A Comprehensive RAM Analysis Tool Using Monte Carlo Simulations for the Oil and Gas Sector: Application and Comparison

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Ensuring the availability and reliability of complex systems, such as those in the oil and gas industry, is critical for operational efficiency and safety. Traditional analysis methods often struggle to account for the variability and uncertainty inherent in failure and repair processes, leading to suboptimal maintenance strategies. This paper introduces a Monte Carlo Simulation (MCS) tool for analyzing Reliability, Availability, and Maintainability (RAM). The tool accommodates various probability distributions and calculates key performance indicators such as availability, reliability, maintainability, and confidence intervals. Applied to a CO_2 separation plant case study, the results demonstrate the tool's enhanced capability to capture a broader range of performance metrics compared to traditional analytical methods.

Keywords: RAM Analysis. Reliability. Availability. Monte Carlo Simulation.

System reliability and availability are fundamental to maintaining operational efficiency and safety in energy, transportation, and manufacturing industries. Traditional methods—such as Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBD)—offer valuable insights into component interactions and potential failure pathways. However, as systems become increasingly complex, these approaches often fail to capture the inherent variability and uncertainty of failure and repair processes. This can hinder accurate system performance prediction and lead to ineffective maintenance planning.

To overcome these limitations, this paper presents a Monte Carlo Simulation (MCS) tool developed in Python, designed to enhance RAM analysis in complex systems. The tool offers a more robust and realistic assessment than conventional analytical methods by simulating a wide range of failure and repair scenarios. The tool is applied to a CO_2 separation plant as a case study. Its results are benchmarked against traditional methods, demonstrating its ability to provide comprehensive and insightful system performance evaluations.

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Theoretical Background

Fault Tree Analysis (FTA)

Fault Tree Analysis (FTA) is a structured analytical method used to identify the root causes of failures in complex systems. The analysis starts with a top event—typically a critical system failure—and systematically traces backward through intermediate and basic events to identify underlying causes [1]. Logical gates such as "AND" and "OR" are used to model the interactions between events: "AND" gates indicate that all input failures must occur for the output failure to happen, while "OR" gates require only one input failure.

Each basic event in the fault tree is assigned a failure rate, which enables the computation of the top event's probability. Minimal cut sets—the smallest combinations of basic events that can cause the top event—are critical for highlighting system vulnerabilities. These insights inform the design of redundancy measures and risk mitigation strategies to reduce the likelihood of catastrophic failures [2].

Reliability, Availability, and Maintainability (RAM) Analysis

Reliability, Availability, and Maintainability (RAM) analysis is a comprehensive approach to evaluating the operational performance of complex systems throughout their lifecycle. Reliability refers to the probability that a system will perform its intended function under specified conditions for a given period. Availability measures the time a system is operational and accessible when needed. Maintainability evaluates the ease and speed with which a system can be restored to operational status after a failure [3].

RAM analysis integrates these three dimensions to inform effective maintenance and operational strategies. While analytical methods such as FTA provide high accuracy for systems with limited complexity, they often lack the flexibility to address systems with numerous interdependencies and stochastic behavior. In contrast, numerical methods like Monte Carlo Simulation enable uncertainty modeling in failure and repair processes, making them particularly effective for evaluating repairable systems and capturing real-world performance variability.

Table 1 summarizes the applicability of stochastic metrics and performance measures across analytical and numerical approaches.

Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a statistical technique widely used to evaluate complex systems' reliability, availability, and maintainability (RAM) by modeling the inherent uncertainty and variability in system behavior. It involves performing numerous simulation iterations to produce a distribution of possible outcomes based on probabilistic models for failure and repair rates.This makes MCS especially effective in scenarios where traditional analytical methods are inadequate due to system complexity or interdependencies [4].

The approach relies on historical failure and repair data to define appropriate probability distributions—such as exponential, Weibull, and log-normal—for modeling time-to-failure and time-to-repair for individual components. The simulation process includes defining the system configuration, sampling failure and repair times, and simulating system operation over time to assess performance under realistic conditions [4].Key performance indicators (KPIs), including reliability, availability, and maintainability, are computed and aggregated across simulations to generate probabilistic outcome distributions.

