AI-Driven Prescriptive Analytics for Hydrate Mitigation in Offshore Petroleum Production

Mateus A. Fernandes
Dept. of Reservoir and Production Engineering
Petrobras
Santos, Brazil
matfernan@petrobras.com.br

Rafael O. Rabelo
Dept. of Reservoir and Production Engineering
Petrobras
Santos, Brazil
rafael.rabelo@petrobras.com.br

Eduardo Gildin
Dept. of Petroleum Engineering
Texas A&M University
College Station, USA
egildin@tamu.edu

Marcio A. Sampaio
Dept. of Mining and Petroleum Engineering
University of São Paulo
São Paulo, Brazil
marciosampaio@usp.br

Abstract— **In offshore petroleum systems, one of the main challenges in production management and flow assurance is preventing blockages caused by natural gas hydrates. These crystalline structures form when water and natural gas combine under specific temperature and pressure conditions, leading to well unavailability and requiring significant resources for restoration. In this study, we evaluate hydrate mitigation strategies and their associated economic aspects using an AI-driven prescriptive analytics approach. We propose a framework based on the probabilistic modeling of influencing events, such as unscheduled shutdowns and the probability of hydrate formation based on the duration of fluid stagnation in subsea pipelines. This probabilistic analysis is combined with deterministic data, including production forecast curves, the duration and priority order of mitigation actions, and economic data related to revenues and expenditures. Using this data, we deploy Monte Carlo simulations alongside a rule-based system to assess differences in cumulative production, blockage probabilities, and net present value (NPV) under various scenarios involving production strategies and improvements in hydrate prevention systems. We demonstrate the practical applicability of this framework through three real-world case studies involving an offshore production platform operating in the Brazilian pre-salt, where the results provide valuable insights for decision-making aimed at maximizing value.**

Keywords—data analytics, predictive models, Monte Carlo methods, petroleum industry, hydrate

I. Introduction

The formation of natural gas hydrates, which may result in the blockage of subsea pipelines transporting fluids from wells to oil platforms, is a significant cause of production loss in offshore systems. Mitigating this issue poses one of the main challenges for production management and flow assurance, particularly in deepwater systems [1, 2, 3].

Hydrate formation can occur when free natural gas and water coexist under pressure and temperature conditions often found in deepwater fields. The risk of reaching these conditions which can lead to blockages increases during unscheduled production shutdowns. This is oftenly associated with a chain of operational events and specific well characteristics that are non-deterministic but can be influenced by controllable mitigation strategies, as we will detail later in this work.

Quantitative assessments of the impact caused by pipeline blockage, along with the benefits of implementing improvements in prevention systems when dealing with multiple wells, are complex due to their probabilistic characteristics and the influence of a combination of factors across different petroleum engineering disciplines, such as reservoir management, flow assurance, operations, and economic evaluations. The ability to handle such integration—combining different types of data, models, and rules to guide decision-making—is a key driver for the development of data analytics frameworks [4].

In this work, we aim to address this topic from the perspective of prescriptive analytics by proposing a novel framework based on statistical modeling and Monte Carlo simulations. Our framework includes the following key features:

- Integration of deterministic and probabilistic assumptions from different disciplines.
- Embedding an intelligent rule-based system, leveraging expert knowledge, into the simulations to enhance realism and accuracy.
- Flexibility to allow for variations in assumptions to assess different scenarios and strategies, as well as sensitivity analyses on parameters.
- Provision of relevant key performance indicators (KPIs) for multidisciplinary evaluation, including cumulative production, risks, demands for physical and financial resources, and economic viability.

We believe that these features are essential for the framework to be effectively applied in complex real-world situations. Our goal is to utilize it in the analysis of production strategies and resource management, ensuring that it remains simple, easily understandable, and replicable for use in other platforms or oilfields.

Following this introduction, we provide a brief review of hydrate formation and mitigation, along with a discussion on prescriptive analytics and its applications in the industry. In the third section, we elaborate on the proposed framework for assessing the impacts of hydrate formation. Next, we present a case study based on a platform operating in the Brazilian pre-salt, including three analyses guided by our framework and a discussion on the sensitivity of the most influential parameters. Finally, we conclude with our key findings and final remarks.

II. Background and Related Work

In this section, we provide further information regarding hydrate formation and how this problem is addressed in offshore oil production. We also present a review of analytics applications related to the oil and gas industry.

A. Formation of natural gas hydrates and its prevention

Hydrates are crystalline solids composed of light gas molecules trapped by water molecules. They can form under conditions of low temperatures combined with high pressures [5]. These are non-stoichiometric inclusion compounds that can maintain long-term stability under a large range of conditions [6], which can bring difficulties to the dissociation process.

The chances of hydrate formation increase even in oil-producing wells as the water fraction becomes more significant in the multiphase flow, which is expected with the maturity of the fields and the advance of injected water. With higher water cuts, hydrates will form more rapidly, increasing the likelihood of pipeline blockage [5]. It is important to note that gas will always be present in the production flow, even if it is not in a free form originally in the reservoir, as it will be released from light fractions of oil when pressure drops below the bubble point along the pipelines [7].

The conditions for hydrate formation can be estimated using a Pressure vs. Temperature envelope, as illustrated in Figure 1. For each well or group of wells under similar conditions, this envelope will be influenced by various factors, including the chemical composition and saturation pressure of hydrocarbons, as well as water salinity (which is inversely proportional). It can also be intentionally altered to some extent using chemical inhibitors [8].

Understanding this envelope is crucial, as it can be employed together with production parameter forecasts (provided by reservoir engineering) and simulations of flow in pipelines (performed by lifting and flow assurance engineering) to identify situations in which wells meet favorable conditions for hydrate formation and, consequently, pipeline blockage [2]. Due to the complexity of modeling this phenomenon, numerous works in industry and academia address it, aiming to predict hydrate formation using numerical methods [2, 3, 9, 10] or machine learning [11], as well as studying its dissociation [8, 12] and methods for locating blockages once they're formed [13].

The highest risk for hydrate formation typically occurs during unplanned well shut-ins [9, 14], such as those caused by platform emergency shutdowns or failures in processing facilities. The interruption in production causes the fluids to become static in the pipelines, resulting in cooling as they move towards thermal equilibrium with the surrounding low temperatures at great depths in the seabed.

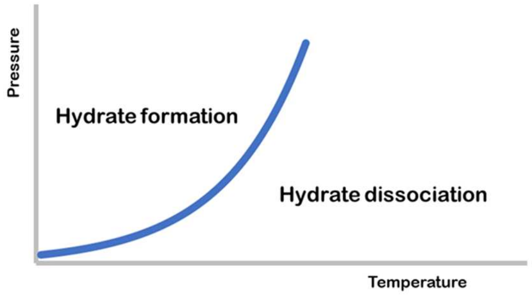

Fig. 1. Example of a P vs. T envelope for hydrate formation.

The readiness of mitigation actions is crucial in these cases, as circulation for cleaning the lines is required using dry gas or diesel to prevent the temperature of the multiphase mixture from dropping until the hydrate formation envelope is reached. The required response times for each well, even on a single platform, can vary significantly and are usually pre-calculated. This so-called cooldown time (CDT) depends on factors such as flow rate, water cut, gas-oil ratio (GOR), water salinity, and line length, among others, and determines the sequence of actions for prevention and line cleaning in the event of a platform shutdown. The challenge arises when there are multiple critical wells and/or a longer time until the return of normal operational conditions, making gas cleaning circulation unfeasible and relying solely on the capabilities of diesel pumps, which have limitations in injection rates and onboard stock. In such cases, it may be inevitable for one or more wells to enter the hydrate envelope.

The analysis of prioritization for cleaning the lines needs to consider all these aspects, as well as the consequences of a potential hydrate blockage. These primarily include production loss, time until dissociation actions, and the costs and critical resources required for these actions. In extreme situations, wells with low CDTs, long flowlines, and low productivity may even have their productive life prematurely ended due to economic infeasibility caused by the risk of hydrate blockage. Factors such as the availability of service lines (auxiliary pipelines that connect the well to the platform for gas lift or auxiliary operations), the condition of subsea christmas tree valves, and the remaining lifespan of the pipelines can also aggravate the situation.

The dissociation process is typically performed through cycles of pressurization and depressurization of the blocked pipeline using dry gas. This can be achieved using the platform's own process gas (if the connection is feasible and compressors with the appropriate pressure capabilities are available), utilizing a Nitrogen Generation Unit (NGU), or relying on resources from a workover rig. The latter two options depend on critical resource competition with other platforms or even other fields. The chances of success are considered higher with a workover rig due to the availability of specialized equipment and personnel for this task. However, this entails higher costs and possibly extended waiting time until prioritization (e.g., in the case of wells with lower productivity). Ideally, an initial attempt at dissociation using the platform's own resources is considered, and if unsuccessful, the alternative of using a workover rig is deployed. It is important to note that, in addition to the costs and production losses, the pipelines are exposed to integrity risks during the blockage and pressurization cycles for dissociation [9].

B. Prescriptive Analytics its application in the petroleum industry

In a complex industry like oil and gas, which generates vast amounts of data and heavily relies on models, the use of analytics methods can bring significant value by assisting both operational and strategic decision-making.

As companies mature in their data culture, we witness an increase in the number of applications advancing through the data analytics pipeline, as shown in Figure 2 and described by [4, 15]. These works highlight that the sequence of stages in this pipeline is correlated to the potential of generating more value for the companies.

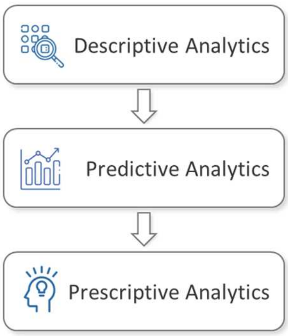

Fig. 2. Pipeline of data analytics.

