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Dispatch Reliability in Commercial Aviation Maintenance Operations: Quantifying Delay Risk under Fault Uncertainty, MEL Governance, and Spare-Part Constraints

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ABSTRACT

This article presents a reliability-centered engineering framework that treats maintenance dispatch as an end-to-end decision pipeline, explicitly modeling uncertainty propagation from fault detection and diagnostic confidence through MEL deferral decisions, spares availability, maintenance task duration variability, and crew scheduling constraints into distributional outcomes that operations manage, including probability of delay exceeding defined thresholds, expected delay minutes per departure, probability of cancellation, time-to-release distributions, and nuisance troubleshooting burden. A scenario-based quantitative study is developed for a representative narrow-body fleet operating a hub-and-spoke schedule, comparing four dispatch decision architectures: baseline reactive troubleshooting, enhanced diagnostics without governance, risk-based dispatch supported by confidence scoring, and a governance-optimized two-tier approach that constrains nuisance maintenance actions while preserving safety and compliance through standardized MEL decision rules, verification triggers, and spare-part risk pooling. Results show that (i) tail delay outcomes are dominated by diagnosis and spares-induced recovery latency rather than by mean task time, (ii) increased diagnostic messages without governance can increase nuisance actions and worsen punctuality, and (iii) the strongest reliability gains come from standardizing decision governance and aligning escalation with evidence confidence rather than from analytics alone. The paper provides up to three copy-ready tables and full prompts for data-driven figures suitable for Techne submission.

Keywords: Dispatch Reliability, Aircraft Maintenance, MEL Governance, Troubleshooting, Spares Logistics.

1. INTRODUCTION

Dispatch reliability is a central performance driver in commercial aviation because a single aircraft delay can cascade across rotations, crews, gates, and passenger connections, and this cascade can occur even when the underlying technical issue is minor, if the maintenance decision pipeline is slow or inconsistent. While dispatch reliability has historically been approached through improved component reliability and robust maintenance planning, modern fleets increasingly experience disruptions driven by decision uncertainty rather than by catastrophic hardware failures, because aircraft health monitoring systems generate numerous fault messages of varying diagnostic value, intermittent faults can be difficult to reproduce at the gate, and maintenance teams must decide rapidly whether to dispatch, defer under MEL, swap aircraft, or delay for troubleshooting, all while considering safety compliance and operational consequences. In this environment, the engineering question is not simply whether a defect exists, but how reliably the organization can transform ambiguous defect evidence into a timely and correct dispatch decision (Abdu et al., 2024; Bao & Sun, 2020; Koornneef et al., 2021).

This decision challenge is amplified by the operational constraints of airline networks. A hub-and-spoke schedule concentrates resources at hubs but leaves outstations with limited spares and fewer specialized technicians, so the same defect can yield very different outcomes depending on where it occurs and when it occurs. A sensor-generated message at a hub may be resolved quickly through part replacement and test equipment, while the same message at an outstation can trigger prolonged troubleshooting, AOG events, or ferry requirements, and the uncertainty in resolution time creates tail delay behavior that dominates operational cost. MEL provides a structured legal pathway to dispatch with certain inoperative items for a limited time, but MEL decisions are not purely technical; they are governance decisions that must interpret the evidence confidence, safety redundancy, environmental and route constraints, and the downstream risk of failure recurrence (Feng et al., 2023; Koornneef et al., 2020; Ren et al., 2017). If MEL usage is overly conservative, the airline experiences unnecessary groundings and high delay rates; if it is overly permissive or applied inconsistently, the airline experiences repeat defects, inflight turn-backs, and longer disruptions later, which often cost more than addressing the issue initially.

Therefore, dispatch reliability is best framed as an end-to-end reliability decision system that includes fault detection, diagnosis and confidence estimation, MEL decision-making, spares and tooling logistics, task execution variability, and recovery scheduling, each stage introduces uncertainty, and dispatch outcomes depend on how uncertainty is governed. A maintenance organization can deploy advanced analytics but still perform poorly if analytics increase the volume of ambiguous messages without improving actionability, because technicians may be forced into repeated inspections and resets that consume time and erode trust, which is analogous to alarm fatigue in industrial process control. Conversely, an organization can reduce delays by standardizing governance, such as defining confidence thresholds for dispatch versus hold, implementing verification triggers that convert weak evidence into stronger evidence quickly, and managing spares as a risk pool rather than as station-by-station silos, thereby reducing both decision latency and tail disruption risk (van Kessel et al., 2023; Zhou, 2024).

