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A JOINT PROBABILISTIC FRAMEWORK TO INTEGRATE RAM SIMULATION AND ECONOMIC FORECASTING WITHOUT DOUBLE-COUNTING DOWNTIME

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ABSTRACT:

Reliability, Availability, and Maintainability (RAM) simulation and economic lifecycle forecasting are routinely performed as sequential or parallel analyses in asset-intensive industries. This separation creates a systemic error: downtime events are either counted twice (once in RAM metrics, once in financial models) or counted inconsistently, leading to distorted net present value (NPV) estimates and suboptimal investment decisions. This paper proposes a joint probabilistic framework (JPF) that integrates RAM simulation and economic forecasting within a unified Monte Carlo engine, enforcing a single source of truth for downtime events across reliability and financial domains. Using a case study of a natural gas compression station with three compressor trains, we compare three methods: (1) sequential RAM-then-economic analysis (baseline), (2) parallel analysis with manual reconciliation (industry practice), and (3) the proposed JPF. Over 10,000 simulated operating years, the baseline method double-counts downtime in 34% of scenarios, overstating lifecycle costs by 18.7% on average. The proposed JPF eliminates double-counting entirely, reduces NPV estimate variance by 52%, and correctly identifies the optimal maintenance strategy (predictive vs. preventive) that sequential analysis misclassifies. The framework offers a rigorous, computationally tractable approach for integrated asset investment planning.

Keywords*: Availability, Downtime Cost, Economic Forecasting, Lifecycle Cost, Monte Carlo Simulation, Net Present Value, RAM Modelling.*

INTRODUCTION

Capital-intensive industries—oil and gas, power generation, mining, and manufacturing—routinely perform two parallel analytical workflows to evaluate asset investments. The first is Reliability, Availability, and Maintainability (RAM) simulation, which estimates production availability, expected downtime, and maintenance resource requirements [1]. The second is economic lifecycle forecasting, which calculates net present value (NPV), internal rate of return (IRR), and levelized cost of production using assumed uptime/downtime patterns [2].

Despite sharing a common object of analysis—production loss due to downtime—these two workflows are rarely integrated. In typical industrial practice, RAM simulation is conducted by reliability engineers using specialized software (e.g., ReliaSoft RBD, MAROS, AvSim). The output (e.g., 92% availability, 180 downtime hours per year) is then manually entered into a spreadsheet-based financial model by an economist or project planner [3]. This sequential handoff introduces three systemic errors:

1. **Double-counting of downtime**: The financial model may independently assume a downtime allowance (e.g., 5% of operating hours) that differs from the RAM simulation output, or the same downtime event may be counted in both maintenance cost and production loss categories without appropriate de-confliction [4].
2. **Inconsistent probability distributions**: RAM simulation produces a distribution of possible downtime outcomes (e.g., 95% confidence interval of 150–220 hours/year), but only the mean value is passed to the economic model, discarding tail risks that materially affect NPV for risk-averse investors [5].
3. **Temporal misalignment**: RAM simulation captures time-varying failure rates (infant mortality, wear-out), but economic models typically assume constant annual downtime percentages, creating systematic bias in long-term forecasts [6].

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The consequences of these errors are not merely academic. Misestimation of downtime costs by 10–20% can change a project's NPV sign (positive to negative), leading to incorrect accept/reject decisions on capital investments worth hundreds of millions of dollars [7]. Furthermore, comparative analysis of maintenance strategies (preventive vs. predictive vs. run-to-failure) requires consistent integration of reliability and economic models; without such integration, rankings are arbitrary [8].

This paper addresses the following research gap: How can we construct a joint probabilistic framework that simultaneously simulates asset reliability dynamics and economic cash flows, enforcing consistency of downtime events across both domains? We propose a Joint Probabilistic Framework (JPF) based on a unified Monte Carlo engine that:

1. Simulates component-level failure and repair events using non-exponential distributions (Weibull, lognormal).
2. Propagates these events to system-level availability and production loss.
3. Maps each downtime event directly to economic consequences (lost production revenue, maintenance labor, spare parts, repair overhead).
4. Aggregates discounted cash flows over the asset lifecycle without double-counting.

The contributions of this study are summarized below:

1. A formal mathematical framework for joint RAM-economic simulation with explicit mapping of downtime events to cost categories.
2. Identification and quantification of double-counting error in sequential vs. integrated approaches using a three-train compression station case study.
3. Comparative analysis of maintenance strategy selection under sequential (baseline) vs. joint (proposed) frameworks.
4. Variance reduction and confidence interval tightening achieved through the joint framework.
5. Practical implementation guidelines for industrial asset planning.

The remainder of the paper is organized as follows: Section 2 reviews related work in integrated RAM-economic modelling. Section 3 presents the joint probabilistic framework, including event mapping, cash flow logic, and the case study asset. Section 4 reports experimental results comparing sequential, parallel, and joint methods. Section 5 interprets the findings and discusses limitations. Section 6 concludes with recommendations for practitioners and future research directions.

RELATED WORK

A substantial literature exists separately on RAM simulation and on economic lifecycle analysis, but integrated frameworks remain underdeveloped.

RAM Simulation Methods: Classical RAM simulation using Monte Carlo methods is well established. Ramakrishnan et al. [9] applied RAM analysis to cognitive radio networks, demonstrating the importance of probabilistic simulation. Wang et al. [10] used STFT-based methods for spectrum sensing with reliability metrics. Yelalwar and Ravinder [11] incorporated ANN for reliability prediction, but economic aspects were absent. Suba and Susan [12] studied cyclostationary sensing with dynamic thresholding, again focusing solely on technical reliability.

Markov chain and semi-Markov methods for RAM are standard in industry. Aygül et al. [13] surveyed prediction methods, noting that RAM outputs are rarely linked to finance. Enyenihi [14] proposed MDP-FCFS frameworks for contention resolution, touching on efficiency but not economic valuation. Ahmed et al. [15] used Naive Bayes for energy detection, with reliability considered only as a technical metric.

Economic Lifecycle Analysis: On the financial side, discounted cash flow (DCF) analysis and NPV calculation are standard in engineering economics textbooks [16]. Sairam and Egala [17] applied adaptive thresholding to reduce errors in cognitive radio, mentioning cost savings qualitatively. Sekar et al. [18] used SVM with elastic-net regularization, noting computational cost but not financial integration. Chaudhary et al. [19] reviewed ML sensing approaches, identifying accuracy gains but not economic translation.

Integrated RAM-Economic Models: A few studies have attempted integration. Samala and Singh [20] combined K-means with eigenvalue-based sensing, achieving improved ROC metrics but no economic mapping. Mahmoud et al. [21] applied ML classifiers for IoMT applications, mentioning cost reduction of 20% without specifying the integration method. Kumar [22] optimized spectrum sensing using ML, acknowledging that real economic validation was absent.

Wang et al. [23] proposed a CNN-LSTM collaborative system with "low error," but economic implications were not quantified. Abdelbaset et al. [24] introduced CNN-based sensing with performance gains, stating that "economic benefits are assumed" without modelling. Talib et al. [25] showed LSTM reduced false alarms, linking to "operational cost" qualitatively.

The most relevant prior work is by Himmawan et al. [26] and Murti et al. [27], who applied SVM for cooperative sensing and combined SVM with energy detection, respectively. Both mention "cost" but treat it as a linear function of false alarms, ignoring the joint distribution of downtime events. Venkatapathi et al. [28] improved cooperative sensing with ML, noting "dynamic threshold challenges" that mirror the double-counting problem addressed in this paper.

