. These try to select representative models by production performance metrics simulated under a base-case production strategy, plus considering uncertain properties of an original ensemble of models. This decreases the sensitivity of the selected representative models to the base-case production strategy. Sarma et al. (2013) proposed a representative model selection approach that selects a few reservoir models from a large ensemble of models by matching pre-defined target percentiles of multiple flow performance metrics, while also obtaining maximally different models in the input uncertain space. Shirangi and Durlofsky (2016) introduced a framework, based on clustering, for selecting a representative subset of models. Prior to clustering, each geological model was represented by a low-dimensional feature vector that contained a combination of permeability-based and flow-based quantities. Calculation of flow-based features required the specification of a base production strategy and simulation over the fullest of models. Hidalgo et al. (2017) in each cycle of closed-loop and from 500 matched models, selected five representative models based on their similarity in reservoir static and dynamic parameters. These parameters were described in four categories of parameters that characterized models (i.e., grid, scalar, volumetric and production parameters). V.L.S. Silva et al. (2017) also proposed a method to select representative models based on the history matching parameters (grid and scalar parameters) in addition to a set of production and volume variables. Recently, Mahjour et al. (2020b) proposed a new workflow to choose the representative models that statistically reflect the same dynamic and static properties of the full ensemble, considering observed production data. Their technique is based on an integrated method including distance-based clustering and data assimilation considering static features.

10.Integrated modeling of production system

A production system is generally defined as the all components that participate in production and transportation of fluids from reservoir to processing units, and also injection and transportation of fluids from injection facilities to the reservoir (Mirzaei-Paiaman, 2013a,b), or simply the reservoir and the entire infrastructure used to bring the oil to the surface (Gaspar et al. 2016a). These components are reservoir, near wellbore region in injectors and producers (e.g., perforations, gravel packs, expandable sand screens, hydraulic fractures, damaged zones) (Salehi-Moorkani et al., 2010; Mirzaei-Paiaman and Nourani, 2012), wellbore and all associated downhole tubular and equipment (e.g., tubing, downhole pumps, gas lift valves, downhole separators), gathering and distributing networks (e.g., wellhead chokes, risers, pipelines, manifolds), processing units (e.g., separation units, desalting units) and injection units (Figure 15).

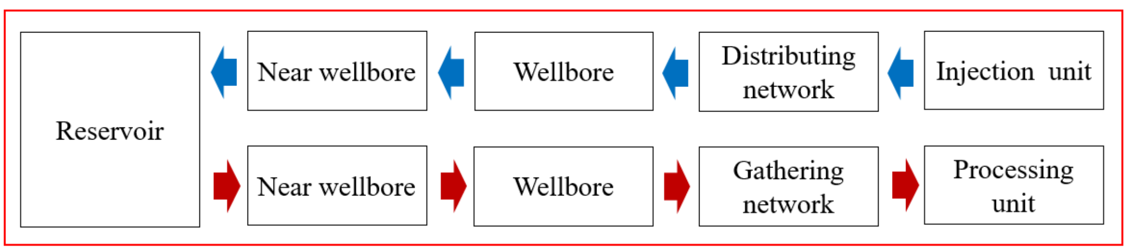

Figure 15: Different components of a production system

Many studies exist in which individual parts of the production system have been optimized separately. Examples are optimization of fluid production in near wellbore regions, wellbores and surface chokes (Mirzaei-Paiaman and Salavati, 2012, 2013; Mirzaei-Paiaman, 2013a), and finding optimal production strategies for standalone reservoirs (Morosov and Schiozer, 2017; Schiozer et al., 2019). As recognition of various components of the production system and understanding their interaction may lead to improved recoveries through analysis of the entire system, more studies integrating reservoir and other components of production system are needed (von Hohendorff Filho and Schiozer, 2017, 2018). von Hohendorff Filho and Schiozer (2018) highlighted that combination of individual optimization processes without a methodology

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to combine and organize them can significantly interfere with the final production strategy selection and the decision-making process. They compared the optimization without integration (i.e., standalone) and optimization with integration (i.e., integrated) and observed important changes that indicated the need to integrate reservoir and other components of production system. The optimized integrated systems resulted in significantly increased NPV, maintaining the same oil recovery factor while requiring lower initial investment. However, as the integration effort to optimize overall system performance presents many technological challenges and also it increases computation time, it was recommended to assess when this integration is necessary and how to choose a suitable coupling methodology (von Hohendorff Filho and Schiozer, 2017, 2018; Schiozer et al., 2019). Integrated modeling of a production system can also be performed by accounting for various sources of uncertainties (e.g., Vera et al., 2007, 2008). Despite the importance of integrated modeling, to the best of our knowledge all the previous closed-loop studies have considered only the reservoir component of the production system and fall within the category of CLRDM.

11. A stepwise standardized methodology for CLFDM

Generally speaking, performing any process needs following a standard and well-documented protocol and procedure in order to be inclusive, organized and effective. In this context, a CLFDM, as a complex process of multidisciplinary and time consuming tasks, needs to be performed following a procedure and workflow that incorporate comprehensively and efficiently all the necessary steps in a clear and organized form. As discussed earlier, the literature works usually describe the complex closed-loop process simply as a combination of data assimilation and production optimization tasks and their main focus has been on these two components, with less attention to all required steps for conducting a standard closed-loop exercise. This could be due to the fact that they are usually associated with several simplifying assumptions in their analyses and also use simple, small and synthetic reservoir models far from the complexity of real fields. Even in the studies that use real and more complex benchmarks, the general steps of the process have not been discussed and reported in details (e.g., Peters et al., 2010). A few studies exist that attempt to describe other fundamental and necessary steps of this process (Schiozer et al., 2015, 2019; Hutahaean et al, 2019).

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To best of our knowledge, only one workflow has been published presenting detailed and comprehensively all elements, components and steps towards a standard closed-loop process (Schiozer et al., 2015, 2019), referred to as Schiozer et al.'s 12-step methodology for decision analysis in CLFDM (Barreto et al., 2016; Gaspar et al., 2016a; Meira et al., 2016; Santos et al., 2017a,b,c; Morais et al., 2017; Morosov and Schiozer, 2017; von Hohendorff Filho and Schiozer, 2018; Santos et al., 2018a,b; Meira et al., 2020). The proposed workflow covers all required steps of a standard closed-loop activity and is suitable for practical applications of complex reservoirs in different field stages (development and management) (Schiozer et al., 2019).

Figure 16 shows the Schiozer et al.'s 12-step methodology for decision analysis in CLFDM in which main components of the proposed methodology are generally divided into colors:

- Green: collection of all data and uncertainties and model construction. Depending on the study objective and to balance quality of the results and computational time, multiple simulation models (low, medium or high fidelity) can be used.
- Red: data assimilation. All historical dynamic data must be within a tolerance range to select models that will be used in the production optimization part. Data assimilation may directly change the simulation models or the high-fidelity geological models (big loop).
- Blue: model-based, life-cycle decisions under uncertainty. The best production strategy is obtained through an optimization procedure.
- Black: implementation of model-based life-cycle decisions and short-term data driven decisions, definition of study objective, and selection of the type of study.

Schiozer et al. (2019) used the blue part to represent model-based life-cycle optimization; the black part is dedicated to short-term optimization. This type of short-term optimization is model-based and can be combined with data-driven practices.

The twelve steps could be summarized as below (Schiozer et al., 2019).

