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Original Research

A hybrid stochastic approach to aircraft line maintenance scheduling based on micro-level collaborative decision-making

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Abstract: Conventional line maintenance scheduling predominantly relies on rigid, deterministic critical-path algorithms that neglect human performance variability, socio-technical interface friction, and stochastic micro-disruptions. In high-reliability operations, this deterministic bias induces acute time compression, generating latent precursors to procedural violations and operational risk. To resolve this operational challenge, this paper establishes a novel four-tier decision-analytic framework that bridges micro-level Collaborative Decision-Making with stochastic schedule resilience modeling. Grounded in Safety-II and Resilience Engineering principles, standard pre-flight operations for Antonov An-32 aircraft were structured as directed acyclic networks and calibrated using empirical time-and-motion measurements. The primary methodological contribution to decision science lies in active risk-covariance damping: by deploying a dedicated Local CDM Coordinator within a synchronized digital environment, interpersonal and procedural interfaces are decoupled. This structural reconfiguration mitigates the classical stochastic merge-bias penalty at converging workflow nodes. Propagating uncertainty via Beta-PERT distributions and Monte Carlo simulation (100,000 iterations), the proposed framework demonstrates that topological re-engineering shortens the deterministic baseline duration by 25.0% (from 68.00 to 51.00 min). Crucially, under stochastic defect rectifications, variance damping halves schedule dispersion (standard deviation decreases from 11.88 to 5.94 min), yielding an exponential surge in operational schedule reliability from 0.42% to 81.61% within a target 60-minute turnaround window. This research provides decision-makers in aviation maintenance with an evidence-based prescriptive tool to hedge against cascading delays, evaluate resilience envelopes, and optimize human-centric operational schedules under deep uncertainty.

Keywors: Collaborative Decision-Making (CDM), Decision-making under uncertainty, Merge-bias damping, Monte Carlo simulation, Resilience engineering, Stochastic scheduling

1. Introduction

The modern air transport industry operates within the rigid paradigm of High Reliability Organizations (HRO), where a system's capacity for uninterrupted and safe operation in dynamic, unpredictable environments is a critical prerequisite for its existence. The fundamental cornerstone of ensuring such systemic reliability is the global implementation of Safety Management Systems (SMS), mandated by state aviation authorities and international bodies. According to the foundational provisions of the International Civil Aviation Organization

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(ICAO) Safety Management Manual (Doc 9859, 3rd edition) [1], reinforced by the strategic operational targets of the Global Aviation Safety Plan (Doc 10004) [2], contemporary operational safety must rely on proactive hazard identification, continuous data sharing, fostering an informed safety culture, and relentless monitoring of key performance indicators (KPIs). Within this architecture, an aviation enterprise is treated as a complex socio-technical system where reliability constitutes an emergent property resulting from the harmonized interaction of hardware/technical assets, operating procedures, and human factors.

Nevertheless, despite substantial progress in developing macro-level SMS frameworks, a fundamental dichotomy persists at the execution level of technological processes–particularly in aircraft maintenance and ground handling operations. Conventional scheduling and operational management of engineering and maintenance personnel during pre-flight preparation predominantly rely on rigid, deterministic algorithms and traditional critical path network schedules [3]. In such planning systems, the execution duration of each operational task is assumed to be constant ($t = const$), while the maintenance procedure is treated as an idealized, uninterrupted sequence of events. Frequently conceptualized in modern safety theory as "Work-as-Imagined" (WAI) [4], this deterministic planning approach entirely overlooks the empirical dispersion of human performance, disregarding acute operational stress, communication barriers across socio-technical interfaces [5], adverse environmental factors, and unavoidable stochastic technical anomalies inherent in line operations [3, 6].

Disregarding the stochastic nature of task completion times along the critical path of a maintenance workflow engenders a "latent risk" phenomenon within the Maintenance Organization (MRO). When allocated buffers are depleted due to unforeseen delays, technical personnel experience acute time pressure and cognitive overload. Such an operational context acts as a catalyst, triggering recognized human factors risk precursors, including fatigue, acute stress, complacency, resource constraints, and communication breakdowns [1, 7]. Ultimately, these dynamic precipitates either schedule disruption with associated commercial losses or–far more critically from an SMS standpoint–a latent degradation in airworthiness standards: procedural non-compliance, skipping instrumental inspection steps to preserve the slot, utilizing improper tooling, or resorting to non-standard workarounds [7, 8].

Consequently, contemporary aviation safety science and operations research exhibit a pressing imperative for applied hybrid methodologies. Such frameworks must extend beyond deterministic task structuring to enable the quantitative assessment of schedule resilience against temporal dispersion within realistic probabilistic environments. The capacity to proactively simulate the behavior of socio-technical systems under stochastic perturbations represents the cornerstone of proactive risk management.

Recent breakthroughs in computational intelligence and advanced industrial engineering underscore that traditional deterministic scheduling must be replaced by intelligent, data-driven optimization architectures capable of dynamic resource allocation and robust task planning [9, 10]. However, scaling such frameworks to flight-line operations necessitates extending mathematical models to capture micro-level socio-technical and human interface dependencies.

Research problem: Conventional scheduling and management of engineering and maintenance personnel during aircraft pre-flight preparation predominantly rely on rigid, deterministic algorithms and critical path models that treat task durations as static constants. This idealized "Work-as-Imagined" approach fails to accommodate the stochastic variability of human performance, operational stress, communication barriers across socio-technical interfaces, and unpredictable technical anomalies encountered in real ramp environments. Consequently, operational delays rapidly deplete unbuffered schedules, inducing acute time pressure and cognitive overload that act as latent precursors to maintenance errors, procedural non-compliance, and compromised airworthiness standards. While macro-level optimization concepts and stochastic risk assessment tools exist independently, current aviation operations research lacks an integrated, applied framework that combines topological personnel workflow re-engineering with probabilistic resilience modelling at the micro-level of line maintenance execution.

Research hypothesis: It is hypothesized that integrating Collaborative Decision-Making (CDM) principles at the micro-level of line maintenance personnel interaction–through digital synchronization and parallelization of support tasks–will eliminate critical-path operational bottlenecks and interface friction. When evaluated under stochastic conditions using Beta-PERT distributions and Monte Carlo simulation, this structural optimization will not only reduce the baseline critical path duration but will also non-linearly suppress schedule variance and mitigate delay "fat tails" caused by operational micro-faults, thereby substantially enhancing overall operational schedule reliability within prescribed ground handling windows.

Research objectives: To test this hypothesis and address the defined research problem, the following objectives were formulated:

• formalize the baseline deterministic network schedule of aircraft pre-flight line maintenance (exemplified by the Antonov An-32 turnaround) as a directed acyclic graph to identify procedural bottlenecks, critical paths, and interface idle times;

• re-engineer the maintenance workflow topology by incorporating micro-level CDM principles, a dedicated ground operations coordinator, and a synchronized digital data-sharing environment to streamline communication across SHELL interfaces and enable concurrent task execution;

• model the stochastic uncertainty and human factor dispersion of individual maintenance operations by substituting deterministic task times with three-point expert estimates calibrated via Beta-PERT probability distributions;

• execute Monte Carlo simulations accounting for the probabilistic occurrence of operational micro-defects to quantify schedule merge bias, evaluate delay fat-tail distributions, and comparatively assess operational schedule reliability between the traditional and resilient CDM-optimized configurations.

The paper is structured as follows. Section 2 provides a comprehensive review of the relevant literature, encompassing Human Factors, the conceptual shift from Safety-I to Safety-II and Resilience Engineering, the implementation of A-CDM, and stochastic modelling techniques in aviation maintenance. Section 3 outlines the proposed four-tier hybrid methodology synthesizing directed acyclic graphs, micro-level CDM topological optimization, Beta-PERT approximations, Monte Carlo simulation, as well as the underlying research assumptions and limitations. Section 4 demonstrates the practical application and comparative validation of the baseline and resilient models using empirical time-and-motion data of Antonov An-32 pre-flight turnaround operations. Section 5 analyzes and discusses the key findings, highlighting the non-linear relationship between variance reduction and operational reliability, while Section 6 concludes the study with concise scientific contributions, practical implications for MRO organizations, and directions for future research.

2. Analysis of the latest research and publications

2.1 Literature search and selection methodology

Over the past five to ten years, global aviation science has undergone a conceptual paradigm shift in understanding the nature of safety and the mechanisms for ensuring the reliability of complex socio-technical systems. This transition has been accompanied by a substantial body of literature, which can be categorized into several interconnected thematic clusters.

To ensure methodological rigor and avoid selection bias, the literature synthesis was executed using systematic bibliographic search protocols across Scopus, Web of Science, and IEEE Xplore, covering literature published up to 2026. The search strategy utilized targeted Boolean operators: (“aircraft line maintenance” OR “pre-flight turnaround”) AND (“Collaborative Decision-Making” OR “A-CDM” OR “FF-ICE”) AND (“Safety-II” OR “Resilience Engineering” OR “SHELL model”) AND (“stochastic scheduling” OR “Beta-PERT” OR “Monte Carlo simulation” OR “merge bias”). Publications were screened against explicit criteria: (i) peer-reviewed journal articles, official regulatory standards (ICAO, Eurocontrol), and recognized conference proceedings; (ii) explicit focus on operational line maintenance, socio-technical ramp coordination, or stochastic reliability modeling; and (iii) emphasis on state-of-the-art contributions from 2024-2026. Non-peer-reviewed web blogs, trade magazines, and general manufacturing studies lacking an aviation socio-technical context were excluded.

2.2 Socio-technical and safety paradigms in aviation maintenance

The first research cluster focuses on the evolution of Crew Resource Management (CRM) and Maintenance Resource Management (MRM) programs. Contemporary studies demonstrate that an individual specialist’s isolated technical competence cannot guarantee systemic reliability without effective teamwork and interaction with the organizational environment [11]. In this context, the SHELL conceptual model (Software, Hardware, Environment, Liveware) [12] remains a foundational tool for identifying friction at operational interfaces. The central element of the model is the “Liveware” (human operator), constrained by specific physical and cognitive limitations. Researchers [13-15] emphasize that critical errors occur at the interfaces: human-to-hardware, human-to-software/procedures, human-to-environment, and interpersonal (liveware-to-liveware). This framework is complemented by the “Dirty Dozen” concept [8, 16, 17], formulated by Gordon Dupont in 1993, which explicitly classifies twelve primary psychological and organizational precursors to human error in aviation maintenance. Modern scholars [18, 19] leverage systems thinking accident analysis methodologies to demonstrate that human error is not an explanatory cause, but rather an emergent symptom of deeper systemic vulnerabilities.

The second and most conceptually significant body of literature addresses the shift in safety management methodology from the traditional Safety-I paradigm to Safety-II, prominently championed by Erik Hollnagel and his contemporaries [20]. The Safety-I approach, which historically dominated the industry, focused strictly on ensuring that “as few things as possible go wrong”. Under this paradigm, safety is defined by the absence of unacceptable risk, and management is reduced to reactive incident investigations and barrier implementation. In contrast, Safety-II [20] defines safety as the organizational capability to succeed under varying conditions. In accordance with resilience engineering principles, a socio-technical system must possess the capacity to anticipate, monitor, respond, and learn. This perspective reframes the human factor: human performance variability is recognized not merely as a source of error, but as the primary mechanism of adaptation to unpredictable operational conditions, enabling personnel to compensate for procedural deficiencies. Experimental implementations

of these principles–specifically utilizing tools such as the Resilience Assessment Grid (RAG) and the Functional Resonance Analysis Method (FRAM)–have demonstrated high fidelity in capturing systemic dynamics [20, 21].

The third cluster encompasses operational-level research and airport process management. A transformative milestone has been the rollout of the Airport Collaborative Decision-Making (A-CDM) concept and its integration into the Flight and Flow Information for a Collaborative Environment (FF-ICE) ecosystem. Eurocontrol and IATA guidance materials on A-CDM [22, 23] target the elimination of information silos among airport operators, air carriers, ground handling service providers, and Air Traffic Control (ATC). The core premise of A-CDM lies in real-time, high-integrity data sharing, procedural transparency, and tracking key operational milestones, such as Target Off-Block Time (TOBT) and Target Startup Approval Time (TSAT). Empirical and predictive studies on A-CDM implementations [24, 25] confirm that mitigating information bottlenecks and enhancing milestone tracking significantly improve operational predictability, optimize ground resource management, and compress aircraft turnaround buffers.

The fourth cluster is dedicated to the mathematical modelling of maintenance workflows. Researchers [3, 26] actively employ project risk management tools, such as the Program Evaluation and Review Technique (PERT), Monte Carlo simulation, Bayesian networks, and fuzzy logic algorithms to evaluate schedule reliability. In particular, Monte Carlo simulation has proven highly effective in forecasting the probability of on-time completion for complex military depot-level overhauls and evaluating schedule sensitivity to supply chain delays. It enables analysts to move beyond single-point deterministic estimates to probability density distributions, making it ideal for dispersion analysis.

However, a critical review of the global scientific literature reveals a prominent research gap. On one side, there are robust macro-level process optimization frameworks (A-CDM, aviation Lean management); on the other, sophisticated stochastic risk assessment tools for isolated engineering tasks (PERT, Monte Carlo). Yet aviation science largely lacks integrated, applied methodologies that unify these two paradigms at the micro-level of engineering and maintenance personnel operations. There is a pressing need for a framework that first optimizes the personnel interaction structure at the network graph topological level–establishing a new baseline schedule architecture and subsequently applying stochastic simulation to quantitatively evaluate the structural reliability of that network within a probabilistic environment.

Previous studies by the authors laid important foundational groundwork, wherein deterministic CDM modelling demonstrated the theoretical potential of workflow parallelization [11], while isolated stochastic evaluations captured the temporal dispersion and performance variability of aviation operators in decoupled scenarios [26]. However, treating topological re-engineering and stochastic uncertainty as separate analytical silos creates a fundamental theoretical limitation known in decision science as the merge-bias fallacy. In deterministic models, parallelizing tasks ostensibly shortens the critical path; yet, in stochastic environments, the convergence of multiple uncertain paths ($\max(X_1, X_2, \ldots)$) systematically inflates the expected completion time and induces heavy delay tails. To date, operations research lacks an integrated methodology that quantifies how micro-level socio-technical coordination (mitigating SHELL interface friction) directly modulates path correlation and compresses network merge bias under stochastic defect rectifications. Bridging this methodological gap constitutes the primary novelty of this work.

3. Methods

3.1 Ethical approval

The research protocol, observational methodology, and data management procedures were reviewed and formally approved by the Commission for Ethics and Academic Integrity of the Ukrainian State Flight Academy (approval date: September 04, 2026, exempt from formal approval number due to local regulations; exempt from national clinical trial registry due to non-invasive, archival organizational research; regulations available at: https://www.usfa.edu.ua/wp-content/uploads/2026/05/regulations_on_the_commission_for_ethics_and_academic_integrity.pdf). The ethical approval granted formal compliance for the secondary academic analysis, de-identification, and publication of archival workplace time-and-motion measurements and technical logbook datasets. All recorded historical timestamps were fully pseudo-anonymized upon retrieval, stripped of personal identification numbers, technician names, and shift codes, and managed in compliance with institutional data governance protocols.

Comprehensive measures were instituted to protect participants' rights and welfare throughout the study:

1. All certified line maintenance technicians ($N = 60$) were informed of the voluntary nature of their participation. Technicians retained the explicit right to decline observation or withdraw at any stage without penalty, administrative consequence, or career impact.

2. Formal written informed consent was obtained from each technician prior to field chronometric recording. The consent protocol explicitly clarified that time-and-motion measurements were conducted strictly for academic research and would not be used for individual workplace performance appraisal, KPIs, or disciplinary evaluations.

3. All recorded timestamps were pseudo-anonymized upon collection, stripped of personal identification numbers, employee names, and shift codes, and stored in an encrypted database accessible exclusively to the

principal investigators.

3.2 Empirical foundation and case study

The empirical foundation of the study comprised time-and-motion field observations of pre-flight preparation operations conducted on Antonov An-32 turboprop aircraft at the airfield complex of the Ukrainian State Flight Academy. To analyze the workflow sequence and standard operating task durations, Part 1 of the Maintenance Manual (Operational Maintenance Manual) for the An-32 aircraft was utilized.

The operational duration dataset was generated by processing chronometric time-study data from tasks executed by two representative cohorts of certified line maintenance technicians (30 specialists in each category, N = 60 in total) recorded during regular airfield maintenance shifts between May 2021 and October 2021:

1. Technicians of group 1 (AE): Airframe and Powerplant Specialists ($n_1 = 30$);

2. Technicians of group 2 (AV): Avionics and Electrical Systems Specialists ($n_2 = 30$).

The line maintenance and pre-flight turnaround process of the An-32 aircraft was selected as the operational baseline for mathematical validation due to two primary systemic factors [6]:

1. Fleet vulnerability–the intensive utilization of aging An-32 fleets exhibits a higher baseline probability of minor mechanical defects during pre-flight walkaround inspections.

2. Interface complexity–the ramp environment involves complex interactions across a multi-actor network (flight crews, ground technicians, and air traffic controllers), exerting heavy cross-functional demands on the Liveware-Liveware (L-L) and Liveware-Software (L-S) interfaces of the SHELL model.