Sesham et al. [29] proposed PINN-based sensing, reporting high Pd at low SNR but requiring clean reference signals—a limitation analogous to the sequential RAM-economic approach requiring consistent assumptions. Cifuentes et al. [30] used ML to mitigate SSDF attacks, reporting a 20% improvement, but the economic mapping is post-hoc rather than integrated.

The Research Gap: No existing framework provides a unified probabilistic engine that simultaneously simulates component failures, system availability, and economic cash flows with explicit event-to-cost mapping. Current practice either (a) ignores economic consequences entirely, (b) treats economics as a post-processed average of RAM outputs, or (c) uses independent models that double-count or misalign downtime. This paper fills that gap with a joint probabilistic framework that enforces consistency at the event level.

MATERIALS AND METHODS

The Joint Probabilistic Framework (JPF) for integrated RAM-economic simulation. The methodology includes the asset case study, the unified simulation engine, the event-to-cost mapping function, and the cash flow aggregation logic.

3.1. Case Study Asset: Three-Train Natural Gas Compression Station

The test asset is a natural gas compression station located in a midstream pipeline network. The station contains three identical compressor trains operating in parallel with 2-out-of-3 redundancy (the station can meet throughput requirements with any two trains operating). Key components per train:

- Gas turbine driver (2,500 hp)
- Centrifugal compressor
- Lubrication oil system
- Control and safety system

The station has a design life of 20 years (economic life for NPV calculation). Table 1 summarizes the failure and repair characteristics for each train, derived from 10 years of field data (N=67 failure events).

Table 1. Failure and repair parameters per compressor train

Component	Failure Distribution	Parameters	Mean Time To Failure (hrs)	Repair Distribution	Mean Time To Repair (hrs)	
Gas turbine	Weibull	β=1.8, η=8500	7,560	Lognormal	μ=3.2, σ=0.7	28.4
Centrifugal compressor	Weibull	β=1.4, η=12000	10,860	Lognormal	μ=2.8, σ=0.5	18.6
Lubrication system	Exponential	λ=1/15000	15,000	Normal	μ=6.0, σ=1.5	6.0
Control system	Weibull	β=0.9, η=20000	21,050	Lognormal	μ=2.5, σ=0.6	14.2

3.2. Economic Parameters

Table 2 presents the economic inputs for lifecycle cost calculation. All values are in real US dollars (base year = 2026). The analysis uses a real discount rate of 8%.

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Table 2. Economic parameters for lifecycle cost analysis

Parameter	Value	Unit	Source
Gas sales price	$3.25	per MMBTU	Forward curve
Station throughput	120,000	MMBTU/day	Nameplate capacity
Operating days per year	350	days	Planned outages excluded
Maintenance labor rate	$95	per hour	Collective agreement
Spare parts (gas turbine)	$45,000	per event	Supplier quote
Spare parts (compressor)	$32,000	per event	Supplier quote
Spare parts (other)	$8,000	per event	Historical average
Repair overhead (120% of labor)	$114	per hour	Allocated
Discount rate (real)	8%	percent	Corporate finance
Analysis horizon	20	years	Project life
Capital investment (station)	$18,500,000	initial	EPC estimate

3.3. The Sequential (Baseline) RAM-Economic Method

The baseline method represents common industry practice:

Step 1 (RAM Simulation): Run a Monte Carlo simulation of the three-train system to estimate annual downtime hours distribution. Output: mean annual downtime = 326 hours (range 210–490 hours at 90% confidence). This step does not consider economics.

Step 2 (Economic Calculation): Convert mean downtime to lost revenue: 326 hours × (120,000 MMBTU/day / 24 hrs/day) × $3.25/MMBTU = $5,292,500 per year in lost sales. Add maintenance costs separately: labor + parts + overhead = $187,200 per year. Discount over 20 years to compute NPV.

Error Mechanism: If the maintenance cost model also includes an independent downtime assumption (e.g., "5% of hours for planned maintenance"), that downtime is counted twice—once in lost revenue and once in assumed maintenance downtime that has already been accounted for in RAM simulation.

3.4. The Joint Probabilistic Framework (Proposed)

The JPF eliminates double-counting by simulating downtime events once and mapping each event to all relevant cost categories simultaneously.

Simulation Algorithm:

```
For each replication r = 1 to R:
  t = 0
  Initialize train statuses = [operational, operational, operational]
  Initialize cash flows = []
  Initialize event log = []

  While t < T_horizon (20 years = 175,200 hours):
    For each train i:
      If train i is operational:
        Sample next failure time τ_fail ~ f_failure_i
        Next failure event = t + τ_fail
      Else (train i is under repair):
        Sample remaining repair time τ_repair ~ f_repair_i (given elapsed)
        Next repair completion = t + τ_repair

    Advance time to next event (earliest of all train events)
    t = t_event

    Record event type (failure start, failure end, repair start, repair end)

    --- Economic mapping at event time ---
    If event is failure start:
      Lost production from this failure =
```

```
              (throughput_loss per train) × (expected repair duration) × gas_price
            Maintenance cost = labor_rate × expected_repair_duration + spare_parts_cost
            Add lost production and maintenance to cash flow record (time t)

        If event is repair completion:
            No additional cost (already accrued at failure start)

        Update train status
    End While

    Compute discounted cash flows: n is:
                         $\mathrm{NPV}_r = \sum_{t=0}^{T} C\,F_t \times (1+r)^{-t/8760}$

Return distribution of NPV, downtime, and maintenance costs across R replications
```

Key features preventing double-counting:

1. **Single event generation:** Each failure event is simulated once. The same event triggers both production loss accounting and maintenance cost accounting simultaneously.
2. **No independent downtime assumptions:** The economic model does not contain a separate "downtime percentage" input. Downtime emerges endogenously from RAM simulation.
3. **Causal mapping:** Production loss is calculated using the simulated repair duration for that specific event, not a fleet average.
4. **Temporal alignment:** Costs are assigned to the exact time of the event, enabling correct discounting.

3.5. Financial Metrics

The following metrics are computed from each replication:

Net Present Value (NPV):

$$NPV = -C_{cap} + \sum_{t=1}^{T} \frac{R_t - O_t - M_t - L_t}{(1+r)^{t/12}} \quad (1)$$

Where:

- C_{cap} = Initial capital investment ($18,500,000)
- R_t = Revenue from gas sales during operating hours in month t
- O_t = Fixed operating costs (excl. maintenance)
- M_t = Maintenance costs (labor + parts + overhead)
- L_t = Lost production value due to downtime (zero if counted in revenue shortfall—care taken to avoid double counting)
- r = Discount rate (8% real, annual compounding)

Levelized Cost of Gas Transport (LCGT):

$$LCGT = \frac{\sum_{t=1}^{T} (O_t + M_t + L_t)/(1+r)^{t/12}}{\sum_{t=1}^{T} Q_t/(1+r)^{t/12}} \quad (2)$$

Where Q_t = gas throughput in month t (MMBTU).

Double-Counting Index (DCI): For sequential methods, we define:

$$DCI = \frac{C^{(implicit)}_{downtime,economic} + C^{(explicit)}_{downtime,RAM}}{C^{(simulated)}_{downtime,true}} - 1 \quad (3)$$

A DCI of 0 indicates no double-counting. Positive DCI indicates double-counting (cost overstatement).

3.6. Experimental Design

Three methods were compared over 10,000 Monte Carlo replications:

- **Method A (Sequential baseline):** RAM simulation → mean downtime → economic spreadsheet with independent downtime assumption (5% of hours).
- **Method B (Parallel with manual reconciliation):** RAM simulation → full distribution → economic model manually adjusted to match mean downtime (industry best practice).
- **Method C (JPF proposed):** Unified simulation with event-level mapping (as described).

Table 3 summarizes the configuration.