(1) Reservoir characterization under uncertainty;
(2) Construction and calibration of the simulation base model;
(3) Verification of inconsistencies on the base model using historical dynamic well data;
(4) Generation or sampling of scenarios considering the full range of uncertainties from all possible conditions;

(5) Reduction of scenarios using dynamic and seismic data (i.e., data assimilation);
(6) Selection of a nominal production strategy using an optimization procedure;
(7) Initial risk estimate using the production strategy obtained in Step 6;
(8) Selection of representative models;
(9) Selection of a specialized production strategy for each representative model through RM nominal optimization;
(10) Selection of the best production strategy from a set of optimal solutions (solutions obtained in Step 9), or from robust optimization on all models or only on representative models (i.e., RM robust optimization)
(11) Identification of potential for changes in the best strategy to mitigate risk or increase value (e.g. information, flexibility, and robustness)
(12) Final risk assessment and decision-making

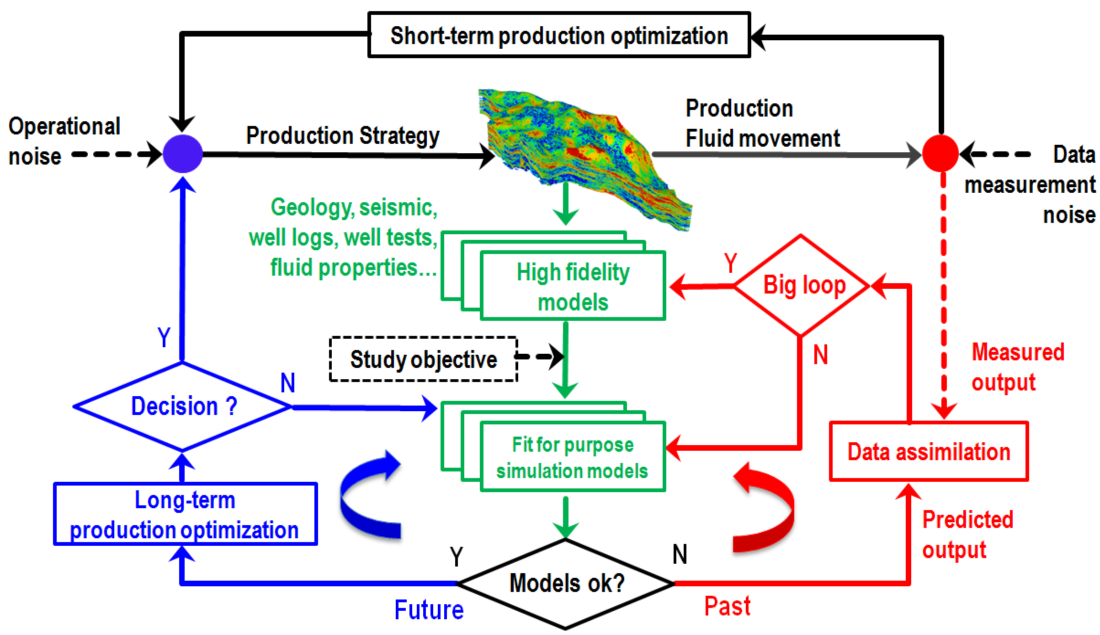

Figure 16: The workflow for CLFDM proposed by Schiozer et al. (2019)

12.Summarizing table

Table 3 summarizes the previously discussed closed-loop studies based on the several criteria covered in the sections of this paper. These criteria are type of the closed-loop (CLRM vs. CLRD), well type (conventional vs. intelligent), uncertainty type, model general description, data assimilation type, assimilation times (or cycle duration), types of the measurement used in data assimilation, optimization type (nominal vs. ensemble nominal vs. RM nominal vs. robust vs. RM robust), objective function and type, decision variables used in the production optimization, and the total field producing life.

It is worth noticing that, except for Aitokhuehi and Durlofsky (2005) who studied a natural depletion case, all the summarized closed-loop studies considered water flooding as the recovery method. Furthermore, all the summarized studies performed life-cycle production optimization using a single objective function.

Table 3: A summary of the previous closed-loop studies

Source	Type	Well type	Uncertainty	Model	Data assimilation	Assimilation times	Measurements	Optimization type	Objective function	Decision variable	Producing life
Brouwer et al. (2004)	CLRM	Conventional	Geological and information reliability	2D synthetic models	100 models were updated	Experiment 1: at day 2, 4, 7, 9, 12, 23, 46, 69, 93 and 116 Experiment 2: at day 8, 16, 28, 36, 48, 92,184, 276, 372 and 464	Simulated production and injection measurements	Nominal optimization on the mean of updated realizations	NPV	G2L (producers and injectors controls)	Experiment 1: 949 days Experiment 2: 3976 days
Overbeek et al. (2004)	CLRM	Conventional	Geological and information reliability	A 2D synthetic model	100 models were updated	At day 2, 4, 7, 9, 11, 23, 46, 69, 92,116, 231, 463 and 694	Simulated production and injection measurements	Nominal optimization on the mean of updated realizations	Undiscounted NPV	G2L (producers and injectors controls)	750 days
Aitokhuehi and Durlofsky (2005)	CLRM	Intelligent	Geological	3D synthetic models	All models were updated	Experiment 1: every 240 days Experiment 2: every 200 days	Simulated production measurements	Robust optimization	Expected cumulative oil recovery	G2L (producer controls)	Experiment 1: 720 days Experiment 2: 800 days
Sarma et al. (2005)	CLRM	Intelligent	Geological	A 2D synthetic model	All models were updated	At day 30, 90, 190, 380, 570, 760 and 950	Simulated production and injection measurements	Robust optimization	Expected undiscounted NPV	G2L (producer and injector controls)	950 days
Sarma et al. (2006)	CLRM	Intelligent	Geological	A 2D synthetic model	All models were updated	At day 30, 90, 190, 380, 570, 760 and 950	Simulated production and injection measurements	Nominal optimization on the maximum likelihood estimate of the permeability field	Undiscounted NPV	G2L (producer and injector controls)	950 days

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Nævdal et al. (2006)	CLRM	Intelligent	Geological and information reliability	A 2D synthetic model	All models were updated	At day 2, 5, 7, 9, 12, 23, 46, 69, 93, 116, 174, 231, 289, 347, 405, 463, 521, 579, 637, 694, 752, 810, 868 and 926	Simulated production and injection measurements	Nominal optimization on the mean of updated realizations	Undiscounted NPV	G2L (producer and injector controls)	946 days
Sarma et al. (2008)	CLRM	Conventional	Geological	A sector of a Gulf of Mexico reservoir	120 models were updated	At day 180, 360, 720, 1260, and 2160	Simulated production and injection measurements	Robust optimization	Expected undiscounted NPV	G2L (producers and injectors controls)	3060 days
Chen and Oliver (2009)	CLRM	Intelligent	Geological, reservoir engineering and information reliability	Brugge benchmark	104 models were updated	At year 10, 11,12,13,14, 16, 18 and 20	Simulated production and injection measurements and time lapse seismic data	Robust optimization	Expected NPV	G2L (producers and injectors controls)	30 years
Chen et al. (2009)	CLRM	Intelligent	Geological and information reliability	A 2D synthetic model	60 models were updated	At day 30, 270 and 450	Simulated production and injection measurements	Robust optimization	Expected undiscounted NPV	G2L (producer and injector controls)	1140 days
Jansen et al. (2009)	CLRM	Conventional	Geological and information reliability	A 3D synthetic model	100 models were updated	Experiment 1: once per 4 years Experiment 2: once per 2 years Experiment 3: once per 1 year Experiment 4: once per 30 days	Simulated production and injection measurements	Nominal optimization on the mean of updated realizations	NPV	G2L (producers and injectors controls)	8 years
Wang et al. (2009)	CLRM	Conventional	Geological and information reliability	2D synthetic models	90 models were updated	Experiment 1: every 120 days Experiment 2: every half year	Simulated production measurements	Nominal optimization on the central model of updated realizations	NPV	G2L (producers controls)	Experiment 1: 960 days Experiment 2: 2190 days
Lorentzen et al. (2009)	CLRM	Intelligent	Geological, reservoir engineering and information reliability	Brugge benchmark	104 models were updated	At year 10 and 20	Simulated production and injection measurements and time lapse seismic data	Robust optimization on 10 randomly selected realizations	Expected NPV	G2L (producers and injectors controls)	30 years
Alhuthali et al.(2009)	CLRM	Intelligent	Geological, reservoir engineering and information reliability	Brugge benchmark	30 models were updated	At year 10	Simulated production and injection measurements	Robust optimization on 10 randomly selected realizations	Expected arrival time of water fronts	G2L (producers and injectors controls)	30 years
Chen et al. (2010)	CLRM	Intelligent	Geological, reservoir engineering and information reliability	Brugge benchmark	104 models were updated	At year 10 and 20	Simulated production and injection measurements and time lapse seismic data	Nominal optimization on the mean of updated realizations	NPV	G2L (producers and injectors controls)	30 years

