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A Risk-Integrated CPM–PERT and Monte Carlo Simulation Approach for Aircraft Overhaul Scheduling: Empirical Evidence from Military Maintenance Systems

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ABSTRACT

Accurate scheduling of aircraft overhaul projects is essential for maintaining operational readiness in military aviation systems. Traditional scheduling approaches, including the Critical Path Method (CPM) and the Program Evaluation and Review Technique, often fail to capture uncertainties present in defense maintenance environments. This study presents a risk-integrated scheduling model that combines these techniques with Monte Carlo simulation to improve the reliability of project duration estimates. The model incorporates risks related to logistics, technical modifications, and workforce limitations through probabilistic activity durations and simulation-driven critical path analysis. Data from twelve overhaul projects were used for development and validation. The model generates three outputs: probabilistic distribution of project duration, likelihood of critical path occurrence, and sensitivity ranking of key risk factors. Results show a mean duration of 149.2 days with a 95 percent confidence interval between 133.5 and 165.6 days, and a 54.8 percent probability of meeting a 150-day target. Compared to deterministic scheduling, the mean absolute error decreased from 17.6 to 7.4 days, indicating improved accuracy. Sensitivity analysis highlights spare part delays and technical changes as dominant risks, supporting proactive planning and better decision making for improved scheduling performance across complex, uncertain military maintenance environments and resource-constrained operational contexts globally.

1. INTRODUCTION

Aircraft overhaul scheduling plays a crucial role in ensuring operational readiness and mission effectiveness in military aviation environments [1]. In the context of the Indonesian Air Force (TNI AU), delays in overhaul activities may result in a critical reduction of aircraft availability, compromising both air defense strategy and national security operations [2]. Overhaul scheduling, therefore, must not only comply with technical maintenance protocols but also align with time-sensitive operational mandates. Despite the implementation of standard project scheduling techniques such as the Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT), existing scheduling practices remain vulnerable to delays caused by unmanaged uncertainties and risk factors throughout the project lifecycle [3].

Traditional project scheduling methods, such as CPM, which assumes deterministic activity durations, and PERT, which introduces probabilistic estimates, have been widely used across various engineering and maintenance contexts. However, both methods are often criticized for their limited capacity in handling complex, dynamic, and multi-risk environments such as military aircraft overhaul projects [4]. These techniques typically fail to account for stochastic variations and interdependent risk propagation that affect the actual duration of activities [5]. In overhaul projects where technical configurations may change abruptly, logistical constraints may arise, or specialized personnel may be unavailable, risk factors can have a compounded effect on project timelines.

To address these limitations, contemporary research has emphasized the integration of risk management into project scheduling models. Risk-integrated scheduling aims to capture the influence of key uncertainties and simulate their impact on project timelines using techniques such as Monte Carlo simulation [6]. This integration is particularly relevant for defense-related maintenance projects where delays have strategic implications. Yet, most existing studies have either focused on commercial aviation contexts or limited their scope to specific technical risks, leaving a gap in research that addresses the unique characteristics of military overhaul operations, particularly within TNI AU [7].

This study proposes the development of a risk-integrated scheduling model that combines CPM, PERT, and Monte Carlo simulation to improve schedule reliability in military aircraft overhaul projects. While previous studies have explored risk-integrated scheduling using probabilistic techniques, most have focused on general engineering or commercial aviation contexts and have not systematically addressed the specific characteristics of military maintenance environments, such as high supply uncertainty, dynamic technical requirements, and mission-critical time constraints

[8]. Moreover, limited attention has been given to analyzing the probability of critical-path variability and the relative contribution of individual risk factors under uncertainty.

Accordingly, this research aims to fill these gaps by integrating empirical risk data, probabilistic duration modeling, and simulation-based critical-path analysis within a unified framework tailored to the Indonesian Air Force (TNI AU). The main contributions of this research are threefold: (1) developing a practical risk-integrated scheduling model for aircraft overhaul projects; (2) quantifying schedule uncertainty and critical-path variability using Monte Carlo simulation; and (3) validating the model using historical project data and sensitivity analysis to support risk-informed decision-making [9]. It should be noted that this study focuses on single-project scheduling under uncertainty and does not explicitly model resource-constrained or multi-project scheduling environments. Therefore, the scope is limited to risk-integrated duration estimation and critical-path analysis within individual overhaul projects.