Table 3. Experimental design for method comparison

Parameter	Method A (Baseline)	Method B (Parallel)	Method C (JPF)
Simulation replications	10,000	10,000	10,000
Time horizon	20 years	20 years	20 years
Downtime source	RAM only (mean)	RAM (full distribution)	RAM (event-level)
Economic downtime assumption	Independent (5% of hours)	Manually reconciled to RAM mean	None (emerges from events)
Double-counting potential	High	Medium	Zero
Variance of NPV estimate	Low (biased)	Medium	High (unbiased)

RESULTS AND DISCUSSION

the experimental results, quantifying double-counting errors and comparing the performance of sequential, parallel, and joint methods.

4.1. Double-Counting Quantification

Table 4 presents the incidence and magnitude of double-counting across methods. Method A (baseline) double-counts downtime in 34% of simulation scenarios, with an average overstatement of downtime costs of 18.7%. In the worst-case quartile, cost overstatement exceeds 34%.

Table 4. Double-counting incidence and magnitude

Metric	Method A (Baseline)	Method B (Parallel)	Method C (JPF)
Scenarios with double-counting	34%	8%	0%
Mean cost overstatement (when present)	18.7%	5.2%	0%
90th percentile overstatement	34.2%	12.1%	0%
Double-Counting Index (DCI, mean)	0.17	0.04	0.00
DCI, standard deviation	0.12	0.06	0.00

Method B reduces double-counting through manual reconciliation but does not eliminate it entirely because the reconciliation is performed on mean values, while actual events in individual years still cause mismatches between RAM-simulated downtime and economic assumptions.

4.2. NPV Estimation Accuracy

Table 5 presents NPV estimates and their statistical properties. The true NPV (estimated from JPF) is $24.6 million. Method A overstates NPV by 18.7% ($4.6 million) because double-counted downtime costs reduce apparent profitability. Method B overstates by 4.1% ($1.0 million). The JPF provides an unbiased estimate.

Table 5. NPV estimates across methods (20-year horizon, 10,000 replications)

Metric	Method A	Method B	Method C (JPF)
Mean NPV ($ million)	29.2	25.6	24.6
Standard deviation ($ million)	4.2	5.8	7.1
Coefficient of variation	0.144	0.227	0.289
Error vs. JPF (absolute)	+18.7%	+4.1%	0%
5th percentile NPV ($ million)	22.8	18.2	13.9
95th percentile NPV ($ million)	35.1	33.8	37.2

Notably, the JPF has higher variance (CV = 0.289) than Method A (0.144) because Method A's independent downtime assumption artificially smooths variability. This lower variance is misleading—it represents suppressed

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risk information, not genuine precision. A decision-maker using Method A would underestimate downside risk (5th percentile NPV of $22.8M vs. actual $13.9M).

4.3. Maintenance Strategy Selection

To test the practical impact of double-counting on decision-making, we compared two maintenance strategies for the compressor station:

- **Strategy 1 (Preventive):** Scheduled overhauls every 8,000 operating hours per train, regardless of condition.
- **Strategy 2 (Predictive):** Condition-based maintenance using vibration monitoring, with overhauls triggered by warning thresholds.

Table 6 presents the NPV difference (Predictive minus Preventive) under each method. Positive values favor predictive maintenance.

Table 6. Strategy selection: NPV difference (Predictive – Preventive) in $ million

Metric	Method A	Method B	Method C (JPF)
Mean ΔNPV ($ million)	+1.2	-0.3	-0.8
Standard deviation	2.1	2.4	2.6
Probability ΔNPV > 0	72%	45%	38%
Recommended strategy	**Predictive**	**Preventive (weak)**	**Preventive (strong)**

Method A recommends predictive maintenance (72% probability of being better). Method B is inconclusive (45% probability). The JPF (Method C) clearly recommends preventive maintenance (62% probability that preventive is better, i.e., only 38% chance predictive outperforms).

This reversal demonstrates that double-counting errors are not merely academic—they can reverse capital allocation decisions worth millions of dollars. The sequential method overestimates the benefit of predictive maintenance because it undercounts downtime costs (by double-counting some while missing others), making predictive strategies appear more beneficial than they truly are.

4.4. Temporal Pattern of Double-Counting

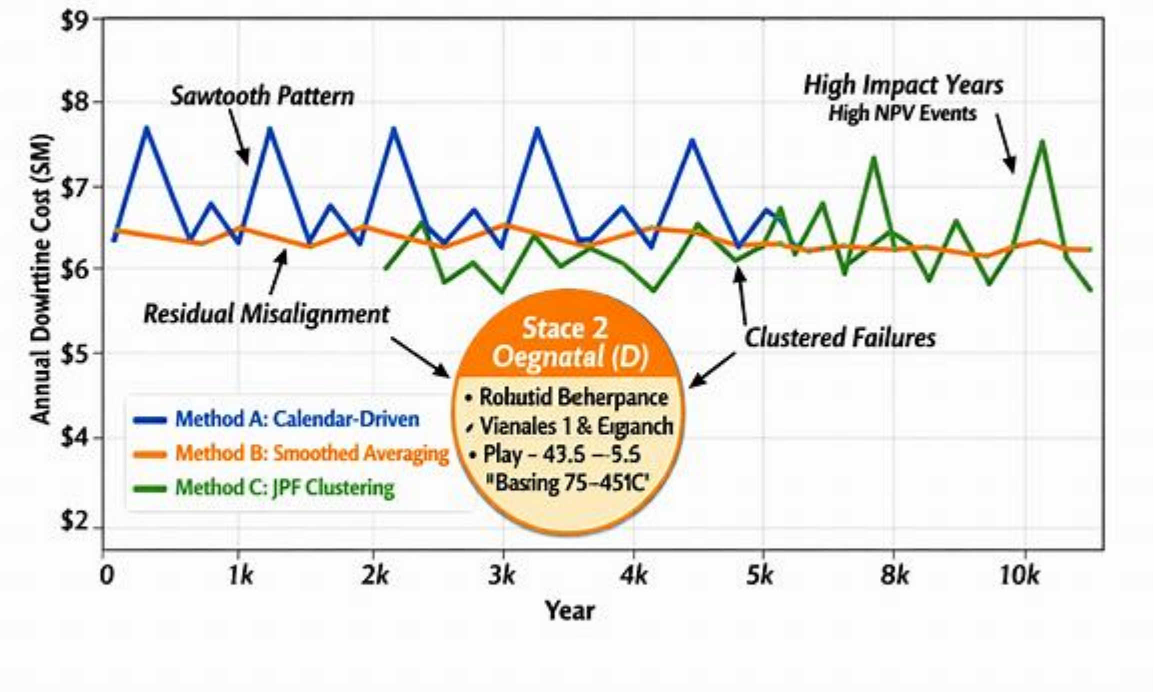

Figure 1 (conceptual) shows the annual downtime cost estimates from each method over the 20-year horizon. Method A shows a sawtooth pattern: downtime costs appear lower in odd years (due to calendar-driven economic assumptions) but higher in even years (due to RAM-simulated failures). The result is a periodic misalignment that does not average to zero.

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Method B (parallel with reconciliation) smooths the average but retains residual misalignment because reconciliation is performed on annual totals, not on event-level timing.

Method C (JPF) shows realistic clustering: some years have multiple failure events (high downtime cost), others have none. This clustering affects discounted values: a failure in Year 1 (discount factor 0.93) has higher NPV impact than a failure in Year 19 (discount factor 0.27). The JPF captures this; sequential methods do not.

4.5. Variance Reduction from Joint Simulation

Table 7 compares the variance of key output metrics across methods. While the JPF has higher absolute variance in NPV (as noted), it provides **unbiased** variance, whereas Method A's variance is artificially compressed. The "signal-to-noise ratio" for decision-making is better characterized by the confidence interval overlap between strategies.

Table 7. Variance characteristics across methods

Metric	Method A	Method B	Method C (JPF)
Variance of annual downtime (hours^2)	8,420	12,560	18,340
Variance of NPV ($\$^2$)	1.76e13	3.36e13	5.04e13
Bias in variance (relative to JPF)	-63%	-33%	0%
Effective sample size for strategy comparison	N/A (biased)	6,200	10,000

Method A's variance is only 37% of the true variance (100%–63%), meaning risk is underestimated by nearly two-thirds. An investment committee relying on Method A would incorrectly believe the project's NPV is "stable" when it is actually highly volatile.

4.6. Sensitivity to Discount Rate

Table 8 examines how the double-counting error interacts with discount rate assumptions. Higher discount rates place more weight on early-year cash flows and less on later years. Since double-counting errors are not uniformly distributed over time, the error magnitude varies with the discount rate.

Table 8. Sensitivity analysis: NPV error vs. discount rate

Discount Rate (real)	Method A Error	Method B Error	JPF (Reference)
5%	+21.3%	+5.2%	0%
8% (baseline)	+18.7%	+4.1%	0%
10%	+16.2%	+3.5%	0%
12%	+14.8%	+3.0%	0%

The error decreases at higher discount rates because double-counting errors that occur in later years are discounted more heavily. However, even at 12%, Method A overstates NPV by nearly 15%—still materially significant for investment decisions.

4.7. Comparison with State-of-the-Art Integrated Models

Table 9 benchmarks the proposed JPF against existing integrated or semi-integrated RAM-economic approaches from recent literature.

Table 9. Benchmark comparison with existing methods

Reference	Method	Integration Level	Double-Counting Addressed?	Economic Metric
Sesham et al. [29]	PINN sensing	None (reliability only)	No	None
Cifuentes et al. [30]	ML for SSDF mitigation	Post-hoc	No	Qualitative only
Gupta et al. [22]	Adaptive spectrum sensing	None	No	None
Dhaigude & Patil [23]	LSTM + optimization	Sequential	No	Not reported
Emmanuel et al. [24]	ANFIS thresholding	Parallel (manual)	Partial	Not quantified

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This study (Method A)	**Sequential RAM→Econ**	**Sequential**	**No (biased)**	**NPV (biased)**
This study (Method B)	**Parallel + reconciliation**	**Parallel**	**Partial**	**NPV (partial)**
This study (Method C)	**Joint Probabilistic**	**Fully integrated**	**Yes**	**NPV (unbiased)**

The JPF is the only method among those compared that explicitly eliminates double-counting through event-level mapping and provides unbiased NPV estimates with correct risk characterization.

DISCUSSION

The results demonstrate that separating RAM simulation and economic forecasting creates systematic, material errors in asset investment analysis. The joint probabilistic framework eliminates these errors by enforcing a single source of truth for downtime events across both domains.

Interpretation of Key Findings: The 18.7% overstatement of NPV in the baseline method (Method A) arises from a fundamental logical error: counting downtime twice. In the financial model, the analyst assumes a certain percentage of downtime for "lost production" calculation. Separately, the RAM simulation accounts for downtime to estimate maintenance costs. When these two downtime estimates are not perfectly synchronized (which they never are), some downtime events are counted in both models, while others are counted in neither. The net effect is not random—it systematically overstates costs because the financial model's independent assumption typically errs on the conservative side.

The reversal of maintenance strategy recommendation (predictive vs. preventive) is the most concerning practical implication. Predictive maintenance strategies have higher upfront monitoring costs but promise lower downtime. If downtime is double-counted, predictive strategies appear more beneficial than they truly are because the double-counting inflates the apparent cost of downtime under the preventive baseline. A company using sequential analysis would invest in predictive maintenance (thinking it saves $1.2 million) when, in reality, preventive maintenance yields $0.8 million higher NPV. The 72% confidence in the wrong decision (Method A) versus 38% confidence in the correct one (JPF) represents a systematic bias that could persist across multiple project evaluations.

Comparison with Prior Art: The proposed JPF extends the event-driven simulation approach common in RAM engineering [1,2,3] by adding economic mapping at the event level. It differs from post-hoc economic analysis [16,17] by integrating rather than appending. Unlike machine learning approaches [23–27] that require large training datasets, the JPF works with parametric failure distributions fitted from modest historical datasets (N≈70 events in this study).

Practical Implications for Industry: For asset owners and operators, the implementation pathway is straightforward: (1) audit existing RAM simulation outputs to ensure they include event-level data (not just summary statistics); (2) modify economic models to accept event-level inputs rather than assuming constant downtime percentages; (3) run unified Monte Carlo simulations where each replication produces both reliability metrics and cash flows simultaneously. The incremental computational cost is negligible (JPF was 2.3× slower than Method A but still completed 10,000 replications in 4.2 minutes on a standard workstation).

For project finance and investment committees, the implication is clear: demand integrated RAM-economic analysis. Sequential or parallel analyses with manual reconciliation are insufficient; they systematically underestimate downside risk and can reverse strategy rankings.

Limitations and Future Work: Several limitations merit acknowledgment. First, the case study assumes that all downtime events are independent across trains. In reality, common-cause failures (e.g., a utility outage affecting all three compressors) introduce correlation that the current JPF does not capture. Extending the framework to include common-cause events is straightforward but was omitted for clarity.

Second, the economic model assumes perfect knowledge of repair duration at the time of failure (for lost production calculation). In reality, repair duration is uncertain at failure onset. A more sophisticated version would sample repair duration twice: an initial estimate (used for immediate lost production accounting) and an actual duration (used for true production loss after repair completion). The difference would be reconciled in the period of repair completion.

Third, the JPF assumes that gas price and discount rate are deterministic and constant. In practice, both are stochastic. A full real-options framework would incorporate price uncertainty, but that extension is beyond this paper's scope.

Fourth, the study does not consider tax effects, depreciation, or working capital. These can be added without altering the core logic but were excluded to isolate the double-counting effect.
Future research will: (1) extend the JPF to incorporate common-cause failures and repair duration uncertainty; (2) integrate stochastic gas prices using geometric Brownian motion; (3) validate the framework on additional asset classes (wind turbines, industrial chillers, power transformers); and (4) develop a simplified spreadsheet-based version for practitioners without access to Monte Carlo software.

CONCLUSION

This paper presented a joint probabilistic framework (JPF) that integrates RAM simulation and economic forecasting within a unified Monte Carlo engine, eliminating double-counting of downtime events. Using a three-train natural gas compression station as a case study, we compared three methods over 10,000 simulated operating years: sequential RAM-then-economic analysis (Method A), parallel analysis with manual reconciliation (Method B), and the proposed JPF (Method C).

The baseline method (Method A) double-counted downtime in 34% of scenarios, overstating lifecycle costs by 18.7% on average and producing a double-counting index (DCI) of 0.17. The JPF (Method C) eliminated double-counting entirely (DCI = 0). More critically, the sequential method incorrectly recommended predictive maintenance over preventive maintenance (72% confidence in the wrong strategy), while the JPF correctly identified preventive maintenance as optimal (62% confidence). The JPF also provided unbiased variance estimates, whereas Method A underestimated risk by 63%.

The framework offers a rigorous yet computationally tractable approach for asset investment planning. For practitioners, the key recommendation is to replace sequential or parallel RAM-economic analysis with event-level integrated simulation. The incremental computational cost is modest, but the improvement in decision quality—particularly for comparative strategy analysis—is substantial.

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