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Petersen et al. (2010)	Halliburton	CLRM	Intelligent	Geological, reservoir engineering and information reliability	Brugge benchmark	Updating the best fitted model	At year 10 and 20	Simulated production and injection measurements and time lapse seismic data	Nominal optimization on the update of best fitted model	NPV	G2L (producers and injectors controls)	30 years
	Roxar					All models were updated		Simulated production and injection measurements and time lapse seismic data	Nominal optimization on the best updated realization	NPV		
	SIEP					104 models were updated		Simulated production and injection measurements and time lapse seismic data	Nominal optimization on the mean of updated realizations	NPV		
	SLB					The best fitted model was selected		Simulated production and injection measurements and time lapse seismic data	Nominal optimization on the best fitted model	NPV		
	Stanford/Chevron					A single realization was updated		Simulated production and injection measurements	Nominal optimization on a single matched model	NPV		
	TAMU					30 randomly selected models out of 104 models were updated		Simulated production and injection measurements	Robust optimization on 10 randomly selected updated realizations	Expected arrival time of water fronts		
Hui et al. (2011)		CLRM	Conventional	Geological and information reliability	A 2D synthetic model	100 models were updated	Every 120 days	Simulated production and injection measurements	Nominal optimization on a single model	NPV	G2L (producers and injectors controls)	1200 days
Shirangi (2013)		CLRD	Conventional	Geological and information reliability	A 2D synthetic model	All models were updated	Every 210 days (8 times)	Simulated production and injection measurements and hard data	Robust optimization on 5 randomly selected realizations	Expected NPV	G1 (well types and locations) and G2L (producers and injectors controls)	3000 days
Bukshtynov et al., (2015)		CLRM	Conventional	Geological, reservoir engineering and information reliability	Brugge benchmark (modified)	One of the realization was updated	Every one year	Simulated production and injection measurements and time lapse seismic data	Nominal optimization on one of the realizations	NPV	G2L (producers and injectors controls)	20 years

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Shirangi and Durlofsky (2015)	CLRD	Conventional	Geological and information reliability	Experiment 1: a 2D synthetic model Experiment 2: a 3D synthetic model	50 realizations were updated	Experiment 1: every 210 days (8 times) Experiment 2: every 210 days (6 times)	Simulated production and injection measurements and hard data	RM robust optimization	Expected undiscounted NPV	Experiment 1: G1 (well types and locations) and G2L (producers and injectors controls) Experiment 2: G1 (well locations) and G2L (producers and injectors controls)	Experiment 1: 3000 days Experiment 2: 2000 days
Hidalgo et al. (2017)	CLRD	Conventional	Geological, reservoir engineering and information reliability	UNISIM-I-D benchmark	500 realizations were updated	8 cycles: the first cycle with four years duration and the remaining cycles every 6 months	Simulated production and injection measurement and hard data from UNISIM-I-R model	RM robust optimization	Expected NPV	G1 (number, type and position of wells)	7.5 years
Morosov and Schiozer (2017)	CLRD	Conventional	Geological, reservoir engineering and information reliability	UNISIM-I-D benchmark	Best matched models were selected out of 500 models	4 cycles each one with length of 4 months	Simulated production and injection measurement and hard data from UNISIM-I-R model	RM nominal optimization	Expected NPV	G1 (position of wells)	2436 days
V.L.S. Silva et al. (2017)	CLRM	Intelligent	Geological, reservoir engineering and information reliability	UNISIM-I-D benchmark (modified)	500 models were updated	At year 5, 7, 9, 13, 17 and 23	Simulated production and injection measurement from UNISIM-I-R model	RM robust optimization, RM nominal optimization, and nominal optimization (on mean of RMs)	Expected NPV (for RM robust optimization), NPV (for RM nominal optimization and the nominal optimization on mean of RMs)	G2L (producers and injectors controls)	30 years
Jahandideh and Jafarpour (2018)	CLRD	Conventional	Geological, operational and information reliability	PUNQ-S3 benchmark	100 models were updated	Every 1 year until drilling of the last well	Simulated production and injection measurement and hard data	Robust optimization	Expected NPV	G1 (position of wells) and G2L (producers and injectors controls)	10 years
Shirangi (2019)	CLRD	Conventional	Geological and information reliability	A 2D synthetic model	50 realizations were updated	Every 180 days until the day 540	Simulated production and injection measurements and hard data	RM robust optimization	Expected undiscounted NPV	G1 (number, type and location of wells) and G2L (producers and injectors controls)	3000 days
Hanea et al. (2019)	CLRD	Conventional	Geological, reservoir engineering and information reliability	A 3D reservoir model (REEK)	45 realizations were updated	Experiment 1: every 2 years Experiment 2: every 1 year Experiment 3: every 6 months	Simulated production and injection measurements	Robust optimization	Expected NPV	G1 (drilling sequence)	4 years
Jahandideh and Jafarpour (2020)	CLRD	Conventional	Geological, operational and information reliability	Experiment 1: a 2D synthetic model Experiment 2: Norne reservoir model	50 realizations were updated	Every 1 year until drilling of the last well	Simulated production and injection measurements and hard data	Robust optimization	Expected NPV	G1 (position of wells) and G2L (producers and injectors controls)	Experiment 1: 10 years Experiment 2: 8 years

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https://dx.doi.org/10.1016/j.petrol.2021.108457

Conclusions and open areas for future works

This paper attempted to provide a review on CLFDM. We also aimed to establish a unified concept definition, notations and workflow for doing closed-loop. The following conclusions and areas for future research could be drawn from this work.

- Uncertainties in field development and management:
  - We presented a new and comprehensive classification of uncertainties in field development and management. Geological uncertainties have been studied well and constitute a large portion of the previous studies. Reservoir engineering and information reliability uncertainties have also been studied but not as much as the geological uncertainties. Incorporation of other types of uncertainties and simultaneously accounting for multiple types of uncertainties are worthy of future research.
  - As most of the closed-loop studies have been performed using simple synthetic models, uncertainty analysis under more real and sophisticated problems needs further research. Continuing release of realistic siliciclastic and carbonate benchmarks, such as Brugge (Peters et al., 2010, 2013), UNISIM-I (Avansi and Schiozer, 2015; Gaspar et al., 2015, 2016b), UNISIM-II (Correia et al., 2015; Maschio and Schiozer, 2019) and Olympus (Fonseca et al., 2017, 2018) provides a good opportunity to evaluate a more diverse set of uncertainties in the decision-making processes in field development and management.
- Closed-loop components:
  - We reviewed the concept of closed-loop and described it as a process containing four components: (1) measurement, (2) data assimilation, (3) production optimization and decision-making, and (4) implementation (or operation/execution). We provided the corresponding definitions and workflows.
  - Closed-loop has always been considered as a practice where, in each cycle, an optimized production strategy is sought for the rest of the field life through a life-cycle optimization. The optimization task in each cycle may also be designed to obtain an optimal solution for a short-term period, depending on the operator interests.
  - The choice of cycle duration in practical closed-loop processes is affected by many factors and is case-dependent. Thus, practical closed-loop processes are far from real time. Choosing realistic cycle durations in future works seems necessary.
- Data assimilation:

- o Data assimilation approaches that update all models, or find the best fitting models result in a better consideration of uncertainties in the decision-making process, since they provide an ensemble of models to the production optimization.
- o As most of the previous works have updated all the models, more studies on the approach that finds the best fitting models can be subject for future works.