Materials and Methods

This section presents the methodology implemented in the developed RAM analysis tool, which integrates Monte Carlo Simulation. The method is designed to systematically evaluate the dynamic behavior of systems under varying operational conditions.

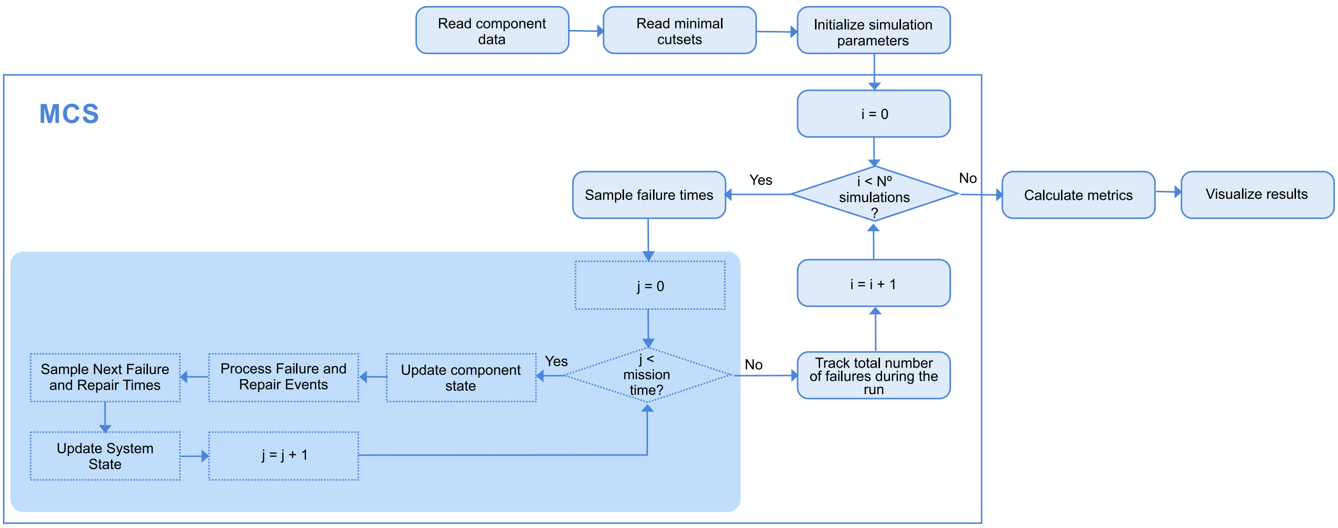
Figure 1 illustrates the methodological flowchart detailing the sequential steps during the simulation process. These include system definition, selection of statistical distributions, simulation execution, and computation of performance metrics.

The developed tool follows a structured simulation process as described below:

Table 1. Applicability of stochastic measures in discrete-time and repairable continuous-time methods.

	Reliability	Availability	MTTF	MTTR	ENF
Discrete-time	✓				
Repairable Continuous-time	✓	✓	✓	✓	✓

Figure 1. Flowchart of RAM analysis algorithm.



Read Component Data: The tool begins by importing system component data, including failure and repair rates, Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR). Users can define probability distributions for time-to-failure and time-to-repair, with optional input of additional parameters for modeling complex statistical behaviors.

Read Minimal Cut Sets: Minimal cut sets derived from Fault Tree Analysis (FTA) are loaded. These sets represent the smallest combinations of component failures that can lead to system failure. This step is essential for identifying critical failure paths and prioritizing components for maintenance or redundancy planning.

Initialize Simulation Parameters: The simulation is initialized by specifying the number of Monte Carlo iterations (N), the total mission time, and the time step increment used to advance the simulation.

Monte Carlo Simulation Process: The core of the methodology includes the following steps:

i. Simulation Loop: Executes the defined number of simulation runs.
ii. Sampling Failure Times: Generates failure and repair times for each component using the selected probability distributions.
iii. Mission Time Loop: Iteratively simulates system behavior across the mission time.
iv. Processing Failure and Repair Events: Dynamically updates component statuses based on sampled event timings.
v. Updating Component States: Continuously reflects real-time changes in the operational status of each component.
vi. Tracking Failures: Logs component and system failures throughout the simulations for performance evaluation.