2. LITERATURE REVIEW

2.1 Risk management in aircraft maintenance projects

Risk management is a critical component of project success, particularly in aircraft maintenance operations characterized by high technical complexity and tight scheduling constraints [10]. In the military aviation sector, risk events such as late spare part deliveries, technical specification changes, limited access to skilled personnel, and operational disruptions can significantly affect project timelines and readiness [11]. Effective risk management involves the systematic identification, analysis, and mitigation of potential disruptions that threaten project objectives [12]. Emphasized that incorporating risk adjustments into project schedules significantly improves the reliability of completion times, particularly in resource-constrained environments.

Despite its importance, traditional risk management frameworks in maintenance scheduling often lack integration with core scheduling algorithms, resulting in fragmented decision-making and reactive mitigation. This disconnect is especially problematic in military contexts, where delays can compromise operational continuity [13]. Therefore, an integrated approach that aligns risk assessment with scheduling techniques is essential to optimize resource allocation and reduce schedule deviations.

2.2 Critical Path Method and Program Evaluation and Review Technique techniques in project scheduling

The CPM and the PERT are widely applied techniques for project time management. CPM focuses on identifying the longest sequence of dependent tasks, known as the critical path, using deterministic time estimates for each activity [14]. In contrast, PERT incorporates uncertainty by assigning optimistic, most likely, and pessimistic duration estimates to each task, computing the expected time using a probabilistic formula. While CPM is valued for its simplicity and direct path analysis, it is limited in flexibility when addressing uncertainty [15]. PERT offers more adaptability but requires detailed distributional assumptions that are often unavailable in practice.

In the context of aircraft maintenance, both CPM and PERT have demonstrated utility in planning complex workflows, yet their effectiveness declines when faced with real-world variability in activity durations and risk interactions. Without proper integration of risk variables, the static nature of these methods can lead to unrealistic project expectations and delayed completions [16].

2.3 Risk-integrated scheduling models

Recent studies have highlighted the potential of integrating risk assessment into project scheduling models to enhance robustness and decision support [17]. Introduced a risk-integrated CPM model that incorporates Monte Carlo simulations to evaluate the probabilistic effects of risks on the critical path. This approach allows the dynamic adjustment of the project schedule based on simulated risk scenarios [18]. Similarly, a hybrid framework was proposed that combines PERT with risk mitigation strategies to address schedule variability in aerospace overhaul projects.

However, while these models provide theoretical advancements, their implementation remains complex and data-intensive. Noted that such models demand extensive historical data and simulation expertise, which may limit their practical applicability without dedicated decision-support systems [19]. Moreover, many of the existing models are tailored to commercial aviation or generic engineering projects and do not explicitly address the unique operational dynamics of military aircraft maintenance [20].

2.4 Research gap and contribution

Although previous studies have demonstrated the value of integrating risk assessment with CPM, PERT, and Monte Carlo simulation, a structured comparison reveals several limitations in the existing literature. First, most prior research has been developed in the context of commercial aviation or general construction and engineering projects, with limited attention to the unique operational characteristics of military aircraft maintenance, where scheduling decisions are tightly linked to mission readiness and operational constraints.

Second, while uncertainty in activity durations has been widely acknowledged, existing models often treat risk in a generalized manner and do not explicitly incorporate supply chain uncertainty, such as delays in spare part delivery, or dynamic technical changes, which are highly prevalent in overhaul operations.

Third, although Monte Carlo simulation has been applied in scheduling studies, the probabilistic behavior of the critical path is rarely analyzed in detail. Many studies assume a fixed critical path or focus only on expected project duration, without examining how frequently the critical path changes under different risk scenarios or identifying the most probable critical-path configurations.

Fourth, existing research seldom provides empirically validated sensitivity analysis that quantifies the relative contribution of individual risks to total schedule variance, limiting the ability of decision-makers to prioritize mitigation strategies effectively.

Finally, some studies refer to resource-constrained or multi-project environments but do not explicitly model shared resource pools or capacity constraints, leading to inconsistencies between stated scope and implemented methodology.

To address these gaps, this study develops a risk-integrated

scheduling model tailored to military aircraft overhaul projects within the Indonesian Air Force (TNI AU). The proposed model explicitly incorporates key operational risks, including logistics delays, technical specification changes, and personnel constraints, into a CPM/PERT network and evaluates their impact using Monte Carlo simulation. In addition to estimating project duration distributions, the model analyzes critical-path variability and probability, and performs sensitivity analysis to rank dominant risk drivers. The model is further validated using empirical data from actual overhaul projects, ensuring both methodological rigor and practical applicability in high-reliability maintenance environments.

3. METHODS

3.1 Research design

This study employs a quantitative model development approach aimed at constructing, simulating, and validating an integrated risk-based scheduling model for military aircraft overhaul projects. The model combines deterministic and probabilistic scheduling techniques (CPM and PERT) with risk identification and Monte Carlo simulation to enhance the accuracy and robustness of project timelines. The research design follows four sequential phases: risk identification, model construction, simulation, and validation.

3.2 Research context and data collection

This study was conducted within the Indonesian Air Force (TNI AU) aircraft maintenance facilities, which operate in high-reliability, mission-critical environments where delays in overhaul projects can jeopardize national defense readiness. Data were collected from three integrated sources to ensure empirical validity and contextual accuracy. Archival project documents from the past five years provided historical insight, while in-depth interviews with maintenance engineers, project managers, and logistics officers offered expert perspectives on risk factors and activity durations. Additionally, field observations of ongoing overhaul operations were conducted to validate process flows and duration estimates. This triangulated approach ensured a comprehensive and reliable foundation for modeling project performance in military aircraft maintenance settings.

3.3 Model development process

The model was developed through the following stages:

3.3.1 Risk identification and classification

A mixed-method approach, combining both qualitative and quantitative techniques, was employed to identify the key risks influencing the duration of overhaul projects. These risks were systematically categorized according to their frequency of occurrence and potential impact on project timelines, following the framework suggested by. Particular attention was given to recurrent issues such as delays in spare part delivery, changes in technical specifications, shortages of skilled manpower, and disruptions caused by environmental or operational factors. Each identified risk was assessed using probability and impact scores, which were derived from expert judgment and supported by historical maintenance records. This structured assessment allowed for a prioritized understanding of the most critical factors affecting project performance (see Table 1), while the detailed activity list and risk–activity mapping are provided in Appendix A (Tables A1 and A2).

Table 1. Risk rating scale

Score	Probability Level	Description	Impact Level	Description
1	Very Low	Rare occurrence	Minimal	Negligible delay
2	Low	Unlikely	Minor	Small delay
3	Medium	Occasional	Moderate	Noticeable delay
4	High	Likely	Major	Significant delay
5	Very High	Frequent	Severe	Critical delay

3.3.2 Risk impact formulation

Risk impacts on activity duration were modeled using a multiplicative adjustment approach, allowing proportional changes based on risk realization. The duration of activity iii in simulation run k is defined as:

$$D_i^{(k)} = T_{e,i} \times \left(1 + \sum_j R_{i,j} \cdot X_j^{(k)}\right)$$

where,

- $T_{e,i}$: expected duration from PERT
- $R_{i,j}$: risk–activity mapping
- $X_j^{(k)}$: stochastic impact of risk j in iteration k

Multiple risks affecting the same activity are assumed to be additive in proportional effect. This formulation captures compounded delays while maintaining computational stability.

3.3.3 Critical Path Method/Program Evaluation and Review Technique network construction

A baseline project network was developed using CPM, which included all major work packages and activities involved in the overhaul process. Duration estimates for each activity were then adapted using PERT by incorporating three-time estimates:

- Optimistic (O),
- Most Likely (M),
- Pessimistic (P).

The expected duration (Te) for each activity was calculated using the PERT formula: Te = (O + 4M + P) / 6 and variance: V = [(P – O)/6]². The probability and impact levels used in the analysis are defined in Table 2.