- CLFDM vs. CLRM and CLFD:
  - o As operating an oilfield is usually achieved through several stages of field development and management, the terminology of CLFDM, as a parent category containing CLRM and CLFD, seems to better describe and fit the problem. In this definition, field corresponds to a production system containing all components of reservoir(s), wellbores, surface gathering/injection networks and surface facilities.
  - o Closed-loop processes in development and management phases differ from the variables used in the production optimization, and from the data assimilation and uncertainty standpoint. While in optimization part, CLFM (or CLRM) considers G2 and G3 variables, CLFD (or CLRD) focuses on G1 variables but can potentially account for all kinds of decision variables.
  - o As most of the previous closed-loop studies have been on management phase, more studies on development phase seem necessary in the future. Specifically for intelligent wells, the literature on closed-loop studies only consider operation of ICVs, with less attention to optimizing position and number of ICVs as design variables. More research in this area could be subject of future works.
- Production optimization:
  - o Nominal optimization of a production strategy for a base case, due to its inherent limitations, may not yield a realistic optimal production strategy.
  - o In ensemble and RM nominal optimizations, the resulting optimal solutions provide objective and quantitative evaluation of how different (and similar) these alternatives are, yielding valuable insights for uncertainty management and decision risk analysis. On the other hand, robust optimization and RM robust optimization give a single optimal average solution.

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- To take advantages of both nominal and robust optimization, we recommend simultaneous use of these two approaches in the decision-making process if time and resources allow.
- Although the literature is rich in data assimilation and optimization of various types of recovery methods such as WAG injection, SAGD, surfactant flooding, among others (e.g., Esmaiel et al., 2005; Yang et al., 2011; Alfi and Hosseini, 2016; Zhang et al., 2019), in previous closed-loop studies, except for one occasion, water flooding has been used as the recovery method. Thus, exercising closed-loop on other recovery methods could be an open area for future research. This will certainly introduce more challenges in both data assimilation and optimization tasks.
- Literature on closed-loop studies has focused mainly on single-objective optimization with NPV or EMV as the objective functions. While multi-objective optimization has been widely applied in optimization publications, it can also be applied in future closed-loop practices.

● Representative models:

- We illustrated the concept of representativeness and representative models in both RM nominal optimization and RM robust optimization. The optimal values of decision variables or performance metrics of the optimized production strategy(s) for the representative models must reflect the optimized production strategy(s) for the full ensemble. Risk curves and cross-plots (scatter plots) are useful tools to demonstrate performance metrics.
- We described the approaches for selection of representative models. We recommend use of flow simulation techniques in selection of representative models to check whether the selected models represent the performance metrics of the entire ensemble (e.g., Meira et al., 2016, 2017, 2020). The selected models should also reflect the wide range of uncertain variables in the ensemble.

● Integration between reservoir and production systems:

- As a production system consists of several subsurface and surface components, in some circumstances their integration in modeling processes may result in a more consistent and efficient decision-making output (von Hohendorff Filho and Schiozer, 2018; Schiozer et al., 2019). To the best of our knowledge, there is no study in the closed-loop literature considering an entire production system. Integrated modeling within a closed-loop remains an open area for future research.

- Standardizing the implementation of CLFDM
  - We reviewed the 12-step methodology by Schiozer et al. (2019) for decision analysis in CLFDM. This could be considered a standard and well-documented procedure and workflow that incorporates comprehensively and efficiently all the necessary steps in a clear and organized form in order to perform a closed-loop for practical applications of complex reservoirs in different field stages.

Acknowledgment

We gratefully acknowledge the support of Energy Production Innovation Center (EPIC) hosted by the University of Campinas (UNICAMP) and sponsored by Equinor Brazil and the São Paulo Research Foundation (FAPESP), grant numbers 2017/15736-3 and 2019/06101-0. We acknowledge the support of ANP (Brazil's National Agency of Oil, Natural Gas and Biofuels) through the R&D levy regulation. We also acknowledge the funding from Energi Simulation and the support of the Center for Petroleum Studies (CEPETRO) and the School of Mechanical Engineering at UNICAMP.

References

- Abreu, A. C. A., Booth, R., Bertolini, A., Prange, M., Bailey, W. J., Teixeira, G., Emerick, A., and Pacheco, M. A., 2015. Proactive and reactive strategies for optimal operational design: an application in smart wells. SPE paper 26209-MS, OTC Brasil, 27-29 October, Rio de Janeiro, Brazil.
- Aitokhuehi, I., and Durlofsky, L.J., 2005. Optimizing the performance of smart wells in complex reservoirs using continuously updated geological models. J. Pet. Sci. Eng. 48, 254-264.
- Alfi, M., and Hosseini, S.A., 2016. Integration of reservoir simulation, history matching, and 4D seismic for CO2-EOR and storage at Cranfield, Mississippi, USA. Fuel 175, 116-128.
- Alhuthali, A., Oyerinde, D., and Datta-Gupta, A., 2007. Optimal waterflood management using rate control. SPE Res. Eval. & Eng. 10 (5), 539–551.
- Alhuthali, A.H., Datta-Gupta, A., Yuen, B., and Fontanilla, J.P., 2008. Optimal rate control under geologic uncertainty. Paper SPE 113628, presented at the SPE/DOE Symposium on Improved Oil Recovery, Tulsa, 20–23 April 2008.
- Alhuthali, A.H., Datta-Gupta, A., Yuen, B., and Fontanilla, J.P., 2009. Field applications of waterflood optimization via optimal rate control with smart wells. SPE paper 118948, SPE Reservoir Simulation Symposium, The Woodlands, Texas, USA, 2–4 February 2009.
- Almeida, L.F., Vellasco, M. M.B.R., and Pacheco, M.A.C., 2010 Optimization system for valve control in intelligent wells under uncertainties. J. Pet. Sci. Eng. 73, 129–140
- Avansi, G.D., Schiozer, D.J., 2015. UNISIM-I: Synthetic model for reservoir development and management applications. Int. J. Model. Sim. Petrol. Ind. 9, 1, 21–30.
- Bagherinezhad, A., Boozarjomehry Bozorgmehry, R., and Pishvaie, M.R., 2017. Multi-criterion based well placement and control in the water-flooding of naturally fractured reservoir. J. Pet. Sci. Eng. 149, 675–685.