Calculate Metrics: Upon completion, the tool computes key metrics, including availability, reliability, maintainability, the expected number of failures, time-to-failure and time-to-repair histograms, and confidence intervals.

Visualize Results: Output metrics are presented graphically to enhance interpretation. Visuals include probability distribution plots, performance indicator trends, and comparative charts, supporting robust decision-making.

Case Study

The proposed tool was applied to a case study involving a CO_2 separation membrane testing system to remove carbon dioxide from natural gas streams. The system includes 30 critical components, such as valves, heat exchangers, filters, and control units. Failures may occur individually or in combination, as identified by predefined minimal cut sets. To ensure confidentiality, all component input data were anonymized and slightly altered without compromising the structure, relationships, or integrity of the system model. This preserves the study's analytical value while protecting sensitive operational details.

Results and Discussion

This section compares results from the analytical and numerical approaches applied to the CO_2 separation plant. It highlights each method's strengths, limitations, and implications in terms of predictive power, accuracy, and applicability to real-world maintenance strategies.

Analytical Solution

The analytical approach evaluated system reliability over a one-year mission time (8,640 hours) using Fault Tree Analysis (FTA). Reliability was computed by assessing the failure probabilities of interconnected components at monthly intervals. However, since this method does not incorporate repair events, it tends to overestimate system degradation and does not reflect the dynamic nature of system recoverability.

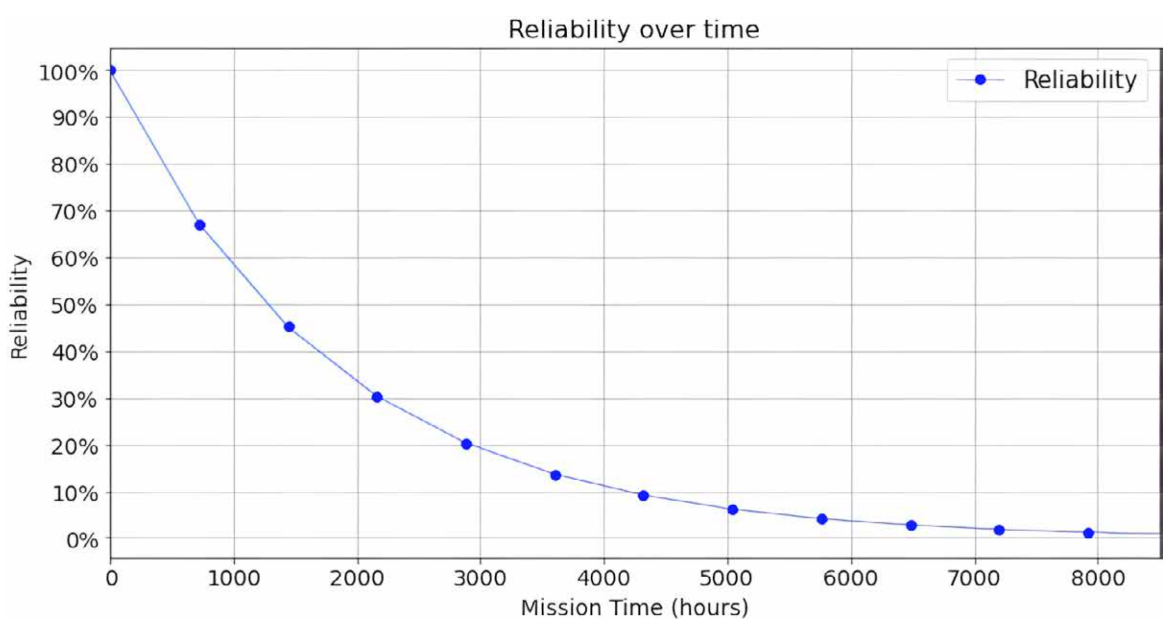
Reliability

As illustrated in Figure 2, the system's reliability follows an exponential decay over time, with noticeable declines at each monthly checkpoint. This trend reflects the cumulative effect of component aging and increased failure risk. Although the analytical method provides a valuable baseline and identifies critical weak points, its inability to model repairs limits its relevance for systems where downtime recovery is a key factor.