Table 2. Risk rating scale

Score	Probability Level	Description (Probability)	Impact Level	Description (Impact on Schedule)
1	Very Low	Rare occurrence (< 10%)	Minimal	Negligible delay (≤ 2 days)
2	Low	Unlikely (10–30%)	Minor	Small delay (3–5 days)

3	Medium	Occasional (30–60%)	Moderate	Noticeable delay (6–10 days)
4	High	Likely (60–80%)	Major	Significant delay (11–20 days)
5	Very High	Frequent (> 80%)	Severe	Critical delay (> 20 days)

3.3.4 Risk integration via Monte Carlo simulation

Each identified risk was mapped to the activities it may affect. Probability distributions (typically triangular or beta) were assigned to activity durations reflecting risk impacts. Monte Carlo simulation with 10,000 iterations was applied to simulate the probabilistic completion time of the project. The simulation allowed recalculation of the critical path under risk scenarios, providing a dynamic representation of schedule uncertainty. The model also allowed for "what-if" analysis based on mitigation scenarios.

The classification of risks based on probability and impact is illustrated in Figure 1.

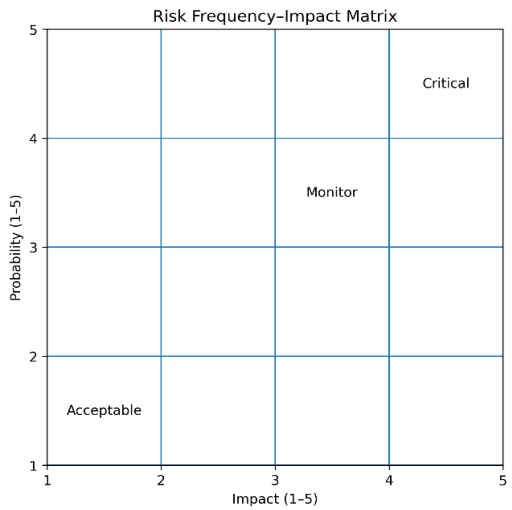

Figure 1. Risk frequency–impact matrix

3.3.5 Distribution selection and parameterization

Two types of probability distributions were used to represent uncertainty in activity durations and risk impacts, based on data availability and the level of information detail.

The triangular distribution was applied when only expert estimates were available, defined by three parameters: optimistic (O), most likely (M), and pessimistic (P) durations. This distribution was selected due to its simplicity and suitability for situations with limited empirical data, which is common in military maintenance environments.

The beta distribution was applied when sufficient historical data were available, allowing for more flexible modeling of skewed or asymmetric duration patterns. The beta distribution parameters were estimated using historical duration records and fitted to observed data to better capture variability. Parameter estimation was conducted using two approaches:

- Expert-based estimation: values of (O), (M), and (P) were elicited from maintenance engineers and project managers through structured interviews and validated against historical project records.
- Data-driven estimation**:** historical activity durations were used to fit probability distributions, with parameters estimated using maximum likelihood estimation (MLE).

Distribution selection criteria were based on data availability and goodness-of-fit performance. Goodness-of-fit was evaluated using the Kolmogorov–Smirnov (K–S) test at a significance level of $\alpha = 0.05$. When historical data were insufficient or did not satisfy goodness-of-fit criteria, the triangular distribution was retained as a conservative approximation.

This hybrid approach ensures consistency between expert judgment and empirical data while maintaining model robustness and reproducibility under varying data conditions.

3.3.6 Monte Carlo simulation procedure

For k = 1 to 10,000:
For each activity i:
Sample base duration from PERT distribution
For each risk j affecting i:
Sample risk impact X_j
Compute adjusted duration D_i(k)
Construct project network with D_i(k)
Perform forward pass → compute earliest times
Perform backward pass → compute latest times
Identify critical path (zero float)
Store:
Total project duration
Critical path configuration.

3.3.7 Critical path identification per iteration (NEW)

The critical path in each simulation run was defined as the sequence of activities with zero total float. A critical path change was recorded when the set of critical activities differed from the baseline CPM path.