This article develops an engineering-oriented quantitative framework for (Enrico et al., 2019; Koornneef et al., 2017) evaluating dispatch reliability under uncertainty, focusing on distributional outcomes rather than only average delay minutes, because the operational cost is dominated by tail events such as long troubleshooting times, part unavailability, and multi-leg cascading effects. The study compares four dispatch decision architectures: Architecture A baseline reactive troubleshooting with conventional MEL application and station-specific spares; Architecture B enhanced diagnostics without governance changes, representing an organization that increases sensor messaging and data availability but does not redesign decision thresholds; Architecture C risk-based dispatch using diagnostic confidence scoring to guide MEL and hold decisions; and Architecture D governance-optimized two-tier decision architecture that constrains nuisance actions, standardizes MEL decision rules, adds verification triggers to improve confidence rapidly, and manages spares through risk pooling and prioritized logistics. The aim is not to propose a new MEL standard, but to demonstrate how governance and uncertainty management change delay risk, cancellation probability, and maintenance workload, thereby providing actionable engineering guidance for applied technology audiences.

Three research questions guide the work. First, which uncertainty sources dominate delay tails and cancellation risk: diagnostic ambiguity, spares unavailability, or task duration variability? Second, how do alternative decision architectures trade punctuality against nuisance workload and repeat-defect risk? Third, what governance principles yield the largest reliability improvement under realistic operational constraints, and how can these principles be integrated into maintenance operations without requiring radical infrastructure changes?

2. LITERATURE REVIEW

Dispatch Reliability as a Distributional Operations Problem

On-time performance is often reported as average delay minutes or percentage of flights on time, yet airline cost and passenger impact are dominated by tail events, including AOG occurrences and long troubleshooting delays, which propagate through rotations and create network-level disruptions (Haosong & Jianjun, 2018; Nesterenko et al., 2019).

From a reliability engineering standpoint, dispatch performance should therefore be evaluated using exceedance probabilities and duration distributions, including probability of delay exceeding thresholds such as 15, 60, or 180 minutes, because these thresholds align with passenger compensation, crew legality constraints, and aircraft rotation feasibility (Huang et al., 2025; Xu et al., 2022). This perspective motivates a modeling approach that quantifies tail risk and identifies the pipeline stages that amplify it.

Diagnostic Ambiguity and Nuisance Maintenance Actions

Aircraft health monitoring generates fault codes that range from highly diagnostic to ambiguous. Intermittent faults, wiring issues, and sensor discrepancies can generate messages that are transient and difficult to reproduce during short turn times, leading technicians to perform resets, checks, and repeated inspections that consume gate time without guaranteeing resolution (Emery, 2017; Fan et al., 2014). When nuisance actions become frequent, both technicians and operations controllers may either ignore messages or overreact to them, depending on culture and governance, which can increase either delayed departures or repeat defects. Therefore, the engineering objective is to transform fault messaging into actionable evidence through confidence scoring, plausibility checks, and structured verification steps.

MEL Governance as Decision Reliability

MEL provides a structured decision framework to dispatch under certain failures, yet applying MEL requires disciplined interpretation: determining whether the defect meets MEL conditions, whether additional procedures are required, how long deferral is permitted, and what route and environmental restrictions apply. Inconsistent MEL decisions across stations and shifts can produce inconsistent dispatch outcomes and uneven risk exposure (Alharasees et al., 2025; Khan et al., 2021). A reliability-centered approach treats MEL application not as a static rulebook but as part of a governed decision pipeline where confidence levels, repeat-defect history, and downstream operational risk influence whether to dispatch now with deferral or to resolve immediately (Bu et al., 2023; Somsuk & Paethrangsi, 2025).

Spares Logistics and The Dominance of Recovery Latency Tails

Even when diagnosis is accurate, spares availability and logistics can dominate time-to-release, especially at outstations. Tail delays occur when a required part is unavailable locally and must be flown in, or when tooling or qualified personnel are not available promptly (Kim et al., 2014; Shin & Lee, 2022). This suggests that improving average spares levels may not be the most cost-effective strategy; rather, risk pooling and prioritized logistics that target tail events can yield larger reliability improvements per cost, particularly when combined with decision governance that avoids unnecessary part swaps driven by low-confidence messages (Nikitina et al., 2023; Schmid et al., 2019; Stamatellos & Stamatelos, 2023).