- Barreto, C. E. A. G., and Schiozer, D. J., 2015. Optimal placement design of inflow control valve using a dynamic optimization process based on technical and economic indicators. J. Pet. Sci. Eng. 125, 117–127.
- Barreto, C. E. A. G., Gaspar, A. T. F. S., and Schiozer, D. J., 2016. Impact of the use of intelligent wells on the evaluation of oilfield development and production strategy. SPE paper 180861-MS, SPE Trinidad and Tobago Section Energy Resources Conference held in Port of Spain, Trinidad and Tobago, 13–15, June 2016.
- Barros, E.G.D., Van den Hof, P.M.J., and Jansen, J. D., 2020. Informed production optimization in hydrocarbon reservoirs. Optimization and Engineering, 21, 25–48.
- Benndorf, J., and Jansen, J.D., 2017. Recent developments in closed-loop approaches for real-time mining and petroleum extraction. Math Geosci 49, 277–306
- Bertolini, A.C., and Schiozer, D. J., 2016. Principal component analysis for reservoir uncertainty reduction. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 38, 1345–1355.
- Bertolini, A.C., Maschio, C., and Schiozer, D.J., 2015. A methodology to evaluate and reduce reservoir uncertainties using multivariate distribution. J. Pet. Sci. Eng. 128, 1-14.
- Botechia, V.E., Gaspar, A.T.F., Avansi, G.D., Davolio, A., and Schiozer, D.J., 2018. Investigation of production forecast biases of simulation models in a benchmark case. Oil & Gas Science and Technology - Rev. IFP Energies nouvelles 73, 23. https://doi.org/10.2516/ogst/2018014
- Brouwer, D.R., Nævdal, G., Jansen, J.D., Vefring, E.H., and Van Kruijsdijk, C.P.J.W., 2004. Improved reservoir management through optimal control and continuous model updating. SPE paper 90149-MS, SPE Annual Technical Conference and Exhibition, 26-29 September 2004, Houston, Texas.
- Bukshtynov, V., Volkov, O., Durlofsky, l.J., and Aziz, K., 2015. Comprehensive framework for gradient-based optimization in closed-loop reservoir management. Comput Geosci 19, 877–897.
- Capolei, A., Suwartadi, E., Foss, B., and Jørgensen, J.B., 2013. Waterflooding optimization in uncertain geological scenarios. Comput Geosci 17, 991–1013.
- Chen Y., Oliver D.S., and Zhang D., 2009. Efficient ensemble-based closed-loop production optimization, SPE J. 14 (4), 634–645.
- Chen, C., Li, G., and Reynolds, A.C., 2012. Robust constrained optimization of short- and long-term net present value for closed-loop reservoir management. SPE J. 17 (3), 849-864.
- Chen, C., Wang, Y., Li, G., and Reynolds, A.C., 2010. Closed-loop reservoir management on the Brugge test case. Comput Geosci 14, 691–703
- Chen, Y. and Oliver, D.S., 2009. Ensemble-based closed-loop production optimization on Brugge field. SPE paper 118962 presented at the SPE Reservoir Simulation Symposium, The Woodlands, Texas, USA, 2–4 February 2009.
- Correia, M.G., Hohendorff, J., Gaspar, A.T.F.S., and Schiozer, D. J., 2015. UNISIM-II-D: benchmark case proposal based on a carbonate reservoir. SPE paper 177140- MS. SPE Latin American and Caribbean Petroleum Engineering Conference Held in Quito, Ecuador, 18-20 November 2015.
- de Neufville R., 2004. Uncertainty management for engineering systems planning and design. Engineering Systems Symposium, 29–31 March, Cambridge, MA.
- Elfeel, M.A., Tonkin, T., Watanabe, S., Abbas, H., Bratvedt, F., Goh, G., Gottumukkala, V., and Giddins, M.A., 2018. Employing smart flow control valves for fast closed-loop reservoir management. SPE paper 192926-MS, Abu Dhabi International Petroleum Exhibition and Conference, Abu Dhabi, UAE, 12-15 November 2018.
- Esmaiel, T.E., Bolandtaba, S.F., and van Kruisdijk, C., 2005. Determination of WAG ratios and slug sizes under uncertainty in a smart wells environment. SPE Middle East Oil and Gas Show and Conference, 12-15 March 2005, Bahrain.
- Floris, F.J.T., Bush, M.D., Cuypers, M., Roggero, F., and Syversveen, A.-R., 2001. Methods for quantifying the uncertainty of production forecasts: A comparative study. Petroleum Geoscience 7 (Supplement, 1 May), 87–96.
- Fonseca, R. M., Della Rossa, E., Emerick, A. A., Hanea, R. G., and Jansen, J. D., 2018. Overview of the Olympus field development optimization challenge. In D. Gunasekera (Ed.), 16th European Conference on the Mathematics of Oil Recovery, ECMOR 2018 EAGE. https://doi.org/10.3997/2214-4609.201802246
- Fonseca, R., Geel, C., and Leeuwenburgh, O., 2017. Description of olympus reservoir model for optimization challenge. Integr. Syst. Approach to Pet. Prod. http://www.isapp2.com/downloads/olympus-reservoir-model.pdf, Accessed date: 7 September 2019.

- Fonseca, R.M., Stordal, A.S., Leeuwenburgh, O., Van Den Hof, P.M.J., and Jansen, J.D., 2014. Robust ensemble-based multi-objective optimization. ECMOR XIV – 14th European Conference on the Mathematics of Oil Recovery Catania, Sicily, Italy, 8-11 September 2014
- Foss, B., 2011. Process control in the upstream petroleum industries. In Proc. of the 2011 4th International Symposium on Advanced Control of Industrial Processes, Thousand Islands Lake, Hangzhou, P.R. China, 23-26 May 2011.
- Gaspar A.T.F., Barreto C.E.A., and Schiozer D.J., 2016a. Assisted process for design optimization of oil exploitation strategy, J. Pet. Sci. Eng. 146, 473–488.
- Gaspar A.T.F.S., Avansi G.D., Maschio C., Santos A.A.S., and Schiozer D.J., 2016b. UNISIM-I-M: Benchmark case proposal for oil reservoir management decision-making, in: SPE Energy Resources Conference, 13–15 June 2016, Port of Spain, Trinidad and Tobago.
- Gaspar A.T.F.S., Avansi G.D., Santos A.A., Hohendorff Filho J.C., and Schiozer D.J., 2015. UNISIM-I-D: Benchmark studies for oil field development and production strategy selection, Int. J. Model. Sim. Petrol. Ind. 9(1), 47–55.
- Glegola, M.A., Ditmar, P., Hanea, R., Eiken, O., Vossepoel, F.C., Arts, R., and Klees, R., 2012. History matching timelapse surface-gravity and well-pressure data with ensemble smoother for estimating gas field aquifersupport-A 3D numerical study. SPE J 17(4), 966–980.
- Gomes, J.C., Geiger, S., and Arnold, D.P., 2019. An open access carbonate reservoir benchmarking study for reservoir characterisation, uncertainty quantification & history matching. SPE paper 196674-MS. SPE Reservoir Characterisation and Simulation Conference and Exhibition held in Abu Dhabi, UAE, 17 - 19 September 2019.
- Hanea, R., Casanova, P., Hustoft, L., Bratvold, R., Nair, R., Hewson, C.W., Leeuwenburgh, O., Fonseca, R.M., 2019. Drill and Learn: A Decision-Making Work Flow To Quantify Value of Learning. SPE Reservoir Evaluation & Engineering 22 (03) 1-13.
- Hanea, R., Evensen, G., Hustoft, L., Ek, T., Chitu, A., and Wilschut, F., 2015. Reservoir management under geological uncertainty using fast model update. SPE paper 173305, SPE Reservoir Simulation Symposium, Houston, USA, 23–25 February 2015.
- Hanssen, K. G., and Foss, B., 2016. On selection of controlled variables for robust reservoir management. J. Pet. Sci. Eng. 147, 504–514.
- Hanssen, K. G., Codas, A., and Foss, B., 2017. Closed-loop predictions in reservoir management under uncertainty. SPE J. 22 (05), 1-11.
- Hasan, A., Foss, B., Krogstad, S., Gunnerud, V., and Teixeira, A.F., 2013. Decision analysis for long-term and short-term production optimization applied to the voador field. SPE paper 166027-MS. SPE Reservoir Characterization and Simulation Conference and Exhibition, 16-18 September 2013, Abu Dhabi, UAE.
- Hidalgo, D.M., Emerick, A.A., Couto, P., and Alves, J.L.D., 2017. Closed-loop field development under geological uncertainties: application in a Brazilian benchmark case. Paper OTC-28089-MS, Offshore Technology Conference, Rio de Janeiro, Brasil, 24-26 October 2017.
- Hou, J., Zhou, K., Zhang, X.S., Kang, X.D., and Xie, H., 2015. A review of closed-loop reservoir management. Pet. Sci. 12, 114–128.
- Hui, Z., Yang, L., Jun, Y., and Kai, Z., 2011. Theoretical research on reservoir closed-loop production management. SCIENCE CHINA Technological Sciences, 54 (10), 2815–2824 doi: 10.1007/s11431-011-4465-2
- Hutahaean, J., Demyanov, V., and Christie, M., 2019. Reservoir development optimization under uncertainty for infill well placement in brownfield redevelopment. J. Pet. Sci. Eng. 175, 444–464.
- Isebor, O.J., and Durlofsky, L.J., 2014. Biobjective optimization for general oil field development. J. Pet. Sci. Eng. 119, 123–138.
- Jahandideh, A., and Jafarpour, B., 2018. Hedging against uncertain future development plans in closed-loop field development optimization. SPE Annual Technical Conference and Exhibition, 24-26 September 2018, Dallas, Texas, USA.
- Jahandideh, A., and Jafarpour, B., 2019. Stochastic oilfield optimization under uncertain future development plans. SPE J. 24 (4), 1526-1551.
- Jahandideh, A., and Jafarpour, B., 2020. Closed-loop stochastic oilfield optimization for hedging against geologic, development, and operation uncertainty. Computational Geosciences, 24, 129–148
- Jansen, J.D., Brouwer, D.R., Naevdal, G., and Van Kruijsdijk, C.P.J.W., 2005. Closed-loop reservoir management. First Break, 23(1), 43–48.