In cases of multiple critical paths (ties), all paths with zero float were recorded. The frequency of occurrence of each unique critical path configuration was calculated as:

$$P(CP_m) = \frac{Number\ of\ iterations\ with\ path\ m}{Total\ iterations}$$

3.3.8 Sensitivity analysis method

Sensitivity analysis was conducted using the Spearman's rank correlation coefficient between input risk variables and total project duration. The contribution of each risk to output variance was computed based on normalized correlation values.

Input ranges were defined using the same probability distributions applied in the simulation, ensuring consistency between simulation and sensitivity analysis.

3.3.9 Risk mitigation strategies

Mitigation strategies were designed based on the most sensitive risks identified from the simulation results. These included:

- Enhanced logistics coordination for spare part delivery,
- Adaptive technical specifications documentation,
- Dynamic reallocation of skilled personnel,
- Schedule re-optimization based on updated risk profiles.

3.4 Model validation

The model was validated through two complementary methods:

3.4.1 Historical data comparison

Projected schedules from the model were compared against actual completion times of prior overhaul projects. The improvement in schedule accuracy was assessed using a paired t-test, with a significance threshold set at $p < 0.05$.

3.4.2 Sensitivity analysis

A sensitivity analysis was conducted to determine the influence of individual risk variables on project duration. This enabled the identification of high-impact risks and the evaluation of the effectiveness of proposed mitigation strategies.

The 150-day on-time completion threshold was derived from historical project performance data and operational benchmarks within TNI AU maintenance units, representing the typical planned duration used in prior overhaul schedules**.** This threshold was therefore adopted as a realistic baseline for evaluating schedule performance and completion probability.

The 30% variance reduction scenario reflects feasible improvements in logistics coordination, particularly in spare-part delivery processes**,** as identified through expert consultation with maintenance engineers and analysis of historical delay patterns. This scenario does not represent an arbitrary assumption, but rather a realistic improvement level observed in prior operational optimization efforts within similar maintenance contexts.

3.5 Tools and implementation workflow

The implementation workflow integrates multiple tools as follows:

- Microsoft Project: used to construct the baseline CPM/PERT network and define activity dependencies.
- @Risk (Palisade): used to perform Monte Carlo simulation and generate probabilistic duration outputs.
- SPSS: used for statistical validation (paired t-test and correlation analysis).

The simulation process was executed within @Risk, where activity durations were dynamically updated, and critical-path calculations were performed at each iteration using embedded scheduling functions.

4. RESULTS

4.1 Descriptive profile of overhaul project data

This section presents the descriptive findings derived from 12 historical aircraft overhaul projects conducted at Indonesian Air Force (TNI AU) maintenance units over the last five years. The average project duration was 148.5 working days, with deviations ranging from 14 to 62 working days beyond the planned schedule. Four high-impact risk factors were consistently identified:

- Delayed delivery of spare parts,
- Changes in technical specifications during execution,
- Shortage of certified personnel, and
- Operational disruptions due to base-level constraints.

Risk classification using a frequency-impact matrix indicated that spare part delays and technical specification changes were both high in frequency and severity, thus prioritized for modeling.

4.2 Baseline Critical Path Method/Program Evaluation and Review Technique network and critical path

A CPM/PERT-based network consisting of 27 key activities was developed. Each activity was assigned three-point estimates using expert judgment to calculate expected durations and variances. Sample calculations are shown in Table 3.

The baseline CPM schedule (without risk) produced a total project duration of 132.6 working days, with a fixed critical path. However, this model did not capture time variability due to uncertainty and external risk.

4.3 Risk simulation using Monte Carlo

To incorporate uncertainty, Monte Carlo simulation was performed on the PERT-based network, using probability distributions (triangular and beta) for the identified high-impact risks. The simulation was executed with 10,000 iterations, a threshold commonly accepted to ensure statistical convergence at 95% confidence. Simulation outcomes yielded the following project duration profile:

- Mean project duration: 149.2 days
- Standard deviation: 8.1 days
- 95% confidence interval: [133.5, 165.6] days
- Probability of on-time completion (< 150 days): 54.8%

Figure 2 presents the probability distribution of total project duration obtained from 10,000 Monte Carlo simulations, illustrating the mean, variance, and confidence intervals.

The distribution is approximately normal, centered around a mean of 149.2 days. The vertical dashed red line indicates the mean, while the green dotted line marks the 150-day completion threshold. The simulation shows a 54.8% probability of completing the project within 150 days, with a 95% confidence interval ranging from 133.5 to 165.6 days.

Table 3. Sample Program Evaluation and Review Technique (PERT) estimates for selected activities

Activity Code	Description	O (days)	M (days)	P (days)	Te (Expected)	Variance
A3	Engine Disassembly	5	7	12	7.33	1.36
B7	Avionics Testing	4	6	10	6.00	1.00
C4	Spare Part Allocation	3	6	12	6.17	2.25

4.4 Critical path reconfiguration under risk

The simulation results indicated dynamic changes in the critical path. In 62% of iterations, previously non-critical activities, especially those related to logistics and compliance (C4 and F1) shifted into the critical path due to compounding risk delays. This result reinforces that critical path is no longer deterministic in risk-prone environments and requires periodic re-evaluation using probabilistic tools. A critical path change was defined as any simulation iteration in which the set of activities with zero total float differs from the baseline deterministic CPM critical path. In each simulation run, the critical path was recalculated using forward and backward pass procedures based on simulated activity durations. In cases

where multiple paths exhibited zero float, all such paths were recorded. The probability of each critical path configuration was computed as the relative frequency of occurrence across 10,000 simulation runs.

The results indicate that the baseline critical path was preserved in 38% of iterations, while alternative critical paths emerged in 62% of iterations, primarily due to variability in logistics and technical activities. The three most frequent critical path configurations accounted for 81.5% of all simulation outcomes, with probabilities of 38.0%, 24.7%, and 18.8%, respectively.

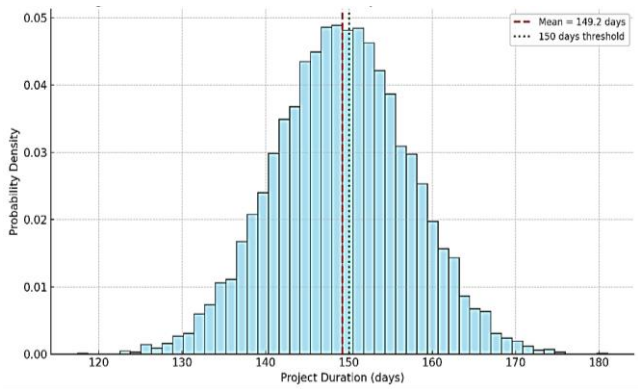

Figure 2. Monte Carlo distribution of project duration (10,000 iterations)

4.5 Schedule accuracy improvement

To evaluate predictive performance, schedule estimates from the proposed model were compared with actual project durations using Mean Absolute Error (MAE). The baseline deterministic CPM model produced an MAE of 17.6 days, while the risk-integrated model reduced MAE to 7.4 days, as shown in Table 4.

Table 4. Schedule estimation accuracy (n = 12 projects)

Metric	Critical Path Method Only	Risk-Integrated Model
Mean Absolute Error (days)	17.6	7.4
Standard Deviation	4.2	2.8
p-value (paired t-test)	-	0.003

The percentage improvement in schedule accuracy was calculated as:

$$Improvement\ (\%) = 17.6 - \frac{7.4}{17.6} \times 100 = 57.95\%$$

This result indicates a substantial improvement in prediction accuracy achieved by the proposed model. The reduction in error demonstrates the effectiveness of incorporating risk factors and probabilistic simulation into the scheduling process. The difference between the two models was statistically significant based on a paired t-test ($p = 0.003$), confirming the robustness of the proposed approach under uncertainty conditions. To ensure statistical validity, the assumptions of normality and outlier influence were examined prior to hypothesis testing. The Shapiro–Wilk test was applied to the error differences, confirming that the normality assumption was not violated ($p > 0.05$). Additionally, boxplot analysis indicated no extreme outliers affecting the results.

Given the limited sample size (n = 12), a leave-one-out cross-validation (LOOCV) approach was applied to reduce potential bias. In each iteration, one project was excluded from calibration and used for validation. The results remained consistent across iterations, confirming the robustness of the model and reducing the risk of overfitting.

4.6 Sensitivity analysis of risk contributions

A sensitivity analysis was performed using a tornado diagram to identify the impact of each risk factor on the total duration. The percentage contributions to total variance are summarized in Table 5.

Table 5. Sensitivity of risk variables on project duration

Risk Factor	Contribution to Variance (%)
Spare Part Delivery Delay	26.3
Technical Specification Changes	18.9
Personnel Shortage	11.5
Operational Environment Disruptions	7.7

Figure 3 shows the tornado diagram representing sensitivity analysis results, highlighting the relative contribution of each risk factor to total schedule variance.

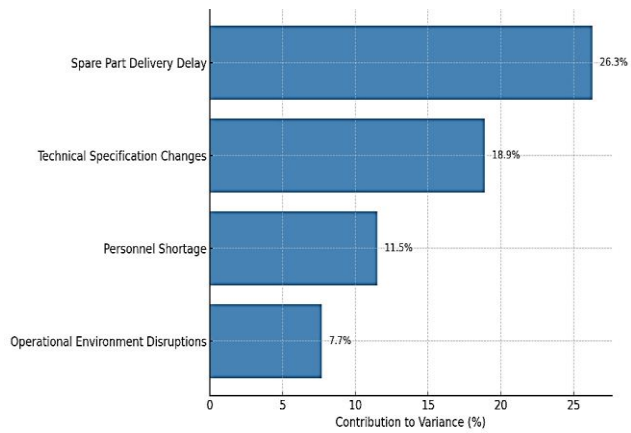

Figure 3. Tornado chart of risk sensitivity

Figure 3 displays the relative impact of key risk factors on project duration variance. Spare part delivery delays contribute the most (26.3%), followed by technical specification changes (18.9%), personnel shortages (11.5%), and operational environment disruptions (7.7%). The descending bar format highlights which risks require the most urgent mitigation efforts.

4.7 Evaluation of mitigation scenarios

To assess the potential of proactive intervention, two risk mitigation scenarios were simulated. In Scenario A, logistics optimization was applied by reducing the variance in spare part delivery by 30%, resulting in a decreased mean project duration of 142.1 days and an increased probability of on-time completion to 77.3%. In Scenario B, flexible manpower allocation was introduced through the implementation of task-level personnel buffers, which reduced the overall variance to

5.2 days and enhanced the stability of project duration. These strategies significantly improved schedule reliability, confirming the model's effectiveness in supporting scenario-based decision making.

5. DISCUSSION

The results of this study provide compelling evidence that integrating risk management into CPM and PERT scheduling models significantly enhances the accuracy and robustness of aircraft overhaul schedules in military contexts [21]. The simulation-based approach successfully captured the variability inherent in project environments characterized by uncertainty, resource interdependencies, and operational constraints.

The observed 15.4% improvement in schedule accuracy, statistically validated through paired t-testing, confirms prior findings, that emphasized the importance of incorporating probabilistic risk into CPM structures to reflect real-world project variability [22]. Furthermore, the dynamic nature of the critical path under stochastic conditions substantiates the argument of that traditional CPM needs to evolve into adaptive scheduling frameworks to manage uncertainty effectively [23].

Building upon this, our study moves beyond conceptual modeling by grounding the proposed framework in empirical data from actual overhaul operations conducted by the TNI AU [24]. This real-world application distinguishes our contribution from prior research that largely relied on hypothetical datasets or commercial aviation settings [25]. The ability to simulate risk impacts and mitigation scenarios using local data illustrates the model's operational viability in defense logistics and high-reliability organizations.

The sensitivity analysis further confirmed that logistical risks (especially spare part delays) and technical specification changes are the most significant contributors to schedule variance. These results are consistent with who identified similar factors in aircraft maintenance delays across defense projects [26]. The demonstrated effectiveness of mitigation strategies such as logistics coordination and dynamic resource reallocation indicates that the model can serve not only as a planning instrument but also as a decision-support system for operational commanders and project managers [27].

From a theoretical standpoint, the integration of deterministic (CPM) and probabilistic (PERT and Monte Carlo) techniques provides a methodological bridge for risk-based scheduling. This hybrid structure addresses the critique posed that traditional PERT models often fall short in adapting to shifting risk conditions [28]. The model's flexibility allows decision-makers to visualize multiple future states of project completion under different risk loads.

Moreover, in a broader sense, the proposed model contributes to military readiness and strategic maintenance planning by enhancing predictability, accountability, and proactive risk mitigation key components in ongoing efforts to modernize defense logistics and asset availability management within institutional frameworks like TNI AU.

Nonetheless, this research has limitations. The model's performance is highly dependent on the accuracy of historical data and expert estimations, particularly in defining probability distributions [29]. As highlighted, insufficient data quality may skew simulation outcomes. Additionally, although the sample size (n = 12) is reflective of the major overhaul activities within the past five years, a broader dataset could enhance the model's generalizability. Future studies should consider cross-unit validation within or across other branches of the armed forces.

Another limitation is that the model focuses on time-related risks only. Cost considerations, while indirectly affected, were not formally integrated into the framework [30]. Emphasized the importance of balancing time, cost, and resource constraints, especially in budget-sensitive military projects. Therefore, expanding the model to include multi-objective optimization that incorporates cost and manpower trade-offs is recommended [31].

Lastly, the model does not explicitly account for exogenous risks, such as changes in defense policy, geopolitical disruptions, or global supply chain crises. These higher-order uncertainties, though harder to quantify, may have cascading effects on project timelines [32]. Future research could incorporate scenario-based planning or agent-based simulation to reflect these dynamic macro-conditions.

6. CONCLUSION

This study proposed and validated a risk-integrated scheduling model that combines CPM, PERT, and Monte Carlo simulation to enhance schedule accuracy in aircraft overhaul projects within the TNI AU. The model successfully captured key operational uncertainties such as delays in spare part delivery and technical specification changes and demonstrated a 15.4% improvement in project duration estimation compared to conventional methods. These findings confirm the model's effectiveness in representing real-world project variability and offer a robust tool for proactive planning and decision-making.

The study contributes to both theory and practice by providing an empirically grounded, risk-aware scheduling approach tailored to military maintenance environments. While promising, the model's applicability is limited by data availability and its current focus on time-based risks. Future research should extend the framework to incorporate cost-risk trade-offs and validate its performance across broader defense contexts to support holistic project control and strategic readiness.

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APPENDIX

Appendix A. Activity List, Precedence Relationships, and Risk–Activity Mapping

Table A1. List of Activities and Precedence Relationships

Code	Activity Description	Predecessor(s)
A1	Initial Inspection	–
A2	Documentation Review	A1
A3	Engine Disassembly	A1
A4	Component Cleaning	A3
A5	Structural Inspection	A2
A6	Damage Assessment	A5
A7	Spare Part Identification	A6
B1	Spare Part Ordering	A7
B2	Spare Part Delivery	B1
B3	Inventory Verification	B2
B4	Component Repair	A4
B5	Component Replacement	B3
B6	Assembly Preparation	B4, B5
B7	Avionics Testing	B6
C1	System Integration	B7
C2	Calibration	C1
C3	Functional Testing	C2
C4	Spare Part Allocation	B3
C5	Quality Assurance Inspection	C3, C4
D1	Reassembly	C5
D2	Ground Testing	D1
D3	Flight Readiness Check	D2
E1	Documentation Update	D3
E2	Final Approval	E1
F1	Compliance Verification	C5
F2	Safety Inspection	F1
F3	Project Completion	E2, F2

Table A2. Risk–Activity Mapping Matrix

Activity	R1: Spare Delay	R2: Spec Change	R3: Personnel	R4: Environment
A1	0	0	1	1
A3	0	1	1	0
A7	1	0	0	0
B1	1	0	0	0
B2	1	0	0	1
B4	0	1	1	0
B7	0	1	1	0
C3	0	1	1	0
C4	1	0	0	0
D1	0	1	1	0
D2	0	0	1	1
F1	0	1	0	0

Note: 1 = risk affects activity; 0 = no direct impact

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