A Markovian Model for Oil Wells Failure and Production Losses Prediction in an Oil Field in Colombia

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Abstract

Efficient management of wells in oil fields is essential to avoid significant economic losses and maximize oil production. This study presents a stochastic model based on Discrete Time Markov Chains (DTMCs) for the temporal evolution of well states. Specifically, the model estimates the dynamics among well working states and failure states due to different operating causes. Moreover, a Monte Carlo method is proposed to simulate future scenarios and forecast oil production losses and potential negative economic performance derived from the unavailability of wells. The approach was applied to an oil development field in Colombia and validated through statistical tests for the DTMCs properties. The proposed model offers immediate practical benefits for the oil industry in the studied region, as well as the potential for successful application in other fields. This provides a valuable and versatile tool for global oil well availability management.

Keywords

Oil and Gas, Reliability, Availability, Data Analysis, Stochastic models, Monte Carlo, Net Present Value

1. Introduction

The oil industry faces major challenges in managing the availability of its wells, as losses associated with unavailability can be significant. Globally, these losses are estimated to reach millions of barrels per day, which translates into economic losses in the millions of dollars [1]. In this context, it is essential to characterize the causes of wells' failure in order to develop effective operation and maintenance strategies, as well as to improve production forecasts.

In this sense, the present work seeks to model the transitions between operating states and failure or unavailability states due to different operational causes in oil wells. From a reliability engineering perspective, a stochastic model based on Discrete Time Markov Chains (DTMC) is proposed. This approach allows more accurate modeling of the behavior of oil wells, considering the stochastic nature of failure causalities and their dynamics. Additionally, Monte Carlo methods are applied to perform production and economic loss forecasts associated with the unavailability of the wells. This approach allows the simulation of multiple scenarios, taking into account the uncertainty inherent to the failure causes and to the operation and maintenance processes. To illustrate the practical application of the proposed methodology, a case study is carried out in an oil production area located in Colombia.

This article is organized as follows. Section 2 presents work related to failure modeling and availability of infrastructure systems with an emphasis on the petroleum industry. Section 3 addresses business understanding, describing the specific characteristics of the petroleum industry and modeling needs. Section 4 focuses on understanding the data, and explaining the nature and source of the data used in the study. Section 5 describes the preparation of the data, including the cleaning and transformation necessary for analysis. Section 6 presents the modeling approach, detailing the implementation of DTMCs and Monte Carlo methods to enhance production forecasting and economic evaluation. Section 7 presents the results obtained and their discussion. Finally, section 8 exhibits the conclusions of the study, along with recommendations generated from the model and future extensions of the proposed approach.

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2. Related Work

The analysis of failures in oil and gas stations has employed a variety of methods and models, contingent upon the availability of data. For instance, Guo-qi Ren et al. [2] analyzed 25 failure cases and their causes in domestic oil and gas stations and valve chambers in recent years in China. The statistical analysis identified the main factors, which included fatigue, corrosion, welding defects, and manufacturing defects, among others. However, no predictive models were applied that could infer correlation effects among these failure mechanisms.

One of the earliest applications of Markovian models in this context was that of Cochran et al., who proposed an alternative method for estimating availability with Markov chains for operational failures in oil refineries. They asserted that the models were more efficient, easier to construct, and provided a comprehensive range of performance metrics [3]. In a more recent study, Colombo et al. presented a Markovian model to quantify the probability of integrity failures in subsea oil wells in Brazil, focusing on the risk of uncontrolled hydrocarbon releases. The model incorporated evidence from inspections and tests to update failure probabilities over time [4].

Recent research on oil well failures and production losses in Colombia has focused on the development of predictive models and the improvement of decision-making processes. For instance, Cardona et al. [5] developed a machine learning approach to predict ESP pump failures in an oil field in Colombia's Upper Magdalena Valley basin, achieving over 60% accuracy and enabling preventive maintenance. In general, the studies have addressed the challenges of maintaining production efficiency and minimizing losses by including information on several operational variables in multiple components and elements of the system. However, none of them applied Markovian models in a Colombian context.

Similarly, the Monte Carlo method has been widely applied in different engineering and economic contexts [6]. In the petrochemical industry, it was used to detect failures due to defects in oil pipelines, allowing a more accurate calculation of pipeline failure probabilities, and a more realistic diagnosis of the system safety in a petrochemical company [7]. Likewise, Monte Carlo simulations have been used to generate production profile distributions, which have been useful for estimating the economic value of a productive property [8]. This methodology has allowed the description of the future production rate of each well in the field through the use of hyperbolic decline equations, taking into account the probabilities of mechanical failure and well repair.