Numerical Solution

The numerical assessment of the CO_2 separation system's Reliability, Availability, and

Figure 2. System reliability - Analytical solution.



Maintainability (RAM) was conducted using Monte Carlo Simulations (MCS) over varying mission times. This approach captures the stochastic nature of system behavior by simulating numerous operational scenarios, thus enabling a more detailed and realistic evaluation of system performance.

Reliability

The system's reliability was analyzed over a mission time of 8,640 hours (one year) using Monte Carlo simulations with sample sizes of 1,000, 10,000, and 100,000 runs. Figures 3(a) and 3(b) illustrate the reliability curves of 1,000 and 100,000 simulations, respectively.

As observed, increasing the number of simulations leads to smoother reliability curves and narrower confidence intervals, reflecting reduced statistical uncertainty. In Figure 3(a), the reliability curve derived from 1,000 simulations shows greater variability and a wider confidence interval, indicating less precision. In contrast, Figure 3(b), based on 100,000 simulations, displays a notably smoother curve with a significantly narrower—almost imperceptible—confidence interval attributable to the Law of Large Numbers [5].

This result underscores adequate sample sizes' critical role in enhancing reliability estimates' accuracy and robustness, especially in complex systems where variability and interdependencies among components can influence overall behavior.

Maintainability

The maintainability of the CO_2 separation system was assessed using time-to-repair (TTR) data generated through Monte Carlo simulations. Figure 4(a) displays the TTR histogram from 100,000 simulations, while Figure 4(b) provides a focused view of the top 81.7% of the dataset. The Mean Time to Repair (MTTR) was calculated as 100.97 hours, establishing a baseline for expected downtime. However, MTTR alone does not adequately reflect the full distribution and variability of repair durations.

The histogram was segmented into bins (Figure 4b) to enhance interpretability, offering a more granular understanding of system performance across various repair scenarios. The TTR data can be characterized by a Probability Density Function (PDF), whose integral over time yields the Cumulative Distribution Function (CDF), representing system maintainability.

Figure 5 presents the maintainability CDF, which enables the estimation of the probability of repair completion within a given time frame. For instance, the analysis reveals that approximately 60% of repairs are completed within 102 hours. Although a specific distribution fit (e.g., Weibull or log-normal) was not performed, the use of Monte Carlo simulations proves valuable for capturing the inherent variability in maintainability across complex, multi-component systems.

Availability

The availability of the CO2 separation system was evaluated using Monte Carlo simulations over mission times of 1, 6, and 12 months, with sample sizes of 1.000, 10.000, and 100.000 runs. Table 2 details the average availability and confidence intervals for each period.

As the number of simulations increases, the confidence intervals for mean availability narrow, consistent with the behavior observed in the reliability analysis. For example, using 1,000 simulations over one month, the 95% confidence interval for availability is relatively wide, ranging from 93.64% to 94.99%. However, with 100,000 simulations, the interval becomes significantly narrower, indicating more accurate and reliable estimates.

Figures 6(a) and 6(b) illustrate the availability curves generated from 1,000 and 100,000 simulations. Both graphs show that availability is initially high but gradually declines over time as system failures accumulate. Eventually, the curves reach a plateau, suggesting that the system enters a steady-state condition prior to the end

Figure 3. System reliability for 1,000 (a) and 100,000 simulations (b).

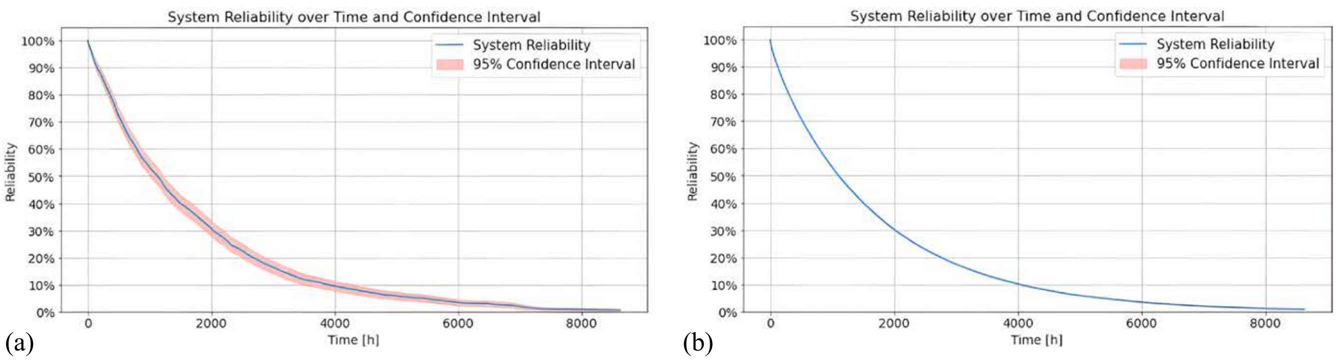


Figure 4. Histogram of all Times to Repair (a) and histogram of the 81,7 percentile of the Times to Repair (b).

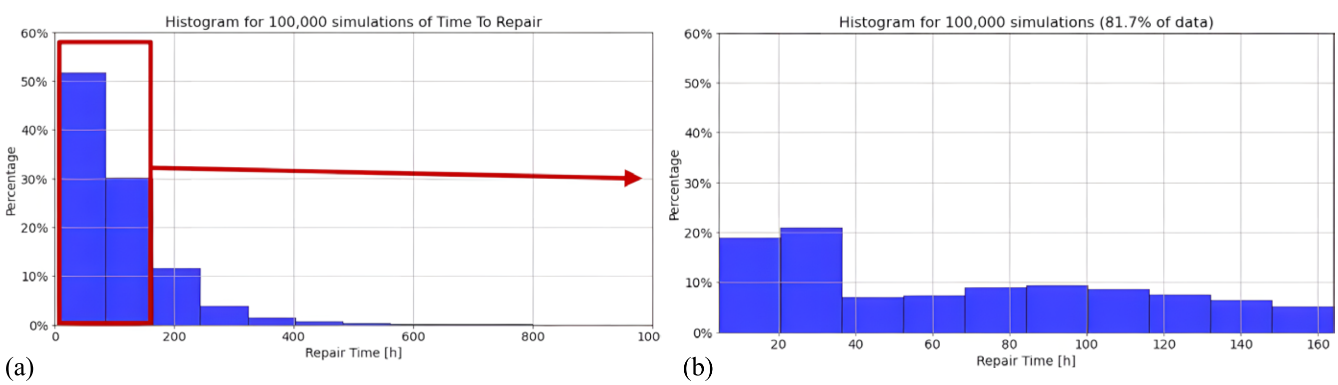


Figure 5. CDF of repair times.

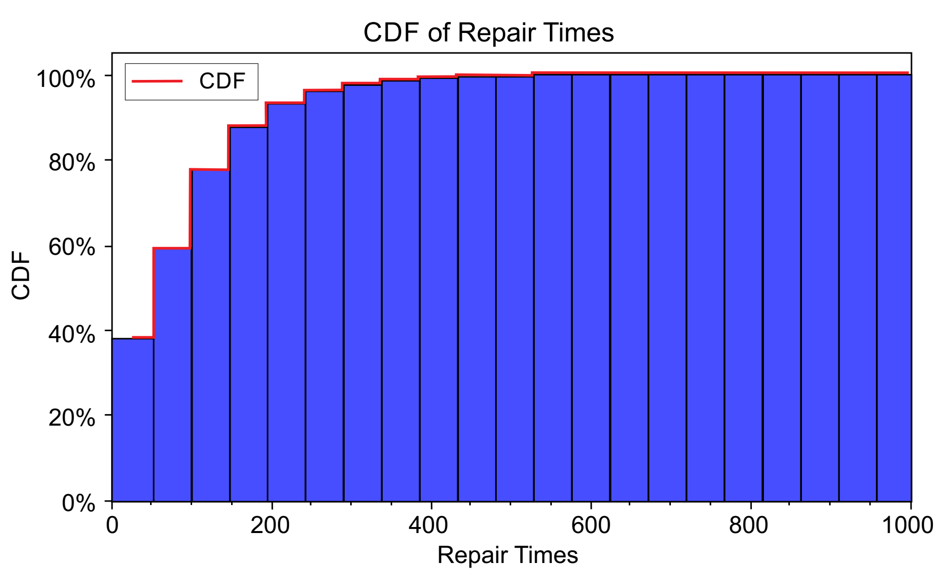
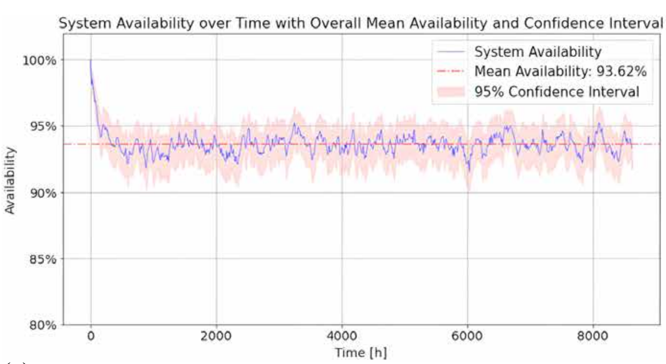


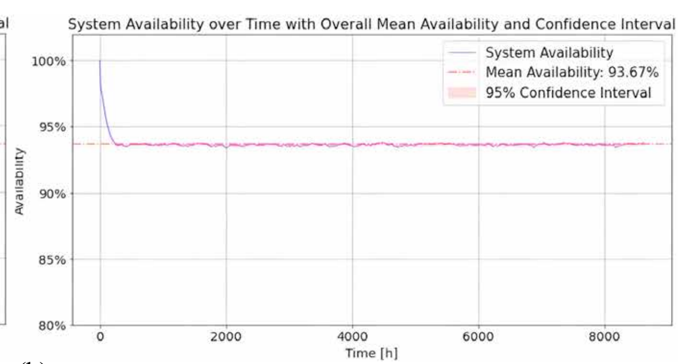
Table 2. Availability results per month.

Mission Time (months)	Number of simulations	Availability	5% percentile	95% percentile
1	1,000	94.31%	93.64%	94.99%
	10,000	94.38%	94.16%	94.59%
	100,000	94.35%	94.28%	94.42%
6	1,000	93.73%	93.43%	94.03%
	10,000	93.73%	93.62%	93.82%
	100,000	93.70%	93.67%	93.73%
12	1,000	93.75%	93.52%	93.97%
	10,000	93.67%	93.60%	93.75%
	100,000	93.67%	93.65%	93.69%

Figure 6. System availability for 1.000 simulations (a) and 100,000 simulations (b).



(a)



(b)

of the mission period. This behavior reflects the balance between failure and repair processes and underscores the value of Monte Carlo simulations in capturing system dynamics over extended operational timelines.

Conclusion

The Monte Carlo Simulation (MCS) tool for Reliability, Availability, and Maintainability (RAM) analysis demonstrated significant advantages in evaluating complex systems, as evidenced by the CO_2 separation plant case study. Compared to traditional analytical methods, the MCS approach delivers more precise and comprehensive insights by incorporating the stochastic variability of failure and repair processes.

This results in narrower confidence intervals and more accurate predictions of system performance. The tool effectively simulates various operational scenarios and calculates key performance indicators—including availability, reliability, maintainability, and the expected number of failures—supporting data-driven maintenance planning and operational decision-making.

In the case study, the model estimated 6.02 individual failures and 4.5 system-level failures over 8,640 hours with 100,000 simulations, providing essential input for preventive and corrective maintenance strategies.

Overall, the findings highlight the relevance and potential of numerical simulations in enhancing the robustness, safety, and efficiency of critical infrastructure in the oil and gas industry and other high-reliability sectors.

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