- Jansen, J.D., Brouwer, R., Douma, S.G., 2009. Closed loop reservoir management. SPE Reservoir Simulation Symposium, The Woodlands, TX, USA, 2–4 February 2009; Society of Petroleum Engineers.
- Jesmani, M., Bellout, M.C., Hanea, R., and Foss, B., 2016. Well placement optimization subject to realistic field development constraints. Comput Geosci. 20, 1185–1209.
- Kang, B., Kim, S., Jung, H., Choe, J., and Lee, K., 2019. Efficient assessment of reservoir uncertainty using distance-based clustering: a review. Energies 12, 1859.
- Khor, C.S., Elkamel, A., and Shah, N., 2017. Optimization methods for petroleum fields development and production systems: a review. Optim Eng 18, 907–941.
- Ligero, E.L., Costa, A.P.A., and Schiozer, D.J., 2003. Improving the performance of risk analysis applied to petroleum field development. SPE paper 81162. SPE Latin American and Caribbean Petroleum Engineering Conference, Port-of-Spain, Trinidad, West Indies, 27-30 April 2003.
- Liu, X., and Reynolds, A.C., 2015. Multi-objective optimization for maximizing expectation and minimizing uncertainty or risk with application to optimal well control. SPE Reservoir Simulation Symposium, 23-25 February 2015, Houston, Texas, USA.
- Liu, X., and Reynolds, A.C., 2016. Gradient-based multi-objective optimization with applications to waterflooding optimization. Comput Geosci 20, 677–693.
- Liu, Z., and Forouzanfar, F., 2018. Ensemble clustering for efficient robust optimization of naturally fractured reservoirs. Comput Geosci 22, 283–296.
- Lorentzen, R.J., Shafieirad, A., and Nævdal, G., 2009. Closed-loop reservoir management using the ensemble kalman filter and sequential quadratic programming. SPE paper 119101, SPE Reservoir Simulation Symposium, The Woodlands, Texas, USA, 2–4 February 2009.
- Mahjour, S.K., Correia, M.G., Santos, A.A.S., and Schiozer, D.J. 2020a. Using an integrated multidimensional scaling and clustering method to reduce the number of scenarios based on flow-unit models under geological uncertainties. J. Energy Resour. Technol. 142(6), 063005 https://doi.org/10.1115/1.4045736
- Mahjour, S.K., Santos, A.A.S., Correia, M.G., and Schiozer, D.J., 2020b. Developing a workflow to select representative reservoir models combining distance-based clustering and data assimilation for decision making process. J. Pet. Sci. Eng. 190, 107078. https://doi.org/10.1016/j.petrol.2020.107078
- Mahjour, S.K., Correia, M..G., Santos, A.A.S., Schiozer, D.J. 2019. Developing a workflow to represent fractured carbonate reservoirs for simulation models under uncertainties based on flow unit concept. Oil & Gas Science and Technology - Rev. IFP Energies nouvelles 74, https://doi.org/10.2516/ogst/2018096
- Marler, R.T., and Arora, J.S., 2004. Survey of multi-objective optimization methods for engineering. Structural and multidisciplinary optimization 26 (6), 369-395.
- Maschio, C., and Schiozer, D.J., 2008. A new methodology for assisted history matching using independent objective functions, Petrol. Sci. Technol. 26 (9), 1047–1062.
- Maschio, C., and Schiozer, D.J., 2015. A new optimization framework using genetic algorithm and artificial neural network to reduce uncertainties in petroleum reservoir models, Eng. Optimiz. 47 (1), 72–86.
- Maschio, C., and Schiozer, D.J., 2016. Probabilistic history matching using discrete latin hypercube sampling and nonparametric density estimation, J. Pet. Sci. Eng. 147, 98–115.
- Maschio, C., and Schiozer, D.J., 2019. A new parameterization method for data assimilation and uncertainty assessment for complex carbonate reservoir models based on cumulative distribution function. J. Pet. Sci. Eng. 183, 106400.
- Meddaugh, W.S., and Champenoy, N., 2012. Reservoir performance forecasting – how well are we really doing?. First EAGE Integrated Reservoir Modelling Conference, 25-28 November 2012, Dubai, UAE.
- Meddaugh, W.S., Meddaugh, W., and McCray, B., 2017. Quantitative assessment of the impact of sparse data and decision bias on reservoir recovery forecasts. SPE 187402-MS. SPE Annual Technical Conference and Exhibition, San Antonio, Texas, USA, 9-11 October 2012.
- Meira, L.A., Coelho, G.P., Santos, A.A.S., Schiozer, D.J., 2016. Selection of representative models for decision analysis under uncertainty. Comput. Geosci. 88, 67–82.
- Meira, L.A., Coelho, G.P., Silva, C.G., Schiozer, D.J., Santos, A.S., 2017. Rmfinder 2.0: an improved interactive multi-criteria scenario reduction methodology. In: SPE Latin America and Caribbean Petroleum Engineering Conference. Society of Petroleum Engineers, Buenos Aires, Argentina, pp. 23. https://doi.org/10.2118/185502-MS.