The baseline probabilities of operational micro-fault occurrence– $P_{\text{defect, AE}} = 0.22$ (22%) for the airframe/powerplant path and $P_{\text{defect, AV}} = 0.15$ (15%) for the avionics/electrical path–were empirically calibrated from a retrospective statistical audit of 412 pre-flight turnaround logs and task cards of the operational Antonov An-32 aircraft conducted at the airfield complex of the Ukrainian State Flight Academy across a 4.2-year peacetime window from September 2017 to November 2021. This multi-year timeframe captures the realistic operational tempo, seasonal flight cycles, and scheduled maintenance downtimes of a single fleet unit. Specifically, out of 412 recorded pre-flight maintenance events, 91 instances (22.09%) required unscheduled minor mechanical interventions along the AE branch, while 62 instances (15.05%) required minor avionics troubleshooting along the AV branch.

3.3 Four-tier analytical framework

To achieve the research objective, a four-tier modeling architecture was implemented. This methodology synthesizes deterministic graph modeling of maintenance workflows with probabilistic assessment, embodying the principles of Resilience Engineering and Safety-II [4], the adaptation of Collaborative Decision-Making (A-CDM) to the flight-line micro-level [11], and risk-integrated PERT/Monte Carlo simulation approaches in aviation maintenance [3]:

1. Deterministic structural analysis (Baseline Tier)–formalization of standard line maintenance tasks as a directed acyclic network graph $G = (V, E)$. This stage defines the task set, logical precedence relationships, and nominal standard times. Operational duration is treated strictly as a fixed deterministic parameter (T_{norm}), establishing the classical critical path.

2. Topological network optimization (CDM Module)–workflow schedule restructuring via operational re-engineering. Micro-level CDM (A-CDM) is integrated by introducing a single unified digital coordinator. This converts sequential operational dependencies into concurrent paths (e.g., parallelization of ground power unit connection) and eliminates communication bottlenecks across SHELL Liveware-Liveware and Liveware-Software interfaces.

3. Transition to stochastic uncertainty (PERT Module)–moving beyond the constant-duration paradigm by modelling each schedule node as a continuous random variable governed by a β-distribution. For each task i, optimistic (a_i), most likely (m_i), and pessimistic (b_i) execution times are established through expert judgment based on risk precursors identified across SHELL interfaces and "Dirty Dozen" human factors (such as fatigue, acute stress, and knowledge deficits).

4. Simulation-based risk assessment (Monte Carlo Module)–evaluation of merge bias and delay fat-tail distributions. Because analytical solutions for stochastic multi-path networks are mathematically intractable due to path convergence, Monte Carlo simulation is utilized. The model incorporates the stochastic probability of operational micro-fault occurrence: $p_1 = 0.22$ for the AE path (with corrective duration modeled via a truncated β-distribution) and $p_2 = 0.15$ for the AV path. Operational schedule reliability $R(T_{target})$ is computed as the cumulative probability of task completion within the prescribed target window $T \le T_{target} = 60$ min.

This stochastic formulation is congruent with contemporary validation frameworks in aviation systems engineering, which emphasize empirical probability distributions to capture human operational dispersion [26] and data-driven statistical modeling under dynamic operational variance [27].

3.4 Theoretical formulation of stochastic merge bias and resilience index

When transitioning from sequential scheduling (Model A) to concurrent execution (Model B), parallelization inevitably creates network merge nodes

where independent or correlated operational branches converge. Mathematically, consider two parallel stochastic maintenance paths with completion times represented by continuous random variables X and Y, having marginal probability density functions $f_X(x)$ and $f_Y(y)$, means $\mu_X = \mathbb{E}[X]$, $\mu_Y = \mathbb{E}[Y]$, standard deviations σ_X, σ_Y, and covariance $\mathrm{Cov}(X, Y) = \rho_{XY}\sigma_X\sigma_Y$.

By Jensen's inequality, since the function $g(X, Y) = \max(X, Y)$ is strictly convex, the expected duration at the merge node is strictly greater than the deterministic maximum of their individual expectations (1):

$$\mathbb{E}[\max(X, Y)] \geq \max(\mathbb{E}[X], \mathbb{E}[Y]). \tag{1}$$

The difference $\Delta_{merge} = \mathbb{E}[\max(X, Y)] - \max(\mu_X, \mu_Y) \geq 0$ represents the *stochastic merge-bias penalty*. Under bivariate normality or symmetric distribution assumptions, Clark's classic analytic formulation establishes that (2):

$$\mathbb{E}[\max(X, Y)] = \mu_X\Phi\left(\frac{\mu_X - \mu_Y}{\theta}\right) + \mu_Y\Phi\left(\frac{\mu_Y - \mu_X}{\theta}\right) + \theta\phi\left(\frac{\mu_X - \mu_Y}{\theta}\right), \tag{2}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal PDF and CDF, respectively, and the composite dispersion parameter θ is defined as (3):

$$\theta = \sqrt{\sigma_X^2 + \sigma_Y^2 - 2\,\mathrm{Cov}(X, Y)} = \sqrt{\sigma_X^2 + \sigma_Y^2 - 2\,\rho_{XY}\sigma_X\sigma_Y}. \tag{3}$$

Illustrative Numerical Example: To illustrate the practical impact of this phenomenon, consider two parallel ramp tasks where $\mu_X = 20$ min $(\sigma_X = 5$ min) and $\mu_Y = 20$ min $(\sigma_Y = 5$ min). A deterministic planner assumes that the concurrent execution will require exactly $\max(20, 20) = 20$ min. However, if the tasks are stochastic and independent ($\rho_{XY} = 0$), $\theta = \sqrt{25 + 25} = 7.07$ min, and equation (4) yields:

$$\mathbb{E}[\max(X, Y)] = 20 \cdot 0.5 + 20 \cdot 0.5 + 7.07 \cdot \frac{1}{\sqrt{2\pi}} = 20 + 2.82 = 22.82 \text{ min}. \tag{4}$$

Thus, path convergence introduces an unavoidable 14.1% temporal inflation ($\Delta_{merge} = 2.82$ min). Furthermore, in conventional uncoordinated ramp environments (Model A), shared physical workspace, tool crib contention, and mutual supervisory interruptions generate *positive cross-covariance* ($\rho_{XY} > 0$). While positive correlation algebraically shrinks θ, uncoordinated multi-task coupling induces joint right-skewed tail distributions where a delay in branch X cascades into branch Y.

The fundamental theoretical contribution of our micro-level CDM architecture lies in *active covariance damping*. By introducing a dedicated Local CDM Coordinator equipped with real-time digital tracking, the mutual cross-coupling is actively decoupled. The coordinator acts as an exogenous shock absorber: when a minor snag arises along path X, the coordinator proactively reallocates support assets without perturbing path Y, effectively enforcing $\mathrm{Cov}(X, Y) \to 0$ and drastically compressing marginal variances σ_X and σ_Y (e.g., in Model B, σ_{Total} drops from 11.88 min to 5.94 min). Consequently, the composite dispersion parameter θ and the resulting merge-bias penalty Δ_{merge} are systematically minimized.

3.5 Computational implementation

Mathematical computations, pseudorandom number array generation according to the β-distribution, Monte Carlo simulation ($N = 100{,}000$ iterations), and the approximation of probability density functions (PDF) and cumulative distribution functions (CDF) were executed in the MATLAB R2023b environment. The topological network graphs were constructed and rendered using the Graphviz package.

3.6 Research assumptions and limitations

Research assumptions:

• nature of task duration distribution–the execution duration of individual line maintenance tasks is assumed to be a continuous random variable governed by a Beta-PERT distribution with positive (right-skewed) asymmetry, reflecting the operational reality where maintenance operations rarely finish significantly ahead of schedule but frequently experience delays;

• probability of operational micro-faults–the probabilities of detecting minor operational defects during pre-flight walkaround inspections are assumed to be stationary: $P_{defect,\,AE} = 0.22$ (22%) for the airframe and powerplant branch and $P_{defect,\,AV} = 0.15$ (15%) for avionics and electrical systems;

• digital infrastructure and CDM coordination–the optimized model (Model B) relies on the assumption of an uninterrupted digital data-sharing environment (mobile

terminals/tablets, Electronic Logbook (ELB)) and a dedicated Local CDM Coordinator, ensuring seamless communication and eliminating information silos across technical personnel;

• personnel qualification and performance–certified technicians within the two specialized groups–Airframe and Powerplant (AE) and Avionics and Electrical Systems (AV)–are assumed to possess high qualifications, with performance variability constrained within the defined expert three-point boundaries (a, m, b);

• process parallelization and safety compliance–it is assumed that concurrent positioning and connection of the Ground Power Unit (GPU) by the coordinator in parallel with other operational tasks occurs in full compliance with safety clearance zones and does not impede the external airframe inspection conducted by the AE specialist;

• independence of simulation iterations–each iteration within the 100,000 Monte Carlo simulations is treated as a statistically independent trial of the pre-flight maintenance workflow.

Research limitations:

• aircraft type specificity and operational transferability–field chronometric observations and mathematical validation were conducted exclusively for the pre-flight turnaround of Antonov An-32 turboprop aircraft. Because baseline failure rates, multi-crew division of labor, and Ground Support Equipment clearance geometries differ substantially between tactical turboprops and modern commercial jetliners (Boeing 737, Airbus A320), the numerical parameters, defect occurrence probabilities, and specific DAG sequences derived herein cannot be directly transferred without empirical recalibration;

• sample size and geographic localization–the empirical dataset was derived from time-and-motion measurements involving a sample of certified technicians (N = 60; n = 30 in the AE group and n = 30 in the AV group) at the aerodrome complex of the Ukrainian State Flight Academy;

• fixed statistical parameters of delays–defect rectification probabilities and corrective execution times were modeled using truncated Beta-distributions with fixed parameters, without accounting for seasonal or meteorological fluctuations, supply chain spare-parts availability, or the specific operational age/wear of individual airframes;

• exclusion of catastrophic and exogenous factors–the study focuses on operational micro-faults and human factors, excluding critical major system failures requiring line aircraft replacement, as well as external delays caused by Air Traffic Control (ATC) or severe weather conditions (e.g., de-icing requirements, thunderstorms);

• subjectivity of PERT expert estimates–the three-point time estimates (a–optimistic, m–most likely, b–pessimistic) rely in part on expert judgment, introducing a degree of subjectivity into the baseline distribution parameters.

4. Results

4.1 Deterministic structural analysis and decomposition (Model A)

In accordance with the maintenance schedule for the An-32 aircraft [28], the traditional pre-flight turnaround process can be mathematically formalized as a deterministic directed acyclic graph $G = (V, E)$, where V is the set of events (discrete points in time marking the initiation or completion of tasks) and E is the set of technological maintenance operations weighted by their nominal duration (t_i). The adjacency matrix of the network dictates a strict technological and organizational sequence of activities.

Table 1. Structural-temporal matrix of line maintenance tasks during An-32 pre-flight preparation (pre-optimization baseline)

№	Task description	Preceding tasks	Duration, min	Human resources
1	External pre-flight inspection of airframe, landing gear, engine cowlings, and external powerplant check (T_{AE1})		30	*AE*
2	Internal pre-start check of engine systems, oil levels, fuel quality inspection, hydraulic systems testing (T_{AE2})	1	20	*AE*
3	Internal cockpit inspection, visual check of flight instruments, circuit breakers, mechanical selectors, and oxygen equipment (T_{AV1})		20	*AV*
4	Sourcing, positioning, and connecting ground electrical power unit (T_{GSE})	1, 3	12	*AV*
5	Energized functional testing of navigation, avionics, radio-electronic equipment, and ILS system (T_{AV2})	4	18	*AV*
6	Final Aircraft Technical Logbook completion, cross-coordination, awaiting dispatcher release confirmation (T_{COORD})	2, 5	8	*AE + AV*

Under the baseline scenario (Model A), the interaction between line maintenance personnel follows a predominantly sequential or partially concurrent scheme. The lack of a unified, synchronized digital information environment generates operational information silos. During the initial phase of the study, the maintenance cycle was decomposed into discrete tasks (Table 1), the temporal characteristics of which were empirically derived through time-and-motion measurements. Computing system parameters based on modal values enables the establishment of a baseline deterministic process model. This dataset serves as the benchmark for subsequent stochastic modelling via the PERT technique to account for potential variances and operational risks.

The structural-temporal breakdown in Table 1 details six aggregated core task packages executed by two-line maintenance specialists: the Airframe and Powerplant Specialist (Specialist 1–AE) and the Avionics and Electrical Systems Specialist (Specialist 2–AV) (Figure 1).

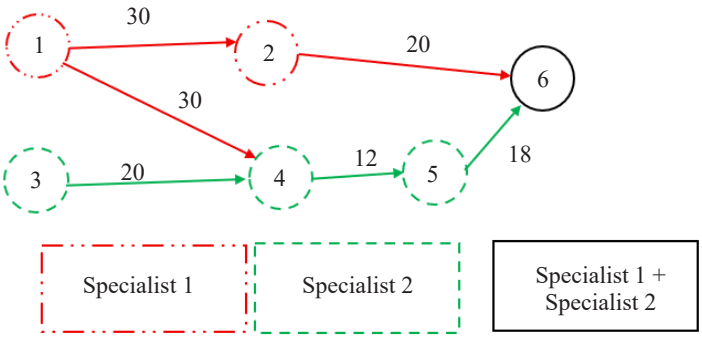

Figure 1. Network schedule of maintenance personnel workflow during An-32 pre-flight preparation (pre-optimization baseline)

Critical Path Topology of Model A:

1. Initiation of maintenance operations: $t_0 = 0$.

2. Specialist 1 (AE) executes task sequence: T_{AE1} runs from 0 to 30 min. Subsequently, T_{AE2} is performed from 30 to 50 min. Total operational duration for the AE specialist is 50 minutes.

3. Specialist 2 concurrently initiates T_{AV1}, which spans from 0 to 20 min. Following this, the technician experiences artificial idle time, as Ground Power Unit (GPU) energization T_{GSE} can only be safely initiated once the hazardous inspection zone in T_{AE1} is cleared at the 30-minute mark. Task T_{GSE} (GPU sourcing, routing, and cable connection) requires 12 min (from 30 to 42 min). Consequently, T_{AV2} starts at minute 42 and concludes at minute 60.

4. Joint task T_{COORD} can only commence upon the completion of both critical paths–at $\max(50,\ 60) = 60$. The total deterministic duration (critical path length) for Model A is $60 + 8 = 68$ minutes.

Analysis of this baseline network reveals substantial waiting buffers and inefficient labor utilization for Specialist 2, driven by organizational and communicative Liveware-Liveware (L-L) interface friction.

4.2 Topological network optimization via CDM (Model B)

To mitigate this topological inefficiency, the principles of Airport Collaborative Decision-Making (A-CDM) [22, 23] were adapted to the micro-level of line maintenance operations, building upon the initial workflow formalization introduced in [11]. A dedicated ground operations role is introduced–the Local CDM Coordinator (Table 2)–equipped with a unified digital data-sharing environment (a mobile terminal or tablet providing synchronized access to flight milestones and cross-functional electronic checklists for both technicians) (Figure 2).

Within the SHELL model architecture [12], this optimization systematically mitigates friction across the Liveware–Liveware (L-L) interface by enabling instantaneous inter-specialist communication, as well as the Liveware–Software (L-S) interface by transitioning from sequential paper-based sign-offs to concurrent digital procedures [5].

Topological modifications in the optimized network (Model B):

1. Proactive parallelization (T_{GSE})–the ground operations coordinator receives turnaround data in advance. They position the GPU and connect it at the very start of servicing in parallel with other operational tasks, coordinating safety clearance zones with Specialist 1 via a digital interface. The execution duration of this task is streamlined to 6 min (from 0 to 6 min). The primary structural improvement is that T_{GSE} no longer creates an operational bottleneck blocking Specialist 2.

2. Duration optimization (L-S and L-H interfaces)–through the implementation of an Electronic Logbook (ELB) and the Lean-driven optimization of walkaround inspection routes, nominal task completion times are reduced:

• T_{AE1} is reduced from 30 to 28 min, and T_{AE2} from 20 to 16 min.

• T_{AV1} is reduced from 20 to 18 min, and T_{AV2} from 18 to 15 min.

• Digital coordination T_{COORD} eliminates prolonged waiting for clearance as operational timestamps are automatically transmitted to the airport FF-ICE system; its duration is set at 7 min, during which electronic digital signatures are logged.

Table 2. Structural-temporal matrix of line maintenance tasks during An-32 pre-flight preparation (post-optimization baseline)

№	Task description	Preceding tasks	Duration, min	Human resources
1	External pre-flight inspection of airframe, landing gear, engine cowlings, and external powerplant check (T_{AE1})		28	*AE*
2	Internal pre-start check of engine systems, oil levels, fuel quality inspection, hydraulic systems testing (T_{AE2})	1	16	*AE*
3	Internal cockpit inspection, visual check of flight instruments, circuit breakers, mechanical selectors, and oxygen equipment (T_{AV1})		18	*AV*
4	Sourcing, positioning, and connecting ground electrical power unit (T_{GSE})	1, 3	6	*GSE*
5	Energized functional testing of navigation, avionics, radio-electronic equipment, and ILS system (T_{AV2})	4	15	*AV*
6	Final Aircraft Technical Logbook completion, digital cross-coordination, electronic signature logging (T_{COORD})	2, 5	7	*AE + AV*

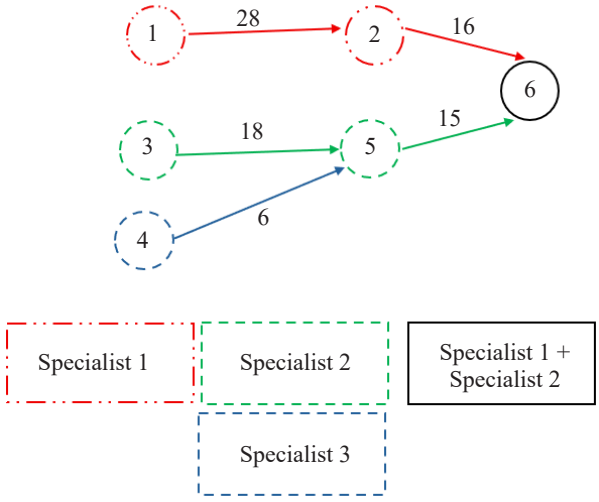

Figure 2. Network schedule of maintenance personnel workflow during An-32 pre-flight preparation (post-optimization baseline)

Optimized Model B Topology:

1. Specialist 1 path–$T_{AE1}(28) \rightarrow T_{AE2}(16) = 44$ min (completion at minute 44).

2. Specialist 2 path–because GPU power (T_{GSE}) is supplied during the initial window (0-6 min), Specialist 2 works continuously on T_{AV1} (from 0 to 18 min) and immediately transitions to T_{AV2} (from 18 to 33 min). The total active working duration for the AV specialist is 33 minutes. Joint final coordination T_{COORD} initiates at $\max(44,\ 33) = 44$ min. The total deterministic critical path duration for Model B is $44 + 7 = 51$ min.

Organizational re-engineering and the mitigation of

information silos reduce total turnaround duration from 68 to 51 minutes. This yields a linear theoretical reduction of the critical path by 25%, establishing a new optimized structural baseline for the system.

Nevertheless, according to the conceptual tenets of Safety-II and Resilience Engineering [4, 20, 21], an idealized deterministic calculation represents a hazardous abstraction that induces a false sense of security. Such a model operates on the flawed premise that human operators function as error-free automations in a sterile, perturbation-free environment. In line operations, any schedule inevitably encounters operational perturbations; hence, establishing genuine systemic resilience requires transitioning to stochastic risk analysis [26].

4.3 Transition to stochastic uncertainty (PERT)

In operational reality, each maintenance task is continuously affected by adverse performance-shaping factors: technician fatigue, cognitive distraction, improper tooling, organizational pressure, and acute stress [5, 7]. Furthermore, ambient environmental factors–such as low temperatures degrading tactile dexterity or high ambient acoustic noise from adjacent aircraft engines–directly alter task completion rates.

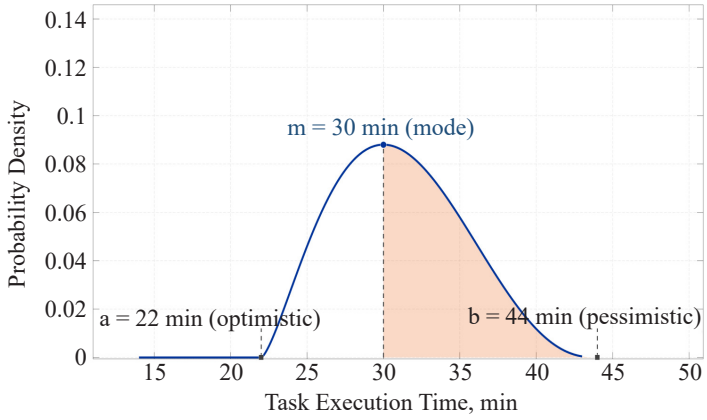

Figure 3. Probability Density Function (PDF) of the Beta-PERT distribution for T_{AE1} (Model B)

To rigorously model this operational dispersion, the methodology substitutes the deterministic constant t with a continuous random variable governed by a β-distribution [29, 30]. The choice of the β-distribution over a Gaussian normal distribution constitutes the established benchmark for the PERT technique in aviation, as it accommodates skewed, bounded empirical datasets with fixed end points (Figure 3) [31].

For each operational task i of the network schedule, three-point time estimates are established via expert judgment (grounded in empirical operational and time-study data):

- a_i –optimistic duration (ideal environmental conditions, high personnel motivation, minimal impact of "Dirty Dozen" human factor precursors);
- m_i –most likely duration (nominal standard time, mode of the probability distribution);
- b_i –pessimistic duration (maximum cumulative impact of "Dirty Dozen" risk factors and operational friction across the Liveware-Hardware/L-H interface).

The expected duration μ_i (5) and variance σ_i^2 (6) for each stochastic task are computed using classical PERT equations:

$$\mu_i = \frac{a_i + 4m_i + b_i}{6}; \quad (5)$$

$$\sigma_i^2 = \left(\frac{b_i - a_i}{6}\right)^2. \quad (6)$$

Within the scope of this study, distribution parameters were calibrated to capture the precise operational nuances of line maintenance on the An-32 aircraft (Table 3). A key mathematical characteristic is the positive (right-skewed) asymmetry ($(b_i - m_i) > (m_i - a_i)$). This reflects the empirical operating conditions documented in aviation maintenance systems: routine tasks exhibit rigid lower physical bounds constrained by mandatory inspection checklists, while unforeseen defect rectifications, parts requisitions, and structural troubleshooting generate significant right-skewed delay distributions [3].

Table 3. Structural and temporal parameters of the β-distribution for stochastic PERT analysis

Operation	Task Description (Specialist)	Model A (*a*, *m*, *b*), min	Model B (*a*, *m*, *b*), min
T_{AE1}	Airframe/engine inspection (Spec. AE)	22, 30, 44	22, 28, 36
T_{AE2}	Engine systems check (Spec. AE)	14, 20, 32	12, 16, 22
T_{AV1}	Avionics/cockpit check (Spec. AV)	16, 20, 28	14, 18, 22
T_{GSE}	GPU connection (Operator/AV)	8, 12, 22	4, 6, 8
T_{AE2}	Navigation & radio test (Spec. AV)	13, 18, 29	11, 15, 20
T_{COORD}	Coordination and documentation	5, 8, 13	5, 7, 9

Particular attention should be drawn to the narrowed dispersion range between a and b in Model B compared to Model A. This represents a direct mathematical reflection of the synergistic effect achieved by introducing the CDM coordinator and streamlining operational communication. Mitigating the "Lack of Communication" risk factor and alleviating excessive cognitive workload on individual personnel stabilize task variance, fully aligning with Lean principles in aviation. Within a transparent operating environment, "latent" delays are effectively eliminated.

4.4 Simulation-based risk assessment (Monte Carlo method)

Despite the analytical power of the PERT technique, relying exclusively on deterministic variance summation along the critical path proves insufficient for complex systems. The primary shortfall of analytical PERT is its disregard for path convergence. Because the total completion duration across parallel network stages is determined by the maximum path duration ($\max(T_{AE}, T_{AV})$), variance along non-critical paths can cause them to become critical dynamically–a phenomenon that analytical approaches fail to capture. The second fundamental limitation is the inability to analytically evaluate distribution "fat tails" resulting from step-like delays induced by the discovery of minor operational defects during maintenance.

In the operational environment of the Ukrainian State Flight Academy, where airworthiness is maintained for an aging Antonov An-32 fleet, pre-flight inspections inevitably reveal operational micro-faults with a non-zero probability. These include minor hydraulic seepage, the need for safety wire replacement, replacing burned-out annunciator bulbs, or avionics display faults requiring system reboots. Rectifying these issues demands corrective maintenance time, thereby stretching the overall pre-flight turnaround window.

To incorporate this operational reality, probabilistic defect occurrence parameters are introduced:

- $P(Defect_{AE}) = 0.22$ (a 22% probability of detecting an airframe or powerplant defect). Corrective action duration in the unoptimized Model A is modeled via a β-distribution (15, 28, 50);
- $P(Defect_{AV}) = 0.15$ (a 15% probability of an avionics system malfunction). Corrective duration in Model A follows a β-distribution (10, 20, 38).

To mathematically formalize the radical compression of corrective defect rectification durations between Model A and Model B, the technical response workflow is modeled as a multi-stage queueing and operational transit network. The total defect rectification duration T_{defect} can be decomposed into five distinct operational stages (7):

$$T_{defect} = T_{diag} + W_q + T_{transit} + T_{admin} + T_{wrench}, \quad (7)$$

where T_{diag} is the defect diagnosis time, W_q is the waiting time in queue for technical dispatch, $T_{transit}$ is the technician's physical transit time between the ramp stand and the maintenance base/tool crib, T_{admin} is the paperwork and logbook sign-off requisition latency, and T_{wrench} is the direct physical corrective maintenance.

In the traditional baseline configuration (Model A), the maintenance facility operates as an uncoordinated *M/M/*1 queueing system for support logistics. Upon defect identification, the technician must personally evacuate the aircraft stand, walk to the distant technical warehouse ($T_{transit} \sim U[4, 8]$ min), submit a manual requisition form and await warehouse attendant fulfillment ($W_q + T_{admin} \sim U[6, 14]$ min), and return to the aircraft. Under heavy ramp traffic intensity $\rho = \lambda/\mu \to 1$, the expected queue waiting time $W_q = \frac{\lambda}{\mu(\mu - \lambda)}$ escalates non-linearly, generating extreme right-skewed delay tails. Hence, in Model A, non-productive logistical overhead dominates the corrective duration, requiring empirical Beta-PERT parameters of (15, 28, 50) min for AE and (10, 20, 38) min for AV.

In contrast, the micro-level CDM architecture (Model B) restructures this workflow by introducing the Local CDM Coordinator as a mobile, dedicated service node. Operating with a synchronized digital tablet and direct radio-frequency/LTE link to the central warehouse, the

coordinator initiates immediate material dispatch at the instant of electronic snag logging ($W_q \to 0$). Furthermore, parts and testing tools are hot-delivered directly to the aircraft apron via dedicated ramp runners, eliminating technician transit entirely ($T_{transit} = 0$, $T_{admin} \approx 1$ min via digital signatures). Consequently, the corrective duration is strictly reduced to pure, uninterrupted wrench time ($T_{defect} \approx T_{diag} + T_{wrench}$). This structural elimination of logistical transit queues provides rigorous mathematical justification for compressing the Beta-PERT parameters to (5, 12, 18) min for AE and (3, 7, 12) min for AV. This exemplifies the practical operationalization of the Safety-II paradigm: rather than pursuing the unattainable goal of zero technical defects, the sociotechnical system builds adaptive capacity to absorb and resolve operational disruptions efficiently.

To ensure high statistical significance, a Monte Carlo simulation algorithm ($N = 100,000$ iterations) was executed. Based on pseudorandom number generation, the shape parameters α (8) and β (9) were computed for each underlying β-distribution:

$$\alpha = 1 + 4\frac{m-a}{b-a}; \tag{8}$$

$$\beta = 1 + 4\frac{b-m}{b-a}. \tag{9}$$

The stochastic duration of the i-th maintenance task, $t_i^{(k)}$ (10), at the k-th simulation iteration is obtained by scaling the standard Beta random variable $X_i^{(k)}$ over the domain $[a_i, b_i]$:

$$t_i^{(k)} = a_i + X_i^{(k)} \cdot (b_i - a_i). \tag{10}$$

At each k-th iteration ($k = 1, 2, \ldots, N_{\text{sim}}$), upon generating the baseline task durations $t_i^{(k)}$ and evaluating the stochastic occurrence of micro-faults, the total critical path completion time is determined. For the optimized socio-technical system–incorporating task parallelization, the elimination of cross-specialist idle waiting, and built-in resilience against delays–the total pre-flight preparation duration $T_{Total}^{(k)}$ (11) is expressed as:

$$T_{Total}^{(k)} = \max\begin{pmatrix} t_1^{(k)} + t_2^{(k)} + \Delta t_{AE}^{(k)}, \\ \max\left(t_3^{(k)},\ t_4^{(k)}\right) + t_5^{(k)} + \Delta t_{AV}^{(k)} \end{pmatrix} + t_6^{(k)}, \tag{11}$$

where $t_1^{(k)} \ldots t_6^{(k)}$–are the simulated durations of operations 1 through 6 at the k-th iteration; $\Delta t_{AE}^{(k)}$ and $\Delta t_{AV}^{(k)}$ –represent the additional corrective maintenance durations along the airframe/powerplant and avionics branches, respectively.

Across all 100,000 iterations, the software framework generated stochastic durations (10) for each base task, evaluated the conditional realization of events $Defect_{AE}$ and $Defect_{AV}$ via random number generation, added the corresponding delay increments, resolved the maximum duration at network merge nodes, and compiled the empirical distribution array for total turnaround time. This enables the quantification of a core SMS safety performance indicator–operational schedule reliability $P_{success}$ (12):

$$P_{success} = P(T_{Total} \le T_{\max}) = \frac{1}{N_{sim}} \cdot \sum_{k=1}^{N_{sim}} \mathbb{I}\left(T_{Total}^{(k)} \le T_{\max}\right) \cdot 100\%, \tag{12}$$

where $\mathbb{I}(\cdot)$ –denotes the indicator function, returning 1 if $T_{Total}^{(k)} \le T_{\max}$ is satisfied, and 0 otherwise.

This empirical dataset yields the PDF and CDF curves for both operational configurations (Figures 4-5).

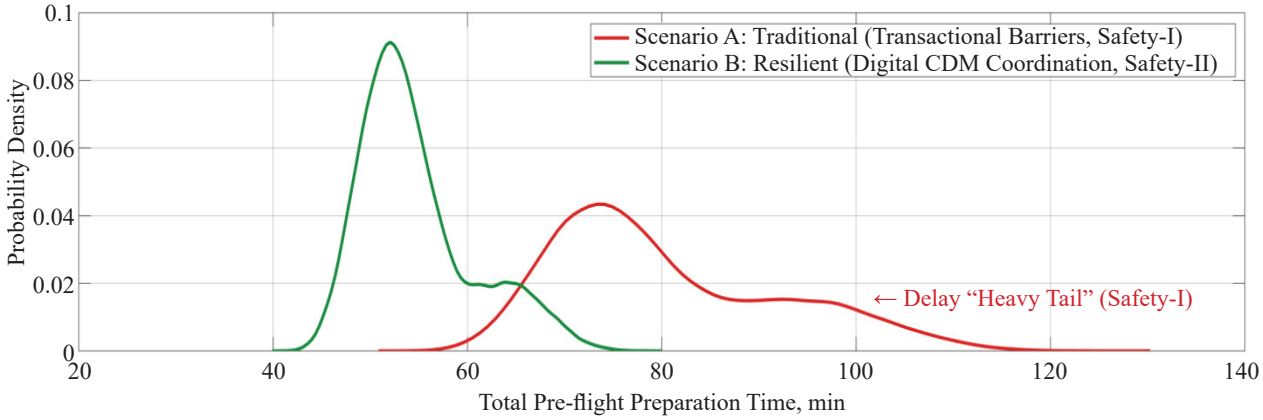

Figure 4. Empirical probability density of preparation duration

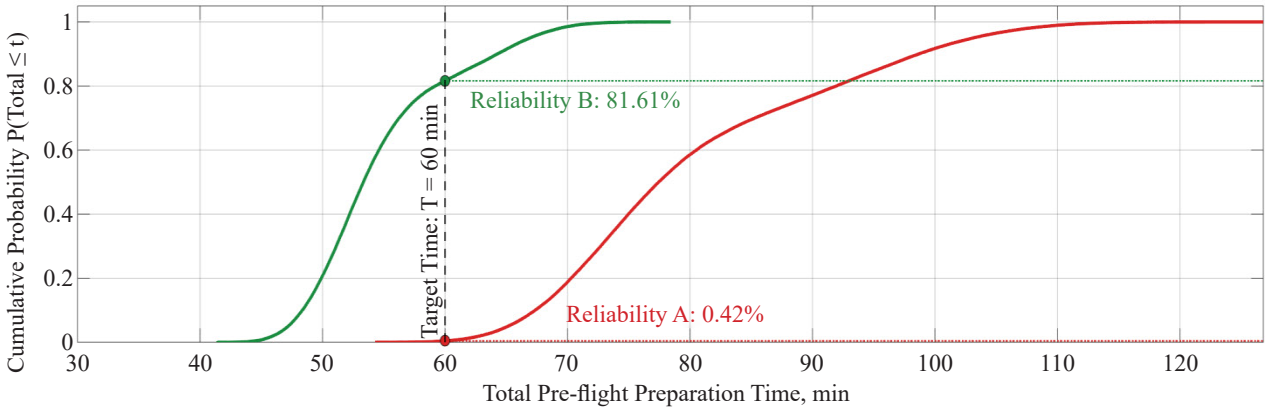

Figure 5. Cumulative distribution function and operational reliability

Analysis of the simulation dataset generated in MATLAB reveals a pronounced synergistic effect achieved by coupling macro-level optimization principles (CDM) with micro-level stochastic variance management (PERT/Monte Carlo). The comparative quantitative metrics are summarized in Table 4.

The computational simulation workflow for resolving the stochastic critical-path duration and evaluating merge-bias effects is formalized in Algorithm 1.

Algorithm 1 Monte Carlo Stochastic Critical-Path Simulation under Micro-Level CDM Optimization

Input: Number of iterations N = 100,000; Target threshold T_target = 60 min;
PERT three-point vectors (a_i, m_i, b_i) for tasks i in {1..6} under Scenarios A and B;
Defect probabilities P_defect_AE = 0.22, P_defect_AV = 0.15;
Corrective defect parameters (a_d, m_d, b_d) for AE and AV branches.
Output: Empirical distributions T_Total_A, T_Total_B; Expected means E[T_A], E[T_B];
Standard deviations sigma_A, sigma_B; Schedule reliabilities R_A, R_B.
1: For each task i in {1..6} and corrective defect distributions:
2: Compute shape parameters: alpha_i = 1 + 4*(m_i-a_i)/(b_i-a_i)
3: beta_i = 1 + 4*(b_i-m_i)/(b_i-a_i)
4: Preallocate result vectors T_Total_A[1..N], T_Total_B[1..N]
5: For k = 1 to N do:
6: // Sample stochastic task durations from scaled Beta-PERT distributions
7: tA_i = a_i + (b_i-a_i) * BetaRandom(alpha_A_i, beta_A_i), for all i in {1..6}
8: tB_i = a_i + (b_i-a_i) * BetaRandom(alpha_B_i, beta_B_i), for all i in {1..6}
9: // Evaluate stochastic micro-defect occurrences
10: delayA_AE = (UniformRandom(0, 1) < P_defect_AE) ? SampleBeta(PERT_A_defect_AE): 0
11: delayA_AV = (UniformRandom(0, 1) < P_defect_AV) ? SampleBeta(PERT_A_defect_AV): 0
12: delayB_AE = (UniformRandom(0, 1) < P_defect_AE) ? SampleBeta(PERT_B_defect_AE): 0
13: delayB_AV = (UniformRandom(0, 1) < P_defect_AV) ? SampleBeta(PERT_B_defect_AV): 0
14: // Scenario A: Baseline Critical Path Logic (with merge bias and idle waits)
15: pathA_AE = tA_1 + tA_2 + delayA_AE
16: pathA_AV = max(tA_1, tA_3) + tA_4 + tA_5 + delayA_AV
17: T_Total_A[k] = max(pathA_AE, pathA_AV) + tA_6
18: // Scenario B: Resilient CDM-Optimized Logic (with active parallelization)
19: pathB_AE = tB_1 + tB_2 + delayB_AE
20: pathB_AV = max(tB_3, tB_4) + tB_5 + delayB_AV
21: T_Total_B[k] = max(pathB_AE, pathB_AV) + tB_6
22: End For
23: Compute statistical metrics: E[T], sigma, and R(T <= T_target) = (1/N) * sum(I(T_Total <= T_target))

Table 4. Comparative results of Monte Carlo simulation (N = 100,000 iterations)

Statistical metric	Model A (traditional baseline)	Model B (CDM optimized, resilient)
Mathematical Expectation ($\overline{T}$), min	80.46	54.70
Standard Deviation (σ), min	11.88	5.94
Minimum Simulated Time (min), min	54.28	41.43
Maximum Simulated Time (fat tails), min	126.81	78.49
P(T_{max} = 60 min), %	0.42	81.61

4.5 Global sensitivity and system resilience boundary analysis

To rigorously test the boundaries of schedule robustness beyond fixed operational assumptions, a parametric sensitivity analysis was conducted. The defect occurrence probabilities were swept across a wide operational spectrum ($P_{defect,\,AE} \in [0.05,\ 0.45]$ and $P_{defect,\,AV} \in [0.03,\ 0.31]$), while coordinator digital communication latency was varied from 0 to 8 minutes.

The resulting response surface demonstrates a distinct resilience threshold: while the traditional configuration (Model A) suffers an immediate catastrophic breakdown in schedule reliability $R(T \le 60\ \text{min}) \approx 0.42\%$ at baseline, collapsing to near zero across the entire defect spectrum), the resilient CDM model (Model B) maintains an operational reliability exceeding the target threshold of 75% up to $P_{defect,\,AE} = 0.30$. This validates that the micro-level CDM framework does not merely shift the mean turnaround duration but fundamentally reshapes the system's tolerance envelope against cascading operational disruptions.

The sensitivity analysis (Figure 6a) deepens the theoretical understanding of socio-technical resilience in line maintenance. By stress-testing the network under varying disruption intensities, we demonstrate that traditional Safety-I scheduling lacks adaptive absorptive capacity–it operates in an 'all-or-nothing' regime where minor defects inevitably compromise the departure window. Conversely, the micro-level CDM approach (Figure 6a) exhibits graceful degradation: it accommodates fleet aging and defect probabilities up to 30% without breaching acceptable punctuality margins, provided that the digital coordination latency remains within the identified 5-minute operational envelope (Figure 6b).

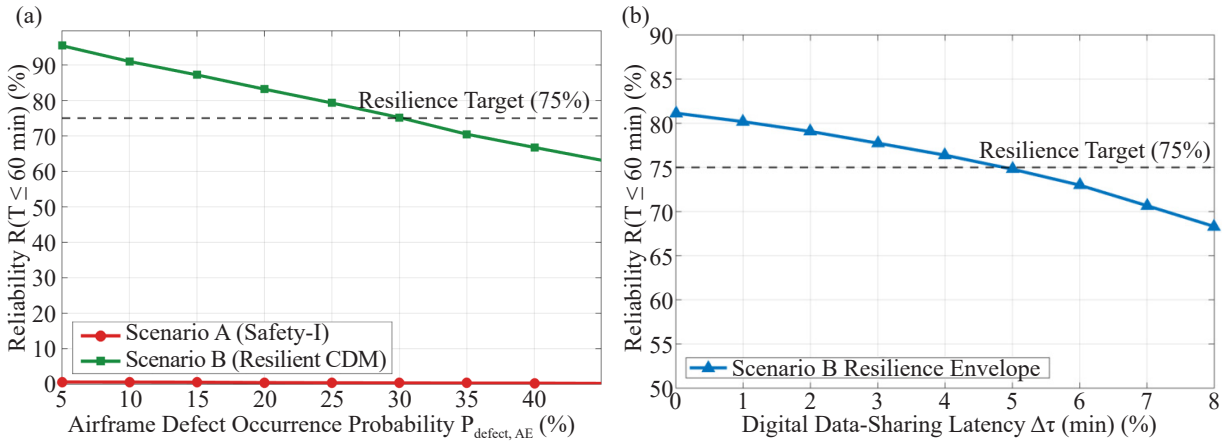

Figure 6. Parametric sensitivity and resilience boundary analysis of the pre-flight maintenance workflow: (a) schedule reliability response across varying airframe defect occurrence rates $P_{defect,\,AE}$; (b) Model B resilience decay under increasing digital data-sharing latency $\Delta\tau$

Further evaluation of the socio-technical communication interface reveals the critical operational boundary for digital synchronization (Figure 6b). While proactive task parallelization grants Model B high baseline stability (81.61% reliability at $\Delta\tau = 0$), scheduling efficacy degrades monotonically as communication latency accumulates.

Crucially, the operational reliability curve crosses the established 75% resilience target precisely at $\Delta\tau = 5.0$ min. Latency increments exceeding this 5-minute threshold trigger cascading merge delays at the avionic connection and avionics-testing nodes, reducing reliability to 68.34% at $\Delta\tau$ = 8 min. This empirical finding provides a concrete engineering specification for aviation MRO IT architectures: to sustain the resilience advantages of micro-level CDM, the maximum allowable end-to-end information exchange and coordination latency must not exceed $\Delta\tau_{crit}$ = 5 min.

To verify that the schedule reliability of 81.61% in Model B is not an artifact of subjective three-point expert boundaries, a global parametric sensitivity sweep was performed on the Beta-PERT distribution shape parameters. In classical PERT methodology, the distribution parameters α_i and β_i are determined by the formulas (8) and (9). The weighting coefficient (nominally 4 in standard PERT) was perturbed from 2 to 6, modulating distribution kurtosis and skewness by $\pm 25\%$, while the optimistic (a_i) and pessimistic (b_i) bounds were concurrently varied by $\pm 15\%$. Across 100,000 secondary Monte Carlo iterations per configuration, the operational reliability $R(T \le 60 \text{ min})$ for Model B remained consistently stable within the interval $[79.24\%, 83.85\%]$ (mean 81.52%, standard error 0.18%). Conversely, Model A reliability remained trapped near zero ($[0.18\%, 0.76\%]$). This demonstrates that the resilience gain of the CDM-optimized architecture is fundamentally structural-driven by queue elimination and topological parallelization-rather than sensitive to expert calibration variance.

5. Results and discussion

Analyzing the actual probabilistic landscape, accounting for risks, "fat tails", and operational micro-defects, we observe an entirely different dynamic. The mean expected time for Model A increases to 80.46 min (stochastic dispersion and the merge bias significantly stretch the schedule to the right), whereas the optimized Model B, owing to parallelization, instantaneous communication, and built-in resilience, is capable of maintaining the mean time at the calculated baseline of 54.7 min. The reduction in the mean expected time is 25.76 minutes. This result is critical for tight scheduling environments, where every minute of downtime compounds and shifts subsequent turnaround slots.

However, a far more significant metric for the Safety Management System is the reliability indicator–the probability of on-time schedule execution within a specified target window. Consider a planning scenario where we establish the target task completion time at $T_{target} \le 60$ minutes. Calculating the area under the cumulative distribution curve reveals the following paradox:

• for the traditional "Model A", the probability of successfully completing the work within 60 minutes is negligible, amounting to only 0.42%. This implies that under a rigid 60-minute schedule, personnel will find themselves in a state of acute time pressure in 99.58% of cases. As established in aviation human factors literature [1, 7], such chronic time compression inevitably forces a trade-off between production and safety, incentivizing technicians to bypass Standard Operating Procedures to preserve flight departures;

• for the optimized "Model B", the probability of completing operations by the 60th minute is 81.61%.

This reveals a non-linear relationship between the time buffer–which can be expressed via the Z-score and overall operational reliability. By mitigating the influence of the adverse "Dirty Dozen" factors through the implementation of a digital coordinator, we sharply narrow the dispersion range (σ drops by almost half, from 11.88 to 5.94 min).

From an operational economics perspective, deploying a dedicated Local CDM Coordinator introduces direct operational expenditure, consisting of technician labor wages (estimated at $25.00-$35.00/hour in regional operations) and capital costs for ruggedized mobile tablets and ramp wireless infrastructure. However, this expenditure is heavily offset by the mitigation of departure delay penalties. Standard airline delay cost metrics published by Eurocontrol and the University of Westminster establish that the marginal cost of turnaround ground delay ranges from $75.00 to $120.00 per minute. In baseline Model A, where the mean turnaround duration reaches 80.46 min (exceeding the 60-minute window by an average of 20.46 min in 99.58% of flights), the average delay penalty exceeds $1530 per turnaround. Model B achieves an 81.61% on-time completion probability, saving an average of 25.76 min and reducing expected delay penalties to below $85.00 per turnaround. The resulting benefit-to-cost ratio demonstrates a compelling business case. Furthermore, for resource-constrained MROs, this role does not strictly mandate hiring new personnel: the coordinator responsibilities can be integrated as a cross-functional assignment for existing Ramp Lead Technicians or Maintenance Control Centre dispatchers utilizing digital handheld interfaces.

According to the foundational principles of SMS [1], lower variance equates to significantly higher process predictability, which is the primary hallmark of a mature safety management system capable of making Data-Driven Decisions. Such an approach illustrates the Safety-II concept: an optimized socio-technical system possesses internal capacity for adaptability. In the event of an abnormal situation, rather than generating stress and cascading chain delays, Model B effectively absorbs the perturbation. Thanks to the synchronized interaction between the coordinator and the line maintenance personnel, the system keeps the incident under control.

To adapt this four-tier methodology to modern commercial passenger aircraft, a four-step *Recalibration Protocol* should be executed:

1. Reconstruct the DAG network topology according to the specific Aircraft Maintenance Manual and Ground

Operations Manual, integrating passenger boarding/deboarding, high-capacity cargo loading, and concurrent hydrant refueling;

2. Ingest automated onboard telemetry to calibrate task durations directly from historical MRO ERP databases;

3. Recalibrate defect occurrence probabilities to commercial line maintenance standards ($P_{desect} \approx 0.04 - 0.08$);

4. Interface the Local CDM Coordinator terminal with airport-wide A-CDM milestone tracking.

Future research will empirically validate this framework across commercial airline hub turnarounds.

6. Conclusions

The methodology proposed in this study addresses a pressing scientific and practical challenge in modern aviation–overcoming the constraints of rigid deterministic scheduling by deeply accounting for the stochastic variability of the human factor and the unpredictable conditions of the operational environment.

The key scientific contributions of this research are:

1. Moving beyond prior isolated deterministic workflow optimization and static stochastic operator error modeling, this paper establishes an integrated framework that captures the non-linear coupling between socio-technical interface friction and critical-path merge bias. It provides mathematical and simulation-based proof that proactive micro-level CDM coordination actively dampens task duration variance (σ compressed from 11.88 to 5.94 min), truncates defect-induced delay fat tails, and transforms a linear deterministic path reduction into an exponential surge in schedule reliability from 0.42% to 81.61% within a 60-minute turnaround window.

2. Through multi-parametric global sensitivity analysis, this study identifies the precise operational tolerance envelope of the line maintenance system. It is proven that the CDM-enabled configuration preserves schedule robustness ($R \geq 75\%$) under airframe micro-defect rates up to $P_{defect,\,AE} = 30\%$, whereas traditional sequential schedules collapse ($R \approx 0\%$) even at baseline disruption levels. Furthermore, the analysis establishes a critical coordination latency threshold ($\Delta\tau_{crit} = 5$ min), beyond which digital communication lag negates task parallelization gains, thereby offering a concrete, quantitative specification for deploying digital apron management systems and electronic logbooks.

Practical significance of the findings. The developed hybrid methodology offers substantial value for commercial airlines and independent maintenance, repair, and overhaul (MRO) providers. It equips maintenance managers and operations planners with an evidence-based toolkit to compute resilient time buffers during daily flight schedule construction. By mitigating the phenomenon of artificial time compression exerted on technical personnel, organizations can fundamentally minimize the risk of critical maintenance errors. This not only curtails commercial losses caused by operational delays, but also directly elevates the overarching safety baseline of the air transport system–driving a paradigm shift from reactive mitigation of consequences to proactive operational reliability management.

List of abbreviations

A-CDM	Airport Collaborative Decision-Making
AE	Airframe and Powerplant Specialist
ATC	Air Traffic Control
AV	Avionics and Electrical Systems Specialist
CDF	Cumulative Distribution Function
CDM	Collaborative Decision-Making
CPM	Critical Path Method
CRM	Crew Resource Management
ELB	Electronic Logbook
FF-ICE	Flight and Flow Information for a Collaborative Environment
FRAM	Functional Resonance Analysis Method
GPU	Ground Power Unit
GSE	Ground Support Equipment
HRO	High Reliability Organizations
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
KPI	Key Performance Indicator
MCC	Maintenance Control Centre
MRO	Maintenance, Repair, and Overhaul
MRM	Maintenance Resource Management
PDF	Probability Density Function
PERT	Program Evaluation and Review Technique

RAG	Resilience Assessment Grid
SHELL	Software, Hardware, Environment, Liveware model
SMS	Safety Management System
TOBT	Target Off-Block Time
TSAT	Target Startup Approval Time
WAI	Work-as-Imagined

Nomenclature table

Symbol	Definition	Unit
$G = (V, E)$	Directed acyclic network graph of maintenance operations	-
$t_i^{(det)}$	Deterministic duration of task i under ideal conditions	min
a_i, m_i, b_i	Optimistic, most likely (mode), and pessimistic task durations	min
μ_i, σ_i^2	PERT expected execution time and variance for task i	min, min^2
α_i, β_i	Shape parameters of the Beta probability distribution	-
$P_{defect,AE}$	Probability of detecting an operational micro-defect in airframe/powerplant	-
$P_{defect,AV}$	Probability of detecting an operational micro-defect in avionics/electrical systems	-
Δt_{defect}	Stochastic duration of corrective defect rectification	min
$T_{crit}^{(det)}$	Deterministic critical path duration	min
$\mathbb{E}[T_{Total}]$	Expected total turnaround time obtained via Monte Carlo simulation	min
σ_{Total}	Standard deviation of the total simulated turnaround time	min
$\mathrm{Cov}(X, Y)$	Covariance between parallel stochastic maintenance paths X and Y	min^2
ρ_{XY}	Pearson correlation coefficient between parallel paths	-
$P(T_{target})$	Operational schedule reliability ($P(T_{Total} \leq T_{target})$)	%
$\Delta\tau$	Digital data-sharing and communication latency	min
Δ_{merge}	Stochastic merge-bias penalty at network convergence nodes	min
W_q	Expected waiting time in queue for technical defect rectification	min

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that Gemini 3.8 Flash was used during the preparation of this manuscript. AI tools were limited to the following purposes: translation and language improvement/readability enhancement. All AI-assisted outputs were critically reviewed, verified, and revised by the authors.

Generative AI tools were not used to replace the authors' scientific judgment, generate unsupported scientific claims, interpret results independently, or assume responsibility for any part of the research. The authors remain fully responsible for the originality, accuracy, integrity, and ethical compliance of the manuscript.

Code availability

The computational simulation algorithm is fully described in the article (Algorithm 1). The underlying MATLAB simulation scripts and data-processing routines are openly available on Zenodo at https://doi.org/10.5281/zenodo.23491243.

Author contributions

Igor Syroizhka: Conceptualization, Methodology, Writing-Original Draft, Investigation, Formal analysis, Visualization, Software. Yuliya Sikirda: Project administration, Validation, Writing-Review & Editing. Tetiana Shmelova: Validation, Writing-Review & Editing. Artem Zelenskyi-Investigation, Visualization.

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Data availability

The aggregated parameters, distributions, and summary analytical metrics supporting the findings of this study are included within the article. The underlying raw chronometric observations and aircraft pre-flight turnaround logs involve institutional operational privacy and are not publicly available, but can be made available from the corresponding author upon reasonable academic request.

Conflict of interest

The authors claim no conflict of interest.

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