3. Business Understanding

Net oil production from oil fields can be reduced by factors such as evaporation and residues in production and transportation equipment, among others, which are typical of the extraction process [9]. Once collected, the oil is treated and separated from water before being sent to a refinery [10]. The total volume produced after discounting these decreases determines the net production.

It should be noted that losses refer to unconventional circumstances that negatively affect production. Usually, these are caused by operational failures, such as electrical failures in generators and components inside the wells, as well as mechanical and chemical failures in the crude processing plant during the separation of water and sediments from the oil [11]. However, external factors can contribute to these losses, such as restrictions in road infrastructure that make it difficult to transport oil to refineries [12]. In some countries, the socioeconomic demands of local communities in oil-producing areas can lead to conflicts and protests that disrupt operations, and in countries with armed conflicts, the presence of illegal armed groups near the facilities also represents a risk, as they can attack the infrastructure and generate insecurity, affecting both production and personnel safety [13].

4. Data Understanding

This article focuses on production data from an oil development field in Colombia, where the operator faces the challenge of decreasing daily net production losses due to the aforementioned factors. These

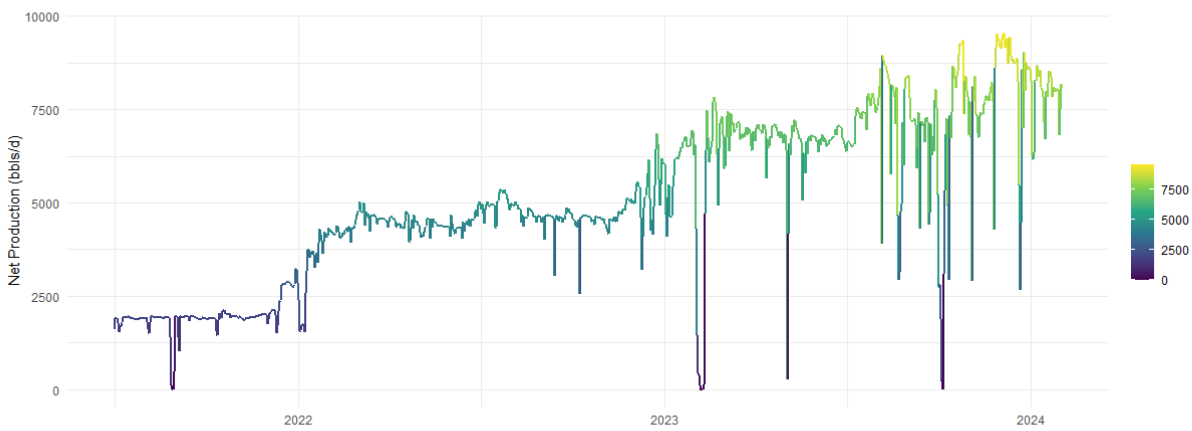

Figure 1: Net Production in the studied oil field from Jul/21 to Jan/24.

Table 1
Data sources and variables.

Data Source	Variables
Net daily oil production	Well, cluster, area, operating day, net oil production, water production, liquid production, lift gas injection, downtime.
Net oil losses	Well, cluster, area, operating day, net oil losses, water losses, liquid losses, cause of loss, type of loss, type of uncontrolled loss.
Production Forecast	Well, cluster, area, month, expected net production.

have contributed to fluctuations in production in recent times, which ultimately have distorted production forecasts and lead to more frequent corrective maintenance activities, resulting in significant economic losses. In total, 61 wells in the field are considered, distributed in 17 geographic clusters, which belong to 3 production areas (x, y, and z). The net daily production of these wells (shown in Figure 1) presents significant fluctuations over the last years, coinciding with the continued development of the field.

The data used in this study comes from a transactional system, which is fed directly by the production team. This team is responsible for recording, reporting, and categorizing production losses, as well as recording the daily production of each well. Through this system, detailed control of operations is performed, allowing precise identification and classification of losses, ensuring that each well has a reliable record of its performance and events that affect its production. For the application case, three data sets were used. The first contains information on daily net oil production from each well in the field over a 2.5-year period, from July 2021 to January 2024. The second one includes the daily net oil losses per well identifying the cause of each loss during the same time period. The third dataset is the production forecast, developed by the team of petroleum engineers using the ARPS model [14] which is based on the premise that the production rate of an oil or gas well decreases non-linearly with time following a hyperbolic decline law. Table 1 summarizes the data sources and variables used.

Deepening into the "Net oil losses" database, the production team has identified 33 different causes of loss, taking into account the actors involved and the scope of each cause after an operational on-site inspection. For a preliminary analysis, a classification is proposed by "type of losses", specifically:

1. External causes: These are not due to operational factors, but to external circumstances that affect the operation. They are associated with sporadic events such as the collapse of bridges, landslides that affect the oil output and force the closure of wells, social protests that hinder the operation, and weather factors such as electrical storms, among others.
2. Internal causes: They derive from corporate decisions and are not classified as failures. These

decisions are based on economic and financial analysis and corporate standards. Examples include profitability per well, insufficient infrastructure for production, plant shutdowns for preventive maintenance, and corrective maintenance postponed due to strategy or supplier contracting policies.

3. Uncontrolled causes: These refer to failures in internal operating systems that affect production.

The developed model focused on the last cause because it is the most common mechanism of failure. External factors are not included, as they are less frequent in the dataset, making difficult its statistical estimation. However, when they occur they have a significant impact on production, as they usually affect the entire field.

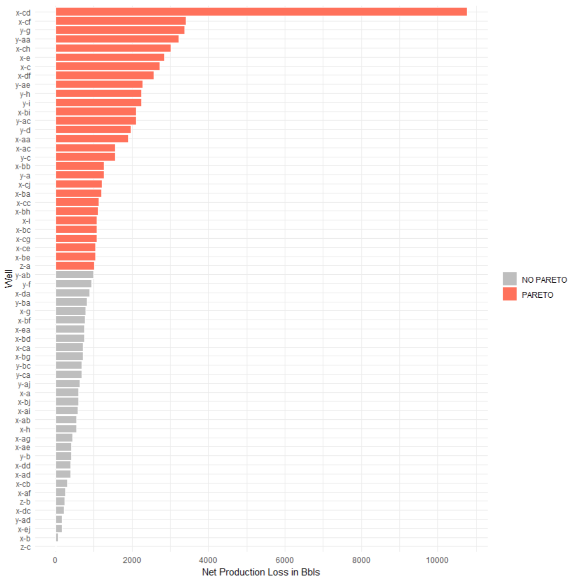

Figure 2: Barrels of net production lost per well, arranged from highest to lowest. The color indicates whether the well is part of the Pareto analysis or not.

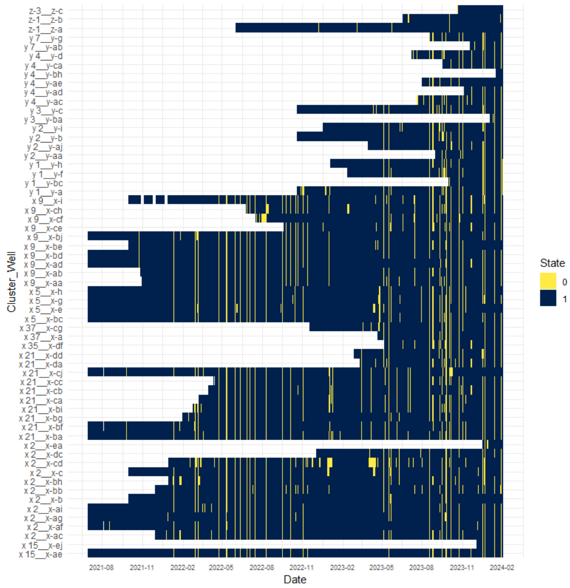

Figure 3: Failure days per Cluster-Well due to an uncontrolled cause of loss. The well availability is represented as a binary state, where a value of 1 indicates that the well was operating normally and 0 indicates that the well was out of service.

Figure 2 shows the net production loss per well due to an uncontrolled cause of loss. At the top, the wells with the 80% highest losses (according to Pareto's law [15]) are highlighted, which corresponds to 29 wells (48% of the 61 wells). On the other hand, Figure 3 depicts a binary representation of good availability by time, where a value of "1" indicates that the well was operating normally and a value of "0" indicates that the well was out of service due to an uncontrolled cause of loss. Similar patterns of behavior are observed by cluster and throughout the operation in general.

5. Data Preparation

From the "Net oil losses" database the state of each well is identified for each day and labeled as "Working State" (WS) if it is working and "Failure State" (FS) if it is off due to uncontrolled causes. To provide greater specificity the "Failure State" is divided into three states representing the causes of failure: "Mechanical" (Mec), "Electrical" (Elec), and "Chemical" (Chm). The production team validated this categorization, the correct classification of the (uncontrolled) causes of loss, and the reinterpretation of some loss causalities in the original database that presented ambiguities. Tables 2 and 3 show the number of records for the above-described well states.

To prepare the dataset for the simulation of failures over time, it is necessary to transform the production forecast, originally expressed in barrels of average daily production per month. Since the

Table 2
Number of records for well states WS and FS.

States	Number of Records	%
WS	31,703	92.5%
FS	2,570	7.5%
Total	34,273	100%

Table 3
Number of records for well states WS, Elec, Chm, and Mec.

States	Number of Records	%
WS	31,703	92.5%
Elec	2,399	7.0%
Chm	137	0.4%
Mec	34	0.1%
Total	34,273	100%

simulation required daily data, values of daily production are replicated for each day in a month. This transformation allows representing the production over the entire month as a daily time series, instead of having the value of the daily average for the month in a single record. This adaptation facilitates overlaying the results with the simulation model in an appropriate manner.

6. Modeling

A Discrete Time Markov Chain (DTMC) is a stochastic process $\{X_t\}_t$ with a discrete state space Ω and a discrete set of times $t = 0, 1, \ldots$, meaning that the temporal measurements progress in individual steps of fixed time intervals. This process satisfies the Markovian property:

$$P(X_{n+1} = x|X_n = x_n, X_{n-1} = x_{n-1}, \ldots, X_0 = x_0) = P(X_{n+1} = x|X_n = x_n), \tag{1}$$

which means that the probability of transition to a future state depends exclusively on the present state and not on previous states.

The complete probabilistic structure of the process can be derived from the 1-step transition probability matrix $\mathbf{P} = [P_{ij}]$ with $P_{ij} = P(X_{n+1} = j|X_n = i),\ i, j \in \Omega$, denoting the probability of transition from state i to state j in a single time step [16]. The n-step transition probability $P^n_{ij} = P(X_{n+k} = j|X_k = i)$ can be obtained from the 1-step transition probabilities by the Chapmann-Kolmogorov equations in matrix form: $\mathbf{P}^{(n)} = \mathbf{P}^n$. Finally, for DTMCs that are irreducible and ergodic, there exists a limiting probability (also called stationary probability) $\pi_j = \lim_{n\to\infty} P^n_{ij}$, which is unique and independent of the initial state i. These probabilities correspond to the proportion of time the system spends in each state j in the long run.

The approach followed in this paper consists of proposing two DTMCs for each well to model transitions between 1) States WS, FS, and 2) States WS, Elec, Mec, and Chm. The time is discrete and is given in days. The methodology applied is detailed below:

1. *DTMC fitting:* The transition probability matrices for each DTMC model for each well are estimated from the datasets of well status. This is performed with the library 'markovchain' in the statistical software R and the function 'markovchainFit' that uses the maximum likelihood estimation method [17]. This method searches for parameters that make the observed data sequence more likely under the DTMC model, thus ensuring that the model fits the historical data appropriately. Recall that the fitted matrices contain the estimated probabilities of transitions from the current state of a well to a future (1-time step) state.

2. *Availability estimation:* Stationary probabilities are calculated for each model based on the estimated transition matrices. This provides an estimation of the well availability in the long run. For this purpose, the 'steadyStates' function from the 'markovchain' library is used.

3. *Verification of the Markovian property:* A chi-square test is applied to verify the Markovian property, equation (1), for each of the fitted models. The test compares the observed frequencies of transitions with the expected frequencies under the null-hypothesis that the process follows the Markovian property [18]. Then, the Markovian property is not rejected when the p-value $> \alpha$, with $\alpha = 0.05$ the chosen significance level. Verification of this property is crucial to ensure that the DTMC models are valid and can be used with confidence for forecasting. If the Markovian property is not met for a particular well, the data should be reviewed and the model possibly adjusted to more accurately reflect the failure dynamics of that well.
Moreover, stationarity and order properties were also verified using similar test statistics. Stationarity in this context refers to the property that the transition probabilities P_{ij} remain constant over time. The stationarity test helps to determine whether the Markov chain process exhibits this property, which is fundamental for the model to be valid over time. The order of the process refers to the number of previous states that must be considered to predict the future state of a well. Determining the proper order is crucial to ensure that the model correctly captures the dependence relationships between past and future well states. The order test helps identify this optimal number of past states to consider in the model. These additional tests complement the verification of the Markovian property and help ensure the validity and accuracy of the DTMC model used in oil well availability estimation. The statistical tests were performed with the commands 'verifyMarkovProperty', 'assessStationarity', and 'assessOrder' in R [19].

4. *Simulation of the production forecast and economic value with losses:* Future states (WS, Mec, Elec, Chm) of a selected well are simulated via Monte Carlo (MC) from the estimated transition probabilities of its Markov model [20]. A total of 10,000 MC simulations are performed, covering a period of 5 years (1825 days) corresponding to its expected production cycle[1]. For each simulation a sequence of states WS or FS is obtained from which the production over time is calculated using a Brent oil futures curve [22]. Finally, an economic evaluation of both scenarios: the current forecast (with no losses) and the simulated forecast with uncontrolled losses, is performed based on the Net Present Value (NPV):

$$NPV = \sum_{t=1}^{T} \frac{F_t}{(1+r)^t} - I, \tag{2}$$

with F_t the net cash flows in period t, r the discount rate or interest rate required by the investment, T the last period in which cash flows are expected, and I the initial investment. No additional investment is assumed, as it is considered a sunk cost that has already been recovered over time while the well was in production [23]. This comparative analysis between the NPVs of the net production curves is crucial to determine the future economic impact of uncontrolled loss causes.

7. Results

Graph representations of the estimated DTMCs and their transition probabilities are shown in Figures 4 and 5 for the model with WS and FS states, and the detailed model with Elec, Mec, Chm, and WS states, respectively, for a specific well. Note that the sum of the probabilities leaving each node is equal to 1, as it is required in these models. Figure 4 indicates that when this well is operational, 94% of the time it remains in this WS state, while 6% of the days results in a transition to an FS. Once in this FS state, in 62% of cases well maintenance lasts one day, transitioning from FS to WS in a single step, but in 38% of

[1]The natural decline of the oil in the well makes it unprofitable, and it is no longer considered a reserve but a resource [21]

the cases it remains in this failure state for another day. Figure 5 provides a more detailed description of these transitions among failure causes. For instance, the occurrence of transitions from a working state (WS) to a failure state due to electrical causes (Elec) is five times more prevalent than the occurrence of transitions to a failure state caused by chemical factors (Qco). Observe also that mechanical failures (Mec) require more than one day to repair in 67% of the cases.

Transition matrices for all wells are represented as heat maps in Figure 6. Each cell of a heat map indicates the probability of a one-step transition from one state to another, with lighter colors representing higher probabilities. Transitions from any failure state (Mec, Chm, Elec) to the working state (WS) are highly probable, indicating that one-day maintenance is common. Noteworthy, there is variability in transition probabilities between wells, which may reflect differences in operational or historical conditions specific to each well. In addition, some wells exhibit transitions among failure states, meaning that failure types could be correlated.

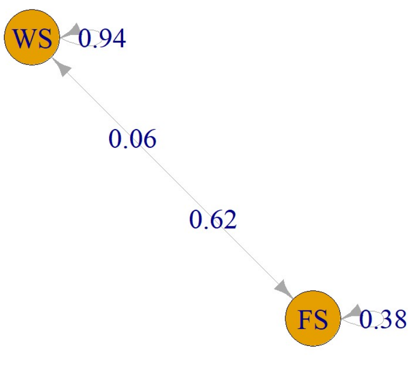

Figure 4: DTMC of a well

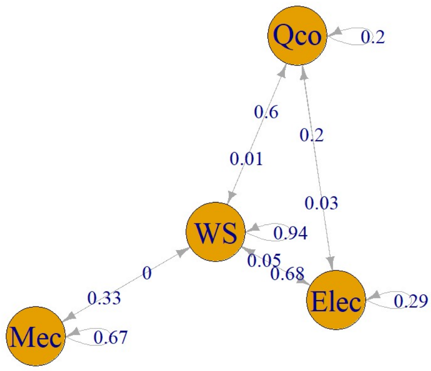

Figure 5: DTMC of a well by cause of uncontrolled loss

Figure 7 shows a scatter plot of the transition probabilities FS→WS and WS→WS for each well. Dot colors represent clusters of wells and sizes indicate the net production of the well. Wells in the upper right of the plot are more reliable as they have high probabilities of remaining in WS being in WS and transitioning to WS from an FS state. Most of the wells are above the probability 0.9 in the WS→WS axis and to the right of 0.7 probability in the FS→WS axis. The variability in net production suggests differences in operating efficiency between wells. Some clusters, such as x15 and x2, show specific groupings, which may indicate similar failure dynamics of their wells.

Table 4

Results of the tests statistics in terms of the number of wells meeting (p-value > 0.05) and not meeting (p-value < 0.05) the properties of DTMCs

Result	Markovian Property	Order 1	Stationarity
Meeting	60	60	61
Not meeting	1	1	0

Regarding validation of the DTMC's models, results of the test statistics for the Markovian property, stationarity, and order of the process of the wells are shown in Table 4. These results indicate that all but one of the wells (60) comply with the Markovian and stationarity properties, with an order of 1. The well that does not follow the Markovian property (x-cd) presents a particular failure dynamics. Its higher energy requirement was not conditioned to plant specifications, resulting in a more recurrent WS→Elec transition, as the failure was iterative and went on for a long time until a proper correction was made. On the other hand, the well that does not meet the order property is only three months old since drilling. During this short production period, it has experienced significant operational developments, but not enough to properly evaluate its dependence on past states.

Figure 6: Transition matrices of types of uncontrolled losses per well. The rows represent the destination states and the columns represent the states of origin. Observe that the most probable transitions ($Probability \approx 1$) occur from any state to a "WS" state ("WS" rows in the matrices). Transitions to "Mechanical" failures are less common (no data in "Mech" rows).

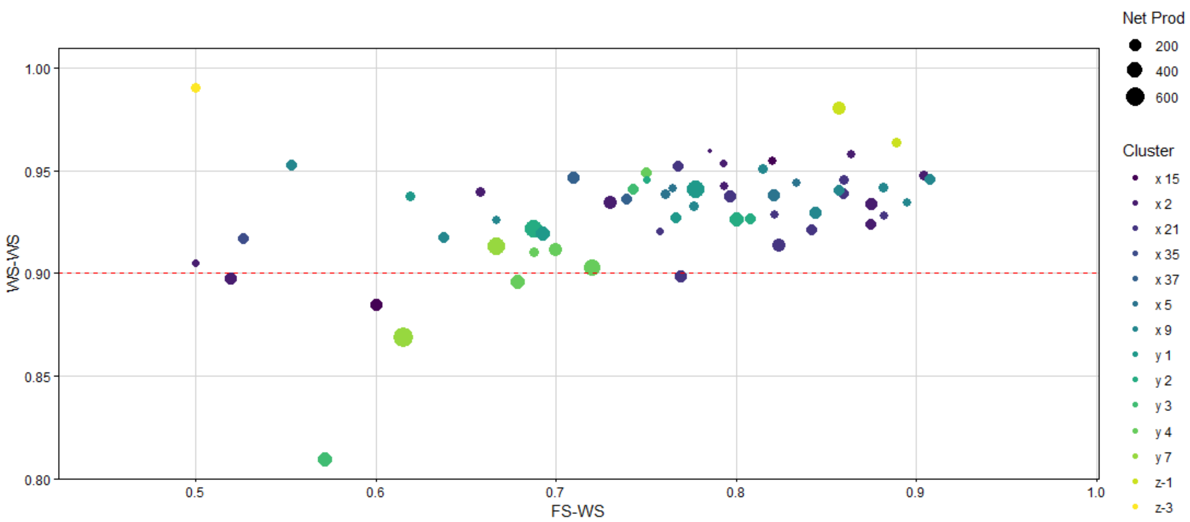

Figure 7: Scatter plot of FS→WS and WS→WS transition probabilities per well, with colors representing groups and sizes indicating net production. Wells in the upper right are more reliable. Most have a WS→WS probability > 0.9 and FS→WS > 0.7, suggesting differences in operational efficiency.

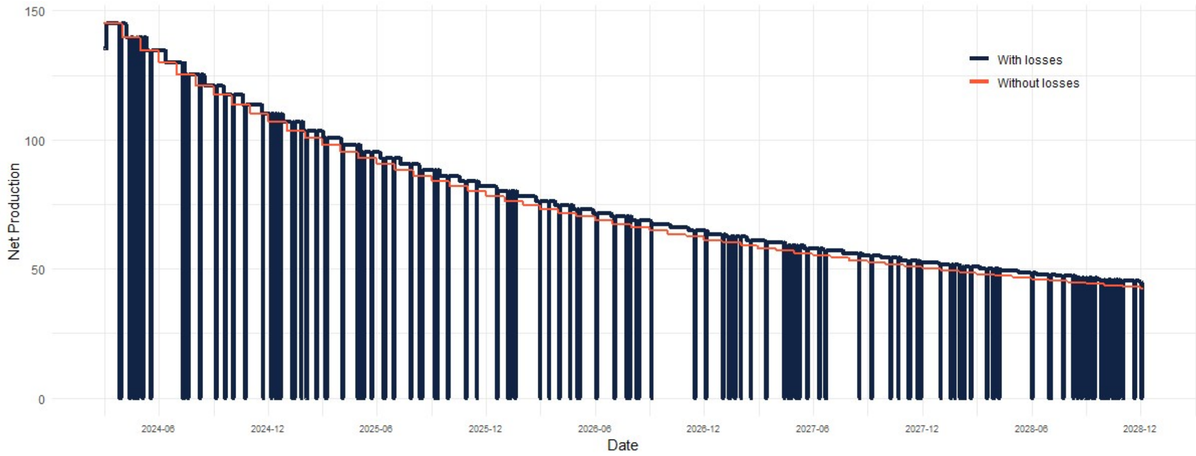

Figure 8: Net production forecast: deterministic (with no losses) and stochastic (with losses of uncontrolled causes) for one MC simulation of a well.

Furthermore, the net production forecast simulation is performed for a well. Unlike the deterministic ARSP forecasting, Monte Carlo simulation considers the stochastic nature of failures and their influence on production. Figure 8 shows a shift of a simulated production curve from the non-failure deterministic curve. Each time a failure occurs, production returns to its pre-failure level and then continues to decrease according to the downward slope given by the ARSP. This process is repeated each time a failure occurs, generating a characteristic pattern in the production curve.

Table 5
Economic comparison of scenarios of a well: deterministic (with no losses) and stochastic (with losses) from 10,000 MC simulations, in terms of NPV's expressed in thousands of US dollars (KUSD).

Discount rates r	$NPV_{NoLosses}$	$NPV_{WithLosses}$ (Mean $\pm$ SD)	ΔNPV (Mean $\pm$ SD)
10%	4,240	4,049$\pm$21	-191 ± 21
15%	3,886	3,708$\pm$20	-178 ± 20
20%	3,579	3,411$\pm$19	-168 ± 19

A total of 10,000 MC simulations of the well state give an equal number of production curves for the stochastic scenario. Then, equation (2) is applied to obtain the periodic NPV for each simulation ($NPV_{WithLosses}$) and with three different discount rates r to evaluate the sensitivity to this parameter. In addition, a margin loss for each simulated curve is evaluated as:

$$\Delta NPV = NPV_{WithLosses} - NPV_{NoLosses}, \tag{3}$$

with $NPV_{NoLosses}$ corresponding to the NPV of the non-failure deterministic curve. Table 5 reports this value and the mean and standard deviation (SD) of $NPV_{WithLosses}$ and ΔNPV from the 10,000 MC simulations and for each discount rate considered. The results show a loss of economic value for the well when considering failures, which increases from 168 to 191 thousand US dollars as the discount rate decreases from 20% to 10%. This can be visualized in the distributions of ΔNPV in Figure 9 that exhibit a moderate variability (see also the SD values) and a significant separation from a null economic loss $\Delta NPV = 0$.

8. Discussion

The transition probabilities between well states demonstrated that the most prevalent state was the working state and that maintenance periods are relatively short, indicating a high probability of good

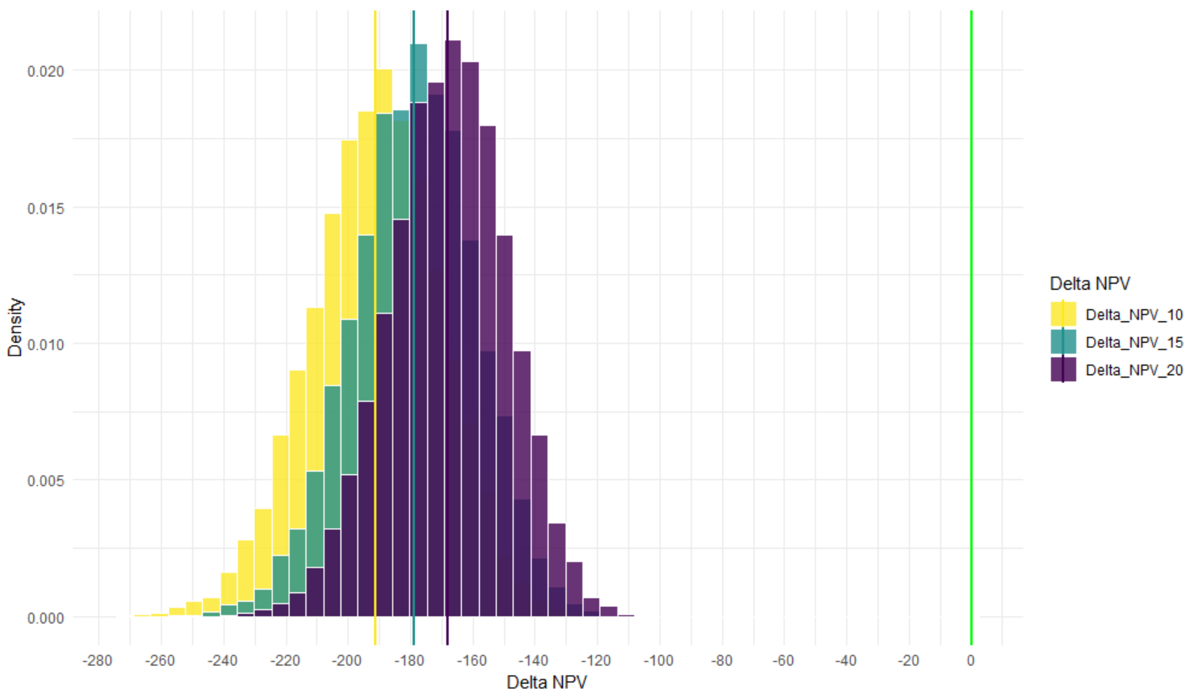

Figure 9: Distribution of ΔNPV for different discount rates as a result of Monte Carlo simulations.

availability under optimal conditions. Furthermore, the statistical tests demonstrated that DTMCs are reliable models for the studied situation. The results showed that 98% of the wells complied with the Markovian property and 100% exhibited stationarity. In the event that these properties were not met, it would be necessary to adjust the model accordingly.

In addition, the NPV comparison between the production forecast (with no failures) and the Monte Carlo simulations that contemplate uncontrolled losses clearly illustrates the diminished profitability and the prolonged production recovery, which negatively impact the economic performance of the well. It is important to mention that the delay in production (due to well failures) also affects the profitability to continue extracting more oil from the reservoir. Longer production periods have greater uncertainty due to fluctuating Brent oil prices, which is the benchmark for the industry in Colombia. The variability of these prices, depending on global macroeconomic and political factors, makes an accurate forecast difficult [21].

To produce more insightful results in the analysis of operational failures in wells, one option is to enrich the data with external factors. Including climatic variables, such as temperature, rainfall, and thunderstorms, could help identify patterns between weather and production failures. Also, factors such as regional energy demand or external events such as roadblocks or government interventions could provide more context to better understand operational disruptions.

Another key aspect would be to incorporate detailed information on well maintenance. Maintenance history, both preventive and corrective, could provide a clearer picture of the relationship between the frequency of interventions and well availability. In addition, including the costs associated with each intervention would allow the financial impact of these actions to be assessed, comparing maintenance costs versus losses due to operational failures.

At the modeling level, the use of Machine Learning or advanced time series models such as ARIMA could be integrated to complement Monte Carlo simulations, providing more robust production forecasts.

Finally, improving the granularity of the data, moving from daily to hourly data, would allow for finer analysis, helping to identify patterns in the timing of failures.

9. Conclusions

This article addresses the challenge of probabilistic estimation of daily net oil production losses in a development field in Colombia, specifically those related to operational uncontrolled loss causes. Based on data of daily net oil production and historical losses, a time series of causes of losses was determined for each well, which allowed modeling its availability using Discrete Time Markov Chains (DTMCs). The findings highlight the importance of managing and mitigating uncontrolled causes of losses to maximize value and operational efficiency. The proposed approach could facilitate informed decision-making, enabling the company to improve production management, optimize available resources, and direct further efforts toward preventive maintenance and regular inspections.

10. Future work

Further extensions of the proposed approach can be mentioned:

External causes of losses: The data used to build the DTMC model were obtained from a transactional platform, which may limit the availability of certain information or its quality. In this context, the model developed effectively addresses uncontrolled well loss causes, but does not consider external causes, such as infrastructure problems or adverse environmental conditions. These causes can have a significant impact on the total proportion of production losses. Therefore, for a more complete and accurate assessment of well availability and risk management, it would be necessary to integrate these external causes into future analyses and models.

Incorporation of new data and variables: Additional variables can be included to enhance the probabilistic modeling of well failures and production. These variables include, but are not limited to, reservoir type and age, environmental factors, oil price fluctuations, and changes in market conditions. Other variables, such as pressure and electrical voltage in wells infrastructure, may require additional investments for their measurement.

Predictive model development: The availability of more data and variables allows for the development of more sophisticated predictive models that can anticipate operational failures before they occur. These models may include Cox regressions, decision trees, support vector machines, and other supervised and unsupervised machine learning algorithms.

Maintenance optimization: Develop optimized preventive maintenance strategies based on model results, to minimize downtime and production losses.

Long-term economic impact: Perform long-term economic analysis to better understand the impact of different loss management strategies on overall project profitability.

Real-time simulation integration: Implement real-time simulation systems that allow companies to quickly adjust their production and maintenance strategies in response to changing well and market conditions.

Expanding the scope of study: Apply the methodology to other oil fields in different regions and countries to validate the effectiveness of the model and adapt the approach to diverse geographic and operating conditions.

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