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https://dx.doi.org/10.1016/j.petrol.2021.108457

- Meira, L.A.A., Coelho, G.P., Silva, C.G., Abreu, J. L.A., Santos, A. A.S. and Schiozer, D.J., 2020. Improving representativeness in a scenario reduction process to aid decisionmaking in petroleum fields. J. Pet. Sci. Eng. 184, 106398. https://doi.org/10.1016/j.petrol.2019.106398
- Mirzaei-Paiaman, A., 2013a. An empirical correlation governing gas-condensate flow through chokes. Petroleum Science and Technology 31(4), 368-379.
- Mirzaei-Paiaman, A., 2013b. Severe loss of well productivity in an Iranian gas condensate reservoir: problem identification and remedy. Energy Sources, Part A, 35(19), 1863-1872.
- Mirzaei-Paiaman, A., 2019c. New concept of dynamic rock typing and necessity of modifying current reservoir simulators. SPE Review London, June, 7-10. https://www.spe-london.org/wp-content/uploads/2019/06/SPE-Review-June-2019.pdf
- Mirzaei-Paiaman, A., Nournai, M., 2012. Positive effect of earthquake waves on well productivity: case Study: an Iranian carbonate gas condensate reservoir. Scientia Iranica 19 (6), 1601-1607. http://dx.doi.org/10.1016/j.scient.2012.05.009
- Mirzaei-Paiaman, A., Ostadhassan, M., Rezaee, R., Saboorian-Jooybari, H., and Chen, Z., 2018. A new approach in petrophysical rock Typing. J. Pet. Sci. Eng., 166, 445–464.
- Mirzaei-Paiaman, A., Sabbagh, F., Ostadhassan, M., Rezaee, R., Saboorian-Jooybari, H., and Chen, Z., 2019a. A further verification of FZI* and PSRTI: newly developed petrophysical rock typing indices. J. Pet. Sci. Eng., 175, 693-705.
- Mirzaei-Paiaman, A., Saboorian-Jooybari, H., Chen, Z., Ostadhassan, M., 2019b. New technique of true effective mobility (TEM-Function) in dynamic rock typing: reduction of uncertainties in relative permeability data for reservoir simulation. J. Pet. Sci. Eng., 179, 210-227.
- Mirzaei-Paiaman, A., Salavati, S., 2012. Application of artificial neural networks for prediction of oil production flow rate, Energy Sources, Part A, 34 (19), 1834-1843.
- Mirzaei-Paiaman, A., Salavati, S., 2013. A New Empirical Correlation for Sonic Simultaneous Flow of Oil and Gas through Wellhead Chokes for Persian Oil Fields. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 35 (9), 817-825.
- Moradi, T., and Rasaei, M.R., 2017. Automated reservoir management using multi-objective simulation optimization and SA model. J. Pet. Sci. Eng., 150, 91–98
- Morais, V. L. R. S., Fioravanti, A. R., and Schiozer, D. J., 2017. Methodology to estimate the economic impact of intelligent wells considering reservoir uncertainties. SPE paper 182591-MS, SPE Reservoir Simulation Conference held in Montgomery, TX, USA, 20–22 February 2017.
- Morosov, A.L., and Schiozer, D.J., 2017. Field-development process revealing uncertainty-assessment pitfalls. SPE Reservoir Eval. Eng. 20, 765–778.
- Nævdal, G., Brouwer, D.R., and Jansen J.D., 2006. Waterflooding using closed-loop control, Comput. Geosci. 10 (1), 37–60.
- Oliver, D.S., and Chen, Y., 2010. Recent progress on reservoir history matching: a review. Computational Geosciences, 15(1), 185–221.
- Overbeek, K.M., Brouwer, D.R. Naevdal, G., Van Kruijsdijk, C.P.J.W. and Jansen, J.D., 2004. Closed-loop waterflooding. 9th European Conference on the Mathematics of Oil Recovery - Cannes, France, 30 August - 2 September 2004.
- Peters, E., Chen, Y., Leeuwenburgh, O. and Oliver, D.S., 2013. Extended Brugge benchmark case for history matching and water flooding optimization. Computers & Geosciences 50, 16–24.
- Peters, L., Arts, R., Brouwer, G., Geel, C., Cullick, S., Lorentzen, R., Chen, Y., Dunlop, N., Vossepoel, F., Xu, R., Sarma, P., Alhutali, A.H., and Reynolds, A.C., 2010. Results of the Brugge benchmark study for flooding optimization and history matching. SPE Reserv. Eval. Eng. 13, 391–405.
- Pinto, J.W.O., Tueros, J.A.R., Horowitz, B., Silva, S.M.B.A., Willmersdorf, R.B., and Oliveira, D.F.B., 2019. Gradient-free strategies to robust well control optimization. Computational Geosciences, https://doi.org/10.1007/s10596-019-09888-7
- Pinto, M.A.S., Gildin, E., and Schiozer, D.J., 2015. Short-term and long-term optimizations for reservoir management with intelligent wells. SPE paper 177255-MS, SPE Latin American and Caribbean Petroleum Engineering Conference Held in Quito, Ecuador, 18–20 November 2015.
- Rahim, S., Li, Z., and Trivedi, J., 2015. Reservoir geological uncertainty reduction: an optimization-based method using multiple static measures. Math. Geosci. 47, 373–396.
- Salehi-Moorkani, S., Safian, Gh.A., Mirzaei-Paiaman, A., 2010. Successful Applications of Expandable Sand Screen in Persian Oil Fields, Part 1. SPE Production and Operations Conference and Exhibition, paper no. SPE 133364, 8–10 June 2010, Tunisia, Tunis.

- Santos S.M.G., Botechia V.E., Schiozer D.J., and Gaspar A.T.F.S., 2017a. Expected value, downside risk and upside potential as decision criteria in production strategy selection for petroleum field development, J. Pet. Sci. Eng. 157, 81–93.
- Santos S.M.G., Gaspar A.T.F.S., and Schiozer D.J., 2017b. Value of information in reservoir development projects: Technical indicators to prioritize uncertainties and information sources, J. Pet. Sci. Eng. 157, 1179–1197.
- Santos S.M.G., Gaspar A.T.F.S., and Schiozer D.J., 2017c. Risk management in petroleum development projects: Technical and economic indicators to define a robust production strategy, J. Pet. Sci. Eng. 151, 116–127.
- Santos S.M.G., Gaspar A.T.F.S., and Schiozer D.J., 2018a. Managing reservoir uncertainty in petroleum field development: Defining a flexible production strategy from a set of rigid candidate strategies, J. Pet. Sci. Eng. 171, 516–528.
- Santos S.M.G., Gaspar A.T.F.S., and Schiozer D.J., 2018b. Comparison of risk analysis methodologies in a geostatistical context: Monte Carlo with joint proxy models and discretized latin hypercube, Int. J. Uncertain. Quan. 8, 1, 23–41.
- Santos, S.M.G., Gaspar, A.T.F.S., and Schiozer, D.J., 2020. Information, robustness, and flexibility to manage uncertainties in petroleum field development. J. Pet.Sci. Eng. https://doi.org/10.1016/j.petrol.2020.107562
- Sarma, P., Chen, W.H., and Xie, J., 2013. Selecting representative models from a large set of models. SPE paper 163671. SPE Reservoir Simulation Symposium held in The Woodlands, Texas USA, 18–20 February 2013.
- Sarma, P., Durlofsky, L. J., and Aziz, K., 2008. Computational techniques for closed–loop reservoir modeling with application to a realistic reservoir. Pet. Sci. Technol. 26 (10-11), 1120-1140.
- Sarma, P., Durlofsky, L.J., and Aziz, K., 2005. Efficient closed-loop production optimization under uncertainty. SPE paper 94241, SPE Europec/EAGE Annual Conference, 13-16 June 2005, Madrid, Spain.
- Sarma, P., Durlofsky, L.J., Aziz, K., and Chen,W.H., 2006. Efficient real-time reservoir management using adjoint-based optimal control and model updating. Comput. Geosci. 10(1), 3–36.
- Schiozer, D., Ligero, E., Suslick, S., Costa, A., and Santos, J., 2004. Use of representative models in the integration of risk analysis and production strategy definition. J. Petrol. Sci. Eng. 44 (1–2), 131–141.
- Schiozer, D.J., Avansi, G.D., and Santos, A.A.S., 2017. Risk quantification combining geostatistical realizations and discretized Latin hypercube. J. Braz. Soc. Mech. Sci. Eng. 39 (2), 575–587.
- Schiozer, D.J., Santos, A.A.S., and Drumond, P.S., 2015. Integrated model based decision analysis in twelve steps applied to petroleum fields development and management. SPE paper 174370-MS, Madrid, Spain. EUROPEC 2015, 1-4 June 2015.
- Schiozer, D.J., Santos, A.A.S., Santos, S.M.G., and Filho, J.C.H., 2019. Model-based decision analysis applied to petroleum field development and management. Oil Gas Sci. Technol. - Rev. IFP Energies nouvelles 74, 46. https://doi.org/10.2516/ogst/ 2019019.
- Shirangi, M.G., 2013. Closed-loop field development optimization. 26th Annual Meeting of Stanford Center for Reservoir Forecasting, Palo Alto, California, USA, 8 May 2013. Available at https://pangea.stanford.edu/departments/ere/dropbox/scrf/documents/reports/26/SCRF2013_Report26/19.SCRF2013mehr2.pdf
- Shirangi, M.G., 2019. Closed-loop field development with multipoint geostatistics and statistical performance assessment. Journal of Computational Physics 390 , 249–264
- Shirangi, M.G., and Durlofsky, L.J., 2015. Closed-loop field development under uncertainty by use of optimization with sample validation. SPEJ. 20(05), 908–922.
- Shirangi, M.G., and Durlofsky, L.J., 2016. A general method to select representative models for decision making and optimization under uncertainty, Comput. Geosci. 96, 109–123.
- Silva, M.I.O., Santos, A.A.S., Schiozer, D.J. and Neufville, R., 2017. Methodology to estimate the value of flexibility under endogenous and exogenous uncertainties. J. pet. Sci. Eng. 151, 235–247.
- Silva, V.L.S., Emerick, A.A., Couto, P., and Alves, J.L.D., 2017. History matching and production optimization under uncertainties–Application of closed-loop reservoir management. J. pet. Sci. Eng. 157, 860–874.
- Steagall, D.E., and Schiozer, D.J., 2001. Uncertainty analysis in reservoir production forecasts during appraisal and pilot production phases. SPE paper 66399-MS, SPE Reservoir Simulation Symposium Held in Houston, Texas, 11–14 February 2001.

- Sudaryanto, B., and Yortsos, Y.C., 2011. Optimization of displacements in porous media using rate control. SPE paper 71509, SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, 30 September-3 October 2001.
- Udy, J., Hansen, B., Maddux, S., Petersen, D., Heilner, S., Stevens, K., Lignell, D., and Hedengren, J.D., 2017. Review of field development optimization of waterflooding, EOR, and well placement focusing on history matching and optimization algorithms. Processes 5, 34; doi:10.3390/pr5030034
- van den Hof, P.M.J., Jansen, J.D., and Heemink, A., 2012. Recent developments in model-based optimization and control of subsurface flow in oil reservoirs. IFAC Workshop on Automatic Control in Offshore Oil and Gas Production May 31 - June 1, 2012. Trondheim, Norway
- van Essen, G., Zandvliet, M., Van den Hof, P., Bosgra, O., and Jansen, J.D., 2009. Robust waterflooding optimization of multiple geological scenarios.SPE J. 14(01), 202–210.
- van Essen, G.M., Van den Hof, P.M.J., and Jansen, J.D., 2011. Hierarchical long-term and short-term production optimization. SPE J. 1, 191–199.
- Vera, R.A.R., Muziotti, C., Caraballo, N., 2008. A model integrating surface to subsurface models under uncertain conditions, for optimizing production in Santa Barbara and Pirital fields, Venezuela. SPE paper 113723. SPE Improved Oil Recovery Symposium held in Tulsa, Oklahoma, U.S.A., 19–23 April 2008.
- Vera, R.A.R., Solano, K., Guevara, S., Velásquez, M., and Saputelli, L.A., 2007. Integration of subsurface, surface and economics under uncertainty in Orocual field. SPE paper 107259, SPE Latin American and Caribbean Petroleum Engineering Conference held in Buenos Aires, Argentina, 15–18 April 2007.
- von Hohendorff Filho, J.C., and Schiozer D.J., 2018. Effect of reservoir and production system integration on field production strategy selection, Oil Gas Sci. Technol. – Rev. IFP Energies nouvelles 73, 44. https://doi.org/10.2516/ogst/2018042.
- von Hohendorff Filho, J.C., Maschio, C., and Schiozer, D.J., 2016. Production strategy optimization based on iterative discrete latin hypercube, J. Braz. Soc. Mech. Sci. 38, 8, 2473–2480.
- von Hohendorff Filho, J.C., Schiozer, D.J., 2017. Evaluation of reservoir and production system integration in production strategy selection. SPE Reservoir Simulation Conference, 20–22 February, Montgomery, Texas.
- Wang C., Li G., and Reynolds A.C., 2009. Production optimization in closed-loop reservoir management, SPE J. 14, 3, 506–523.
- Wen, X., and Chen, W.H., 2006. Real-time reservoir model updating using ensemble Kalman filter with confirming option. SPE Journal11 (4), 431-442.
- Yang, C., Card, C., Nghiem, L., and Fedutenko, E., 2011. Robust optimization of SAGD operations under geological uncertainties. SPE Reservoir Simulation Symposium, 21–23 February, The Woodlands, Texas.
- Yasari, E., and Pishvaie, M.R., 2015. Pareto-based robust optimization of water-flooding using multiple realizations, J. Pet. Sci. Eng. 132, 18–27.
- Yasari, E., Pishvaie, M.R., Khorasheh, F., Salahshoor, K., and Kharrat, R., 2013.Application of multi-criterion robust optimization in water-flooding of oil reservoir. J. Pet. Sci. Eng. 109 (1), 1–11.
- Yeten, B., Brouwer, D. R., Durlofsky, L. J., and Aziz, K., 2004. Decision analysis under uncertainty for smart well deployment. J. Pet. Sci. Eng. 44(1), 175-191.
- Yeten, B., Durlofsky L.J., and Aziz, K., 2002. Optimization of nonconventional well type, location and trajectory. SPE Annual Technical Conference and Exhibition, 29 September–2October 2002, San Antonio, Texas.
- Yeten, B., Durlofsky, L. J., and Aziz, K., 2003. Optimization of nonconventional well type, location, and trajectory. SPE J. 8(3), 200-210.
- Zabalza-Mezghani, I., Manceau, E., Feraille, M., and Jourdan, A., 2004. Uncertainty management: From geological scenarios to production scheme optimization. J. Pet. Sci. Eng. 44 (1-2) 11-25.
- Zakirov, I. S., Aanonsen, S. I., Zakirov, E. S., and Palatnik, B.M., 1996. Optimizating reservoir performance by automatic allocation of well rates. 5th European Conference on the Mathematics of Oil Recovery, September 1996, Leoben, Austria.
- Zhang, Z., Jung, H.Y., Datta-Gupta, A., Delshad, M., 2019. History matching and optimal design of chemically enhanced oil recovery using multi-objective optimization. SPE paper 193860-MS, SPE Reservoir Simulation Conference, 10-11 April, Galveston, Texas, USA.