In the first stage, Descriptive Analytics helps us to understand our data and the events. We then can deploy Predictive Analytics tools to obtain more reliable forecasts, and eventually reach the pinnacle with Prescriptive Analytics actions, the most advanced stage in the pipeline, which brings more intelligence and new insights to our businesses [15].

In each of these stages, a vast variety of methods and techniques can be used individually or combined, as listed (non-exhaustively) by [15] and [16], including statistical analysis, mathematical programming, data mining, and machine learning. The latter highlights one key point for more complex analytics applications: the ability to integrate data from different sources, such as sensors, operational data, and external data. The former also emphasizes that most of the current research on prescriptive analytics still relies on models primarily or entirely based on expert knowledge, including human subjectivity. This indicates that there is room for significant advances in this area of study.

Specifically, in the oil industry, the large volume and diversity of data create demands for analytics in numerous applications across all its branches and disciplines, as reviewed by [17, 18]. The work by [19] highlights that information science improves the oil and gas industry by optimizing subsystems, increasing accuracy and confidence in decision-making, and ultimately reducing risk.

These considerations motivate us to apply the full analytics pipeline in this work, incorporating the benefits of descriptive, predictive and, ultimately, prescriptive analytics.

III. Methodology

The quantitative analysis required for assessing the impact of hydrate formation and planning mitigation actions in a Prescriptive Analytics task relies on a sequence of probabilistic events combined with deterministic assumptions. The framework we propose addresses this by first obtaining probability distributions of events using historical operational data. Subsequently, we utilize production forecast curves, information about the pipelines and cleaning procedures for each well, and economic assumptions, gathered together in Monte Carlo simulations that compute indicators of cumulative production, blockage risks, and economic viability. In each iteration of the Monte Carlo simulation, a defined number of time steps represent the analysis horizon. At each time step, a rule-based reasoning approach determines the prevention priority, ranking wells based on criticality criteria.

We illustrate the proposed steps as a workflow in Figure 3 and describe the details in the following paragraphs.

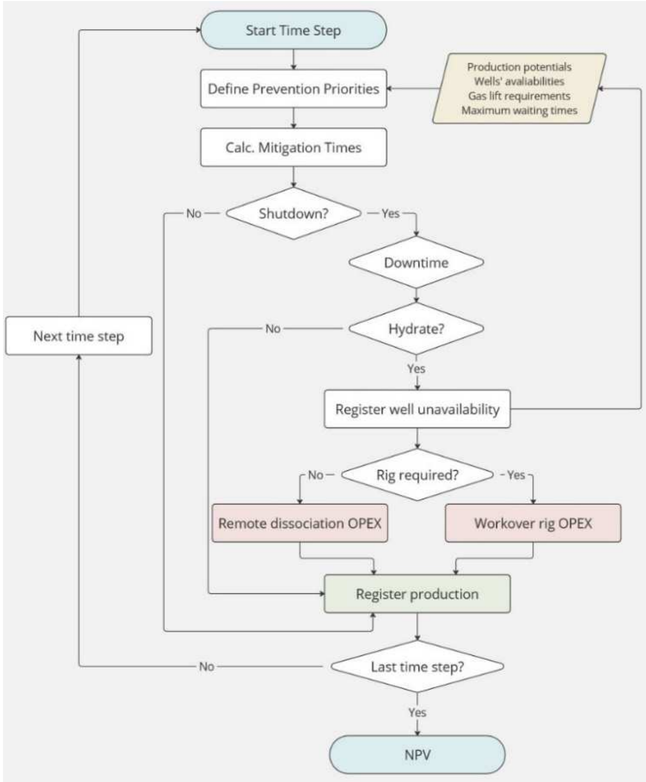

Fig. 3. Workflow proposed for using data analytics in the analysis of impacts of hydrates in petroleum production.

1) In the initialization phase, we consider the following deterministic inputs:

- Curves for oil production potential and water cut for each well, obtained from simulations conducted by the reservoir engineering team.
- Schedule of well availability, including maintenance, workovers, and pipelines' lifespan.
- Requirements for gas lift, estimated based on specific simulations for lift methods.
- Cooldown times (CDT), calculated by the flow assurance team using as inputs production rate curves, water salinity, and subsea flowline lengths.

2) The previous data are used to define prevention priorities at each time step, and for that purpose we deploy a rule-based AI. Given the dynamic nature of operational conditions for each well, including availability and production parameters, it is necessary to assess and establish a priority ranking for hydrate mitigation at each time step in the event of a shutdown. To achieve this, we encode operational expertise into a rule-based system, enhancing the fidelity of simulations by aligning them more closely with real-world decision-making.

In this rule-based system, the primary criterion for ranking priorities is the wells' CDT, starting with the shortest times, as exceeding these significantly increases the probability of hydrate formation and pipeline blockage. If two wells have similar CDT, we prioritize the one with shorter cleaning time, which is determined by the product of pipeline's internal volume and the diesel pump flow rate. The next criterion is the oil production rate, as higher-producing wells generate significantly more revenue and are therefore prioritized.

An additional factor considered in this prioritization is gas lift utilization, which we penalize by placing related wells at the end of the sequence. This penalty is necessary due to the long dead time required for fluid inversion during the mitigation procedure, including valve and flange operations on the topside. These delays could significantly impact the timely execution of mitigation actions for other wells.

By combining these criteria using conditional and sorting functions, we established our rule base for defining prevention priorities. At each time step, this ranking is updated based on well availability feedback (step 6) and other a priori premises.

3) The next step is to calculate the mitigation times required for each well, based on the ranking defined in the previous step and by calculating the cumulative sum of the times required for cleaning diesel circulation for every well. We assume an initial dead time of two hours as a margin for detection and personnel mobilization in the event of a shutdown. This list of estimated mitigation times is valid only for the current time step, regardless of whether a shutdown event occurs or not.

4) Next, we consider the first probabilistic event: the occurrence or non-occurrence of an unscheduled platform shutdown. During continuous operation, when wells and the processing plant are operating normally, the chances of hydrate blockage are very low and would only occur in atypical cases, such as procedural errors. However, during an unscheduled shutdown, the temperature drop due to the interruption of flow can bring certain wells within the hydrate envelope if it is not possible to perform the cleaning circulation within the cooldown time. To address this, we gathered recent data on unscheduled shutdowns for the platform under analysis, tabulating dates and durations to obtain the expected frequency of occurrences and modeling the probability distribution of the time required to restore the plant and reopen wells. This probability distribution is fitted to a known function, such as the Gaussian, based on histograms of shutdown durations.

The data collection period should represent expected conditions in the near future, considering factors such as plant characteristics, equipment degradation, and implemented improvements. These characteristics are often represented by the "bathtub curve," which maintenance management uses to predict failure rates more accurately, as illustrated by [20]. This type of curve typically shows a higher incidence of failures during initial implementation, followed by a period with fewer events, and a subsequent increase in failure rate as the plant nears the end of its useful life. Depending on the specific case, we can use this type of modeling or other estimates, such as moving averages of failure occurrences.

To determine if an unplanned shutdown will occur at a given time step, we randomly draw a number and compare it to the probability of occurrence at that time. If no shutdown occurs, the production from all operating wells is recorded in a curve to be delivered at the end, and we move on to the next time step. If a shutdown does occur, we proceed to subsequent probabilistic analyses.

5) A second random draw determines the shutdown duration. The sampled value is mapped onto the probability distribution curve of platform restoration times, which is derived from operational history and reflects the time required to restart the processing plant and reopen the wells after a shutdown.

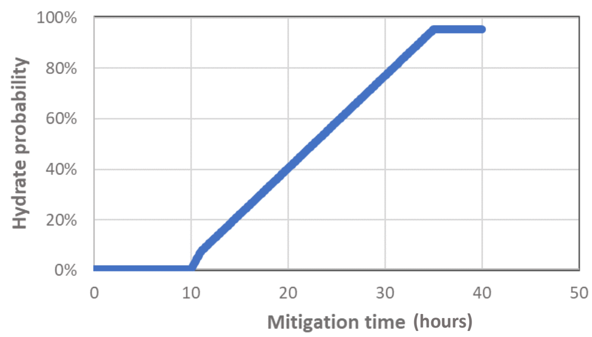

Fig. 4. Example of hydrate blockage probability distribution as a function of mitigation or reopening time for a case where CDT = 10 hours.

6) Based on the shutdown duration, we estimate the time before cleaning or reopening actions begin for each well, using the list of estimated mitigation times from step (3). However, we do not automatically assume blockage once the CDT is exceeded. Due to the complexity of the physical-chemical modeling of hydrate formation, a probability curve for blockage is developed based on the well's shutdown duration until reopening or cleaning. This curve can be constructed from historical data or from a set of simulations. In this study, we consider piecewise linear curves as a modeling approach, as illustrated in Figure 4. These curves are tailored for each well based on its specific CDT, with the main feature being the change in slope once the CDT is exceeded, and stabilization occurring after additional 24 hours.

The mitigation times calculated for each well are compared to their respective probability curves to determine the likelihood of hydrate formation during each time step. To assess hydrate formation in each well, we perform random number draws and compare them against each probability. If no hydrate blockage occurs, we record production and proceed to the next time step. If hydrates do form in one or more wells, we register the unavailability of those wells for a specified period, feeding back into step (1) and moving forward to evaluate hydrate dissociation.

7) The final probabilistic event is the success of hydrate dissociation. As mentioned earlier, we typically prioritize the option with lower OPEX, which utilizes platform resources directly. If this approach fails, a specialized rig workover will be required, resulting in higher costs. The probability of each outcome is based on the company's historical data, and we use these probabilities in the simulation by comparing them to another random number draw. The result determines the OPEX cost for the current simulation iteration. Production from the unblocked wells is then recorded, and we move on to the next time step.

8) The Monte Carlo simulations follow this process along the production curve timeline, repeating the loop until the end of the defined horizon. Cumulative production is converted into revenue based on an assumed net price per barrel, from which any dissociation costs are subtracted, yielding the Net Present Value (NPV) for this simulation iteration. The key advantage of the Monte Carlo method is that it allows us to repeat this procedure thousands of times until the average NPV converges to a value that accurately reflects the range of event combinations modeled. Additionally, we can calculate other average values to generate a set of KPIs, including cumulative production, hydrate formation probabilities, and resource demand for workovers. This framework is adaptable to different scenarios for sensitivity analyses, such as varying CDTs, well events, or mitigation times. To conduct such analyses, a new set of Monte Carlo simulations is performed with the modified assumptions, and the resulting KPIs are compared. This comparison provides crucial input for planning future activities, as expected from Prescriptive Analytics frameworks.

The framework was implemented in *Visual Basic for Applications* (VBA) built into a *Microsoft Excel* spreadsheet to allow for easier general utilization and integration with some of the required input data.

IV. Practical Applications and Results

In this section, we present real-world scenarios that require decision-making regarding hydrate prevention actions and improvement implementations, illustrating how our method supports decision-making.

A. Case study

To demonstrate the application and potential of our framework, we selected case studies based on an offshore production platform operating in a Brazilian pre-salt oilfield. The platform is a FPSO (Floating Production Storage and Offloading) unit and has been operating in this field for over 10 years, with seven oil-producing wells. For the purpose of confidentiality, we modified the real data, while ensuring it remains representative of real-world conditions. For the same reason we don't disclose economic assumptions as prices curves and workovers' costs, used to calculate the NPVs.

The statistical modeling necessary to power our framework, corresponding to the descriptive analytics stage, begins with assessing failure rates—specifically, the probability that a shutdown will occur at each time step—and the probability distribution for the time until the processing plant restarts. For this study, since the platform is in a mature operational stage yet not in the steepest phase of the "bathtub curve" of failure rates, we chose a relatively short historical period of the most recent two years to best capture the current reliability trend.

We considered for this study an average of approximately six shutdown events per year, indicating a 50% chance of occurrence in any given month. The durations of these events were modeled using a Gaussian distribution with a mean of 10 hours and a standard deviation of 9 hours, truncated to include only positive values. The resulting probability distribution is illustrated in Figure 5.

The probability curves for hydrate formation in relation to time until mitigation are piecewise linear functions, as illustrated earlier in Figure 4. Each well has distinct control points, and these may vary over time based on factors such as flow rates, water cut, and water salinity. Most wells have values between 6 and 16 hours; however, in cases where the water cut falls below the 10% threshold, the time to hydrate formation can extend up to 50 hours. For certain wells, an additional mitigation time of up to 100 minutes can be achieved by partially depressurizing the line shortly after shutdown. The modeling approach using the piecewise function is as follows:

$$\begin{cases} p_{hyd} = 0\%, \text{for } t_{SD} < \text{CDT} \\ p_{hyd} = 0\% \text{ to } 7\%, \text{for } t_{SD} \text{ from CDT to extended} \\ p_{hyd} = 7\% \text{ to } 95\%, \text{for subsequent 24 h} \\ p_{hyd} = 95\%, \text{ after 24 h} \end{cases} \tag{1}$$

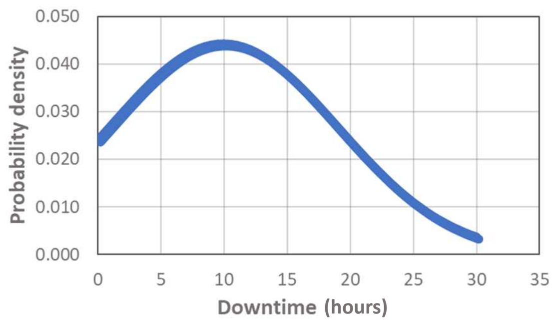

Fig. 5. Probability distribution of downtimes for the platform of our case study.

where p_{hyd} is the probability of hydrate blockage and t_{SD} is the duration of the shutdown (downtime). The curves for each well are updated at every time step during the simulation, using their expected CDTs over time.

Completing our statistical modeling, we calculated the probabilities of successful hydrate dissociation using platform resources versus requiring an external workover rig, based on historical data from similar cases within our company. In this example, we considered a success rate of 75% for dissociation using platform resources, with the remaining 25% requiring a workover.

For the deterministic assumptions, the inputs include production curves, water cut, gas lift requirements, and CDT values. Figure 6 illustrates these data for the seven oil-producing wells in our case study within an illustrative timeframe, along with the prioritization ranking for mitigation actions, as explained in step (2) of the previous section. The estimated times to complete the cleaning circulation for each well, depending on the volume of the pipelines, are initially calculated and kept constant throughout the simulated period. Note that there is only one diesel pump for circulation, which means wells are conditioned sequentially. We also assumed that wells operating with gas lift will experience a delay before the start of hydrate prevention, allowing time for necessary operational procedures on the topside, such as aligning injection headers from process gas to the diesel pump and isolating pipeline sections using blind flanges. In this study, we assume an average time of 20 hours for these procedures.

Finally, Figure 7 provides a timeline of mitigation activities in the event of an unscheduled shutdown. In this example, we assume an event occurs at time $t1$, referring to Figure 6, when six oil-producing wells were operating on the platform, with prioritization for diesel circulation following the illustrated sequence (P-2, P-4, P-6, P-5, P-3, P-1). In the case of extended downtime, the CDT for P-1 would be significantly exceeded, leading to a high probability of hydrate formation. It is important to note that this operational sequence varies at each time step, depending on which wells are actively operating and their priority ranking.

While there is no strict timeframe for running the hydrate model, it is recommended to perform updates every three months to align with the periodicity of well tests, updates to CDTs, and comprehensive production forecast revisions. Additionally, specific operational events, such as well reopening, changes in operating conditions, or the need to assess platform investment opportunities, can serve as triggers for re-running the model.

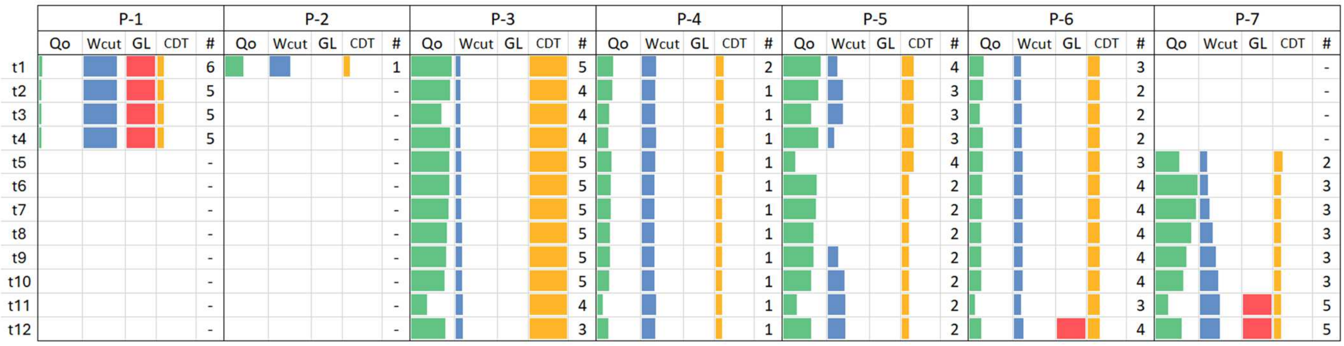

Fig. 6. Example of variations in operational conditions of wells over time. Green bars qualitatively represent oil production rates (max. 20,000 bpd), blue represent water cut (max. 100%), red represent the use of gas lift (yes or no), and yellow represent CDT (max. 50 h). For each well, at each time step, we also indicate the ranking (#) for hydrate prevention priority in case of a platform shutdown.

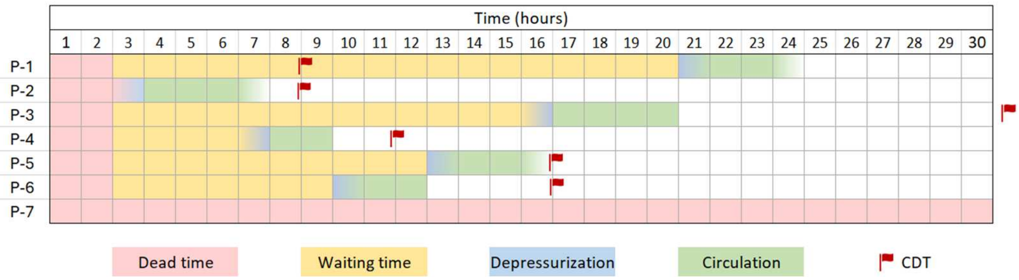

Fig. 7. Example timeline of hydrate mitigation activities during an unscheduled shutdown.

B. *Evaluation of Well Reopening Viability Considering Hydrate Risk*

The first practical application of our framework was to analyze the operational and economic feasibility of keeping well P-1 in operation. This well was producing at relatively low oil rates, with a high water cut, and requiring artificial lift using continuous gas lift. As shown in Figure 6, these characteristics cause the well to be consistently deprioritized compared to other producers when hydrate prevention actions are needed. Consequently, well P-1 is classified as high-risk for hydrate formation during unscheduled shutdowns due to the high probability that its pipelines cannot be cleaned or its choke reopened within a timeframe shorter than its CDT, which is one of the shortest in the platform. This was also shown in the example from Figure 7.

The viability analysis was performed by comparing two sets of Monte Carlo simulations based on our framework: the first set assumed well P-1 was operational for several months (reflecting deterministic assumptions of availability and flow rates), while the second set assumed the well remained closed throughout the entire period. After completing both simulation sets, we calculated the differences between them for the three main KPIs. Results showed that keeping the well open led to an increase of 140,000 barrels in cumulative oil production, with a 40.3% chance of hydrate blockage for this well during the studied period. Most importantly, there was a positive NPV variation of US$3.4 million. Figure 8 presents these results, supporting decision-makers by indicating that reopening the well is favorable despite associated risks, with a higher probability of positive economic outcomes.

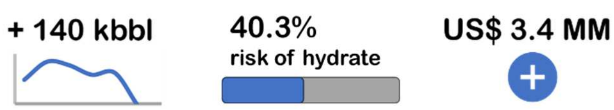

Fig. 8. KPIs for the evaluation of reopening well P-1.

C. *Economic evaluation of a rapid response system for hydrate prevention*

Our second example of application considers the same platform, this time evaluating the economic viability of installing a topside system that would enable faster isolation of sections using blind flanges and alignment of the injection header for cleaning fluid, applied to the producing wells that operate with gas lift. This system would significantly reduce the time that produced fluids remain static in the production lines following a shutdown. Considering the Monte Carlo simulations in this case, the only difference between the base scenario and the improvement scenario was the elimination of the dead time for fluid inversion in the service line. As a result, non-surgent wells benefit significantly in our timeline of action, while the other assumptions for the producing wells remain fixed.

The quantification of the benefit is again based on the differences between the indicators from both simulated sets: with and without the rapid response system for fluid inversion. The KPIs from this comparison indicate a gain of 98,300 barrels in cumulative oil production, an 18.3% reduction in the overall chance of hydrate blockage in any well, and a US$3.3 million increase in NPV over the period. These results are highlighted in Figure 9. In this case, we did not directly include the capital expenditures (CAPEX) of the improvement in the simulations, as this is a value dependent on a negotiated contract, which will be a fixed (deterministic) cost. However, our evaluation provides valuable quantitative references for the contract manager, supporting optimal decision-making regarding the benefits offered by the system

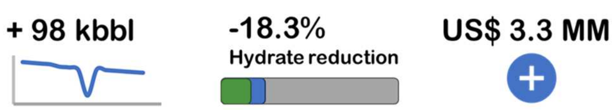

Fig. 9. KPIs for the evaluation of the installation of the rapid response system for hydrate prevention.

D. Economic evaluation of installing a new pump for pipeline cleaning circulation

Our third example focuses on the economic evaluation of an alternative investment proposal to enhance the hydrate prevention system on the platform. This proposal involves acquiring and installing an additional diesel pump, allowing for simultaneous cleaning operations in up to two wells.

To simulate this new configuration, we modified our algorithm to calculate the time until mitigation for each well. We still follow the prioritization ranking as previously explained, but now we split the wells into two action fronts. The impact on response time can be significant; for example, a well that would be sixth in the queue with a single pump may now be third to be cleaned by one of the two pumps.

This advantage is evident in terms of operation, risk mitigation, system backup, and production gains. However, the final decision should consider the CAPEX value for the acquisition and installation of the supplementary system. Once again, our framework will serve as an important decision support tool. To achieve this, we analyzed the difference in results between two sets of simulations: the first based on the current situation of the diesel pump and the second representing the modified version to reflect the benefit of a supplementary pump. The KPIs for this difference, as shown in Figure 10, indicate an oil production gain of 335,000 barrels, a 16.9% reduction in the overall chance of hydrate blockage in any well, and an increase of US$10.4 million in NPV over the period. These indicators do not consider the CAPEX required for the improvement, but this value can serve as a reference in contract negotiations aimed at its implementation.

We highlight that, in this case, the increase in production and economic indicators are more relevant, because the supplementary pump benefits all wells, including those with higher flow rates that were not or were minimally benefited in the previous case, where the improvement only applied to wells operating with gas lift.

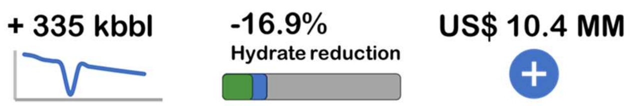

Fig. 10. KPIs for the evaluation of the installation of a supplementary diesel pump.

Based on the Monte Carlo simulation results for each case, we plotted the NPV distributions for comparison and better understanding of the outcomes, shown in Figure 11. Compared to the base case, we observe that the first alternative (shutting in well P-1) exhibits a slightly different distribution for lower values due to a reduction in hydrate occurrences.

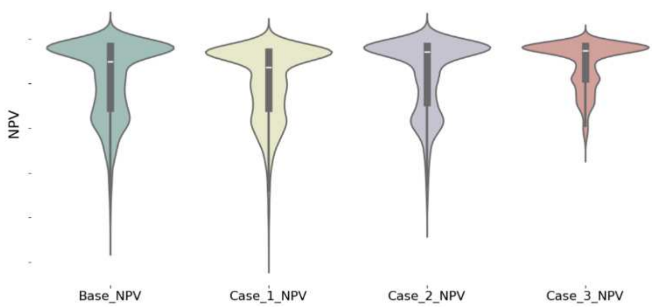

Fig. 11. NPV distribution based on Monte Carlo simulation results for the base case and the three proposed studies.

However, the lower production in this case reduces the average NPV. In the second alternative, there is a decrease in hydrate occurrences in wells operating with Gas Lift, leading to an increase in the average NPV. The most significant improvement, however, is observed in the third alternative, where a more efficient mitigation system for all wells drastically reduces the number of hydrate occurrences and, consequently, the number of low NPV outcomes.

E. Sensitivity analysis

Finally, we present a sensitivity analysis conducted to assess the impact of key input parameters on the outcomes of our prescriptive analytics methodology. This analysis aims to quantify how variations in shutdown probabilities, average shutdown duration, oil barrel price, and workover costs influence our performance indicators.

The results for the impacts on NPV, cumulative production, and hydrate formation probabilities are presented in Figures 11, 12, and 13, respectively.

For NPV, the most influential factor is the oil price, with an almost one-to-one relationship, as the workover dissociation CAPEX is small compared to the total revenue of the platform over the period. The remaining variables exhibit an inverse proportionality, with shutdown durations having a greater impact than their frequency. The cost of hydrate dissociation operations has significantly smaller effect on total NPV.

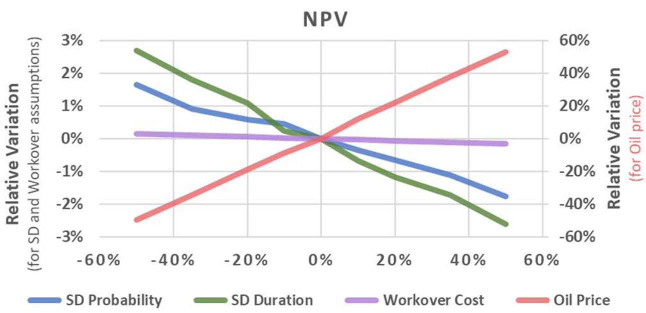

Fig. 12. Sensitivity analysis of NPV to variations in key assumptions.

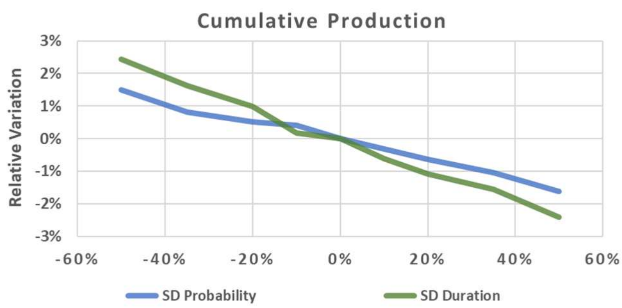

Fig. 13. Sensitivity analysis of production to variations in key assumptions.

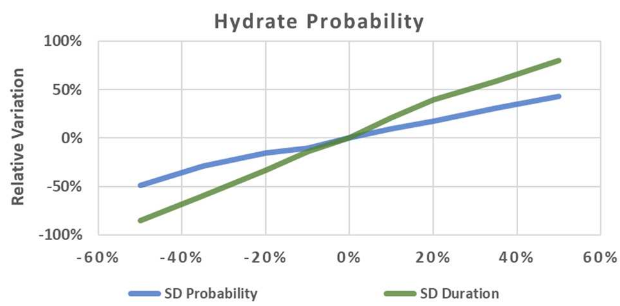

Fig. 14. Sensitivity analysis of hydrate probability to variations in key assumptions.

Economic assumptions do not apply to influences on cumulative production and hydrate formation probability. However, in these cases, shutdown duration once again emerges as the predominant factor, with an inverse relationship to production and a direct relationship to blockage probability, both in non-linear patterns, as we could expect from the governing relations.

V. Conclusions

In this work, we propose an AI-driven prescriptive analytics methodology to deal with multidisciplinary evaluations aimed at preventive actions on the formation of natural gas hydrates in oil wells' production pipelines.

Our framework combines statistical modeling for probabilistic operational events with a set of deterministic assumptions, which, together, feed Monte Carlo simulations to calculate key performance indicators, notably cumulative oil production over the analyzed period, the expected number of hydrate blockage events, workover demands, and, ultimately, the NPV. We incorporate an AI-driven rule-based system to enhance realism by capturing expert-driven decision-making, ensuring that the simulations more accurately reflect operational practices.

A key advantage of this approach is its ability to integrate information from multiple disciplines—reservoir engineering, operations, and flow assurance—while handling diverse data formats, one of the major benefits of Data Analytics. Additionally, the framework allows users to adjust deterministic assumptions to generate different scenarios for each simulation batch, such as considering well openings and closures or implementing improvements in the hydrate prevention system.

We presented some real-world examples of using this feature in case studies based on a platform operating in the Brazilian pre-salt. Simulation results enabled us to compare the KPIs from different scenarios, providing a basis for decision-making regarding CAPEX allocations for facility improvements and production management strategies.

This approach offers a systematic way to enhance flow assurance, ensuring more effective resource allocation and production continuity, and can be adapted to be used in other types of analyses. The findings emphasize the growing role of AI and data analytics in petroleum engineering, showcasing the potential for prescriptive analytics to drive cost-effective and risk-informed decision-making in production operations.

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