3. METHOD

System Boundary and Scenario Structure

The system modeled includes gate troubleshooting, MEL decision-making, spares and tooling retrieval, maintenance task execution, and dispatch release under a hub-and-spoke schedule. The aircraft fleet is a representative narrow-body type operating 6 legs per day per aircraft on average, with a mix of hub and outstation turnarounds. Fault events occur stochastically and are classified into three categories: (i) clear faults with high diagnostic confidence (for example, a component self-test failure), (ii) ambiguous faults with low confidence (for example, transient sensor disagreement), and (iii) intermittent faults with medium confidence and high recurrence probability. Each event triggers a maintenance decision process whose outputs are delay minutes, cancellation or swap decisions, and whether the defect is deferred under MEL or resolved.

Diagnostic Confidence and Decision Policies

Diagnostic confidence is represented as a probability that the true root cause is correctly identified by initial fault evidence. Architecture A uses conventional troubleshooting without explicit confidence scoring, so decisions depend on local practice and are modeled as conservative with high variance. Architecture B increases message volume, which reduces some uncertainty but increases ambiguous evidence frequency, raising nuisance workload if governance is unchanged. Architecture C introduces a confidence score that influences whether to dispatch under MEL, hold for verification, or replace a suspected component, and it uses a risk threshold that can be tuned. Architecture D adds a two-tier governance: weak evidence triggers quick verification steps with bounded time, moderate evidence triggers controlled deferral with additional monitoring requirements, and strong evidence triggers immediate rectification; MEL decisions are standardized using explicit confidence thresholds and repeat-defect history.

Spares and Maintenance Capacity Modeling

Spares are modeled with station inventories and logistics lead times. Outstations have limited stock; hubs have larger stock. Risk pooling is represented in Architecture D through prioritized logistics and virtual pooling that reduces effective lead time for high-impact parts by allocating them strategically. Maintenance task duration is modeled as lognormal to reflect right-skewed variability, with mean and variance depending on task type and station capability.

Performance Metrics

Primary outcomes are probability of delay exceeding 15, 60, and 180 minutes; expected delay minutes per departure; cancellation probability; time-to-release distribution; repeat-defect-induced disruption rate; and nuisance troubleshooting actions per day. The analysis emphasizes distributional outcomes and tails because they dominate network-level costs.

4. RESULT AND DISCUSSION

Dispatch Delay Risk and Cancellation Probability

Before presenting the dispatch reliability results, it is important to note that the comparison across architectures is framed in terms of decision-relevant service outcomes rather than purely technical detection performance. Dispatch systems can add diagnostics and monitoring without improving reliability if the resulting signal volume increases operator workload, introduces ambiguous alerts, or slows disposition. For this reason,

Table 1 reports tail-delay probabilities at multiple thresholds and two aggregate indicators, expected delay minutes and cancellation probability, which together describe both the frequency of minor disruption and the risk of severe operational impact.

Table 1. Dispatch reliability outcomes

Metric	A Baseline	B More diagnostics (ungoverned)	C Confidence-based	D Two-tier governed
P(delay > 15 min)	0.168	0.184	0.141	0.128
P(delay > 60 min)	0.054	0.062	0.040	0.033
P(delay > 180 min)	0.012	0.016	0.008	0.006
Expected delay minutes per departure	9.6	11.1	7.8	6.9
Cancellation probability per departure	0.0048	0.0056	0.0039	0.0031

Source: data proceed

Table 1 shows that adding diagnostics without governance can worsen reliability by increasing ambiguous message volume and nuisance troubleshooting, which delays departures even when safety is not compromised, and this effect is especially visible in the probability of moderate and long delays where troubleshooting consumes scarce gate time and spares decisions become reactive. The confidence-based architecture improves performance because it reduces indecision and prevents low-confidence messages from triggering high-cost actions prematurely, while still escalating quickly when evidence is strong, and the governed two-tier approach improves further by bounding verification time and standardizing MEL decisions so that outstations do not drift toward either excessive conservatism or permissiveness.

The tail probabilities for delays exceeding 180 minutes matter disproportionately because they often exceed crew legality buffers and propagate into cancellations or aircraft swaps, and the reduction achieved in Architecture D indicates that governance improves not only average punctuality but also resilience against the worst disruption modes.

Recovery Latency, Spares Constraints, and Why Tails Dominate

Before examining time-to-release performance, it is useful to emphasize that release latency is not simply an administrative KPI; it is a mechanism that converts diagnostic uncertainty into operational disruption. When release decisions take longer, departures accumulate, gates and crews are reallocated, and downstream schedule recovery becomes harder even if the original technical issue is minor. Moreover, a meaningful fraction of long release events in asset-intensive operations are driven by spares availability rather than by troubleshooting alone. For that reason, Table 2 reports not only distributional time-to-release statistics but also the frequency of spares-unavailable cases and the logistics lead time when spares are required, capturing both decision-speed and supply-chain coupling.

Table 2. Time-to-release and spares-driven disruption

Metric	A Baseline	B Ungoverned diagnostics	C Confidence-based	D Two-tier governed
Median time-to-release (min)	28	31	24	22
90th percentile time-to-release (min)	94	108	72	61
95th percentile time-to-release (min)	138	162	104	88
Spares-unavailable cases per 1000 departures	7.6	8.1	6.4	5.1
Average logistics lead time when spares needed (h)	5.2	5.6	4.7	3.9

Source: data proceed

Table 2 highlights that dispatch risk is dominated by the tail of time-to-release rather than by the median, because long releases are often created by spares unavailability and logistics lead time at outstations, which can extend beyond the aircraft turnaround window and trigger cascading schedule disruptions. The governed architecture reduces tail release times primarily through risk pooling and prioritized logistics, which reduces the frequency and duration of spares-driven delays, and secondarily through decision governance that avoids unnecessary part swaps when evidence is weak, thereby reducing demand on spares and preventing self-inflicted shortages.

The increase in tail times under ungoverned diagnostics reflects a system-level effect: when ambiguous messages prompt more troubleshooting and part changes, the spare system experiences more variability and higher utilization, which increases the probability that a later high-confidence event cannot be resolved quickly, producing a long-tail disruption that is expensive and operationally disruptive.

Nuisance Workload, Repeat Defects, and Operational Sustainability

It is important to recognize that operational degradation is often driven by the accumulation of low-value actions rather than by a single catastrophic failure. Metrics such as nuisance troubleshooting, repeat defects, and MEL-related deferrals capture how diagnostic and maintenance governance shapes workload, rework, and deferred-risk exposure.

A system that generates too many low-confidence alerts can consume technician capacity, delay resolution of high-consequence issues, and increase the likelihood that defects recur or that temporary deferrals remain in place longer than intended. The table below therefore focuses on indicators that connect decision quality directly to maintenance burden and operational stability.

Table 3. Decision-system sustainability metrics

Metric	A Baseline	B Ungoverned diagnostics	C Confidence-based	D Two-tier governed
Nuisance troubleshooting actions per 100 departures	21.4	33.6	18.7	17.9
Repeat-defect disruptions per 1000 departures	10.8	12.5	9.1	7.8
MEL deferrals per 1000 departures	38.2	41.7	35.6	33.9
MEL removals overdue probability	0.031	0.036	0.026	0.021

Source: data proceed

Table 3 shows that sustainability depends on controlling nuisance workload and managing repeat defects through disciplined governance, because technician time and operational attention are limited resources and high nuisance rates create a feedback loop where teams either become desensitized to messages or spend excessive time chasing low-value anomalies. The confidence-based and governed architectures reduce nuisance actions by filtering weak evidence and by using bounded verification steps, which preserves gate time for high-value tasks and improves overall dispatch performance.

Repeat-defect disruption decreases in the governed architecture because standardized MEL decisions incorporate repeat history and verification triggers that prevent the organization from repeatedly deferring the same ambiguous issue without confirmation, thereby reducing the probability that a deferred defect becomes a later disruption. The reduction in overdue MEL removals is also operationally important because it reduces compliance risk and prevents compounding scheduling complexity that occurs when aircraft carry multiple deferrals across rotations.

Discussion

The comparative results demonstrate that dispatch reliability in commercial aviation maintenance is governed by decision reliability, in which the most consequential outcomes arise from how uncertainty in fault evidence and spares availability propagates through troubleshooting, MEL decision-making, and recovery scheduling into tail delay behavior that dominates operational cost. The baseline architecture performs acceptably in many cases but exhibits significant tail risk because ambiguous faults lead to variable decision paths and because outstation constraints amplify spares-induced latency; this tail risk is the primary driver of delays exceeding 180 minutes and of cancellations that occur when recovery cannot be completed within crew and rotation constraints. Enhanced diagnostics without governance worsens outcomes because it increases the volume of ambiguous evidence and triggers more nuisance troubleshooting and part swaps, which consumes gate time and strains spares logistics, producing a systemic effect where the organization becomes less resilient to truly urgent defects due to resource saturation.

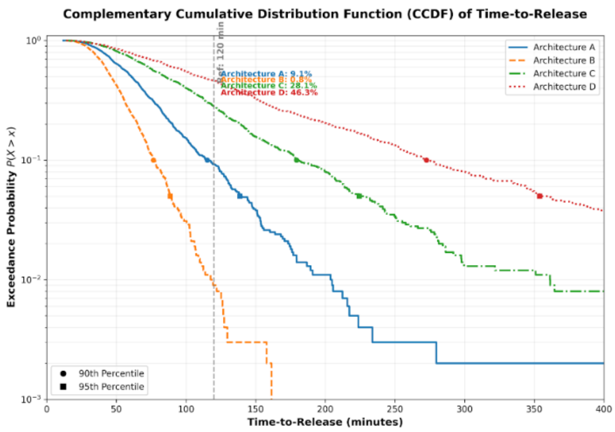

Figure 1. Complementary cumulatives distribution function (CCDF) of Time to release

The analysis of the CCDF curves reveals a sharp contrast in performance and reliability across the four tested architectures. Architecture B emerges as the benchmark for peak efficiency; its steeply declining curve indicates that nearly all release processes are completed within a very short timeframe. With an exceedance probability of only 0.8% beyond the 120-minute threshold, this architecture is the sole candidate capable of guaranteeing compliance with strict Service Level Agreements (SLAs). Following behind, Architecture A displays a balanced profile as a reliable system for standard operations. Its 90th percentile falls just below the 120-minute mark, offering sufficient predictability without the risk of extreme temporal fluctuations.

Architectures C and D present significant operational risks characterized by "long tail" distributions. Architecture C exhibits clear signs of inefficiency, with a 28.1% exceedance probability at the 120-minute mark—effectively meaning nearly one-third of all releases suffer from delays. The most critical condition, however, is observed in Architecture D. The slope of its curve is exceptionally shallow, with the probability of exceeding the reference time reaching 46.3%. The substantial gap between its 90th and 95th percentiles confirms a high degree of systemic uncertainty. Within Architecture D, a delay is no longer an anomaly but a risk nearly equivalent to a coin flip, making it highly unsuitable for mission-critical systems.

The confidence-based architecture improves reliability by making decision thresholds explicit and by reducing variance in decision pathways, which is critical because operational performance is sensitive not only to expected task time but to the variability and tail behavior of task completion, particularly when schedules have limited slack. Confidence scoring alone is insufficient if verification is not governed and if spares are not managed as part of a risk system, because uncertainty can remain high and spares constraints can still dominate long-tail releases (Baghaee et al., 2016; Chedrik, 2018; Denholm et al., 2014). The two-tier governed architecture addresses these limitations by aligning actions with evidence strength and by converting weak evidence into stronger evidence through bounded verification, while simultaneously reducing spares-induced tail risk through risk pooling and prioritized logistics. The key engineering mechanism is the decoupling of nuisance evidence from high-cost actions: instead of letting weak evidence trigger disruptive maintenance, the system triggers low-cost verification, and only escalates when confidence increases, which reduces both nuisance workload and spares demand variance (Nikitina et al., 2023; Shin & Lee, 2022).

From an applied engineering management perspective, the results imply that dispatch reliability programs should track and optimize distributional metrics such as the 90th and 95th percentiles of time-to-release and the probability of delays exceeding thresholds, because these metrics capture the tail behaviors that drive network disruption and passenger impact. Governance improvements should be treated as technical interventions: standardized MEL decision rules, explicit confidence thresholds, repeat-defect incorporation, bounded verification workflows, and spares risk pooling are engineering controls that shape decision-system reliability. Such interventions can often be implemented more rapidly than fleet-wide hardware upgrades or major analytics overhauls, and they may yield larger marginal gains because they address the main bottleneck: variability and latency in decision execution under uncertainty.

Practical implementation should emphasize three principles. First, nuisance control must be explicit: diagnostic message streams should be filtered or prioritized under a nuisance budget so that technicians and controllers remain responsive to high-value signals. Second, verification must be bounded: weak evidence should trigger fast verification that increases confidence rather than open-ended troubleshooting that consumes turn time, and verification outcomes should feed back into confidence scoring. Third, spares should be treated as a tail-risk resource: risk pooling and prioritized logistics should target the parts and stations that dominate long delays, rather than optimizing average spares levels uniformly. Together, these principles convert dispatch reliability from a reactive maintenance function into an engineered reliability decision system.

5. CONCLUSION

Dispatch reliability is determined not only by component reliability but by the reliability of the maintenance decision pipeline that converts uncertain fault evidence into timely and correct dispatch outcomes under MEL governance and spares constraints. The scenario-based comparative analysis shows that tail delays and cancellations are dominated by diagnostic ambiguity and spares-induced recovery latency, that increasing diagnostics without governance can worsen performance by inflating nuisance troubleshooting and spares variability, and that the strongest reliability gains arise from governance that constrains nuisance actions, standardizes MEL decisions using explicit confidence thresholds and repeat history, bounds verification time, and manages spares through risk pooling and prioritized logistics.

REFERENCES

1. Abdu, N. J., Ighravwe, D. E., Etangetuk, A., Amole, A. O., & Ajayi, S. T. (2024). Aviation Power-System Maintenance: Challenges, Innovations, and Operational Continuity. *2024 IEEE 5th International Conference on Electro-Computing Technologies for Humanity (NIGERCON)*, 1–5.
2. Alharasees, O., Zolfaghari, F., Kilikeviius, A., & Kale, U. (2025). Integrating PEAR-Based Human Factors Assessment with SEM-AHP for AI-Assisted UAV Operations. *2025 New Trends in Aviation Development (NTAD)*, 11–16. https://api.semanticscholar.org/CorpusID:284157956
3. Baghaee, H. R., Mirsalim, M., & Gharehpetian, G. B. (2016). Multi-objective optimal power management and sizing of a reliable wind/PV microgrid with hydrogen energy storage using MOPSO. *Journal of Intelligent & Fuzzy Systems*, *32*, 1753–1773. https://api.semanticscholar.org/CorpusID:31162609
4. Bao, D., & Sun, J. (2020). Research on Dispatch Reliability Allocation in Commercial Aircraft Development. *2020 Global Reliability and Prognostics and Health Management (PHM-Shanghai)*, 1–5.
5. Bu, J., Man, Y., Tan, L., Li, Z., Ou, Y., & Shao, C. (2023). Joint Optimization Model for Wind Turbine State-opportunity-based Maintenance Threshold Settings and Vehicles Dispatching Strategies. *2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE)*, 729–734. https://api.semanticscholar.org/CorpusID:268254846
6. Chedrik, V. V. (2018). *Probabilistic Method Of Determination of Allowable Design Parameter Scatters on Flutter and Strength Criteria*. https://api.semanticscholar.org/CorpusID:203594948
7. Denholm, P. L., Margolis, R. M., Palmintier, B., Barrows, C., & Ibanez, E. (2014). *Methods for Analyzing the Benefits and Costs of Distributed Photovoltaic Generation to the U.S. Electric Utility System*. https://api.semanticscholar.org/CorpusID:16499654
8. Emery, H. (2017). *Commercial aviation language testing: Barriers to success? A case study*. https://api.semanticscholar.org/CorpusID:116317661
9. Enrico, Z. I. O., Mengfei, F. A. N., Zhiguo, Z., & Rui, K. (2019). Application of reliability technologies in civil aviation: Lessons learnt and perspectives. *Chinese Journal of Aeronautics*, *32*(1), 143–158.
10. Fan, J., Jiao, J., & Zhao, T. (2014). Dispatch reliability of civil aviation simulation based on Generalized Stochastic Petri nets (GSPN). *2014 10th International Conference on Reliability, Maintainability and Safety (ICRMS)*, 1033–1038. https://api.semanticscholar.org/CorpusID:23192733
11. Feng, Y., Song, Z., & Cheng, L. (2023). Mechanical Dispatch Reliability Prediction for Civil Aircraft Considering Operational Parameters. *Computer Modeling in Engineering & Sciences*, *134*(3), 1925.
12. Haosong, H., & Jianjun, H. (2018). Dispatch Reliability Oriented MMEL Formulation Technology Research. *2018 3rd International Conference on System Reliability and Safety (ICSRS)*, 203–209. https://api.semanticscholar.org/CorpusID:116885072
13. Huang, K., Jia, G., Jiao, Z., Wang, Q., Huang, F., & Cai, Y. (2025). Remaining Useful Life Prediction Through Adaptive Spatiotemporal Graph Neural Network Based on Relationship Mining for Complex Aviation Equipment. *IEEE Sensors Journal*, *25*, 40775–40792. https://api.semanticscholar.org/CorpusID:281408909
14. Khan, K., Sohaib, M., Rashid, A., Ali, S., Akbar, H., Basit, A., & Ahmad, T. (2021). Recent trends and challenges in predictive maintenance of aircraft's engine and hydraulic system. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *43*. https://api.semanticscholar.org/CorpusID:238800347
15. Kim, J.-D., Choi, S.-B., Lee, J.-M., Kim, M. K., Choi, S.-C., Hwang, I.-J., & Choi, J. (2014). Conceptual design of a web-based LNG plant management system through adoption of the integrated environment for design and maintenance. *Journal of Mechanical Science and Technology*, *28*, 3759–3767. https://api.semanticscholar.org/CorpusID:110329467
16. Koornneef, H., Verhagen, W. J. C., & Curran, R. (2017). A multi-criteria decision making framework for aircraft dispatch assessment. In *Transdisciplinary Engineering: A Paradigm Shift* (pp. 11–20). IOS Press.
17. Koornneef, H., Verhagen, W. J. C., & Curran, R. (2020). A decision support framework and prototype for aircraft dispatch assessment. *Decision Support Systems*, *135*, 113338.
18. Koornneef, H., Verhagen, W. J. C., & Curran, R. (2021). A web-based decision support system for aircraft dispatch and maintenance. *Aerospace*, *8*(6), 154.
19. Nesterenko, K., Rahulin, S. V, Syroizhka, I. O., Dmitriev, O., Zhivitsky, N., & Sharabaiko, A. N. (2019). The Application of Information Technologies during Maintenance to Ensure The Reliability of The Operation of Aviation Equipment. *Системи Управління, Навігації Та Зв'язку. Збірник Наукових Праць*. https://api.semanticscholar.org/CorpusID:132636343
20. Nikitina, V. N., Kalinina, N. I., Dubrovskaya, E. N., & Plekhanov, V. P. (2023). Hygienic Studies of Electromagnetic Fields in the Work Environment during Operation of Ground-Based Radio Navigation and

Aircraft Landing. *ЗДОРОВЬЕ НАСЕЛЕНИЯ И СРЕДА ОБИТАНИЯ - ЗНиСО / PUBLIC HEALTH AND LIFE ENVIRONMENT*. https://api.semanticscholar.org/CorpusID:259783841

21. Ren, H., Chen, X., & Chen, Y. (2017). *Reliability based aircraft maintenance optimization and applications*. Academic Press.
22. Schmid, D., Korn, B., Wies, M., & Stanton, N. A. (2019). Managing a Data-link Failure of a Single-piloted Airliner during Flight: A System-Theoretic Process Analysis. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *63*, 106–110. https://api.semanticscholar.org/CorpusID:209068751
23. Shin, D., & Lee, S. (2022). *HPC Analytics of Fused Thermal Plants Data to Optimize Operating Envelope*. https://api.semanticscholar.org/CorpusID:261976316
24. Somsuk, N., & Paethrangsi, N. (2025). A multi-theoretical SEM model of strategic enablers driving airline operational performance in Thailand. *Archives of Transport*. https://api.semanticscholar.org/CorpusID:284557375
25. Stamatellos, G., & Stamatelos, T. (2023). Short-Term Load Forecasting of the Greek Electricity System. *Applied Sciences*. https://api.semanticscholar.org/CorpusID:257133800
26. van Kessel, P. J., Freeman, F. C., & Santos, B. F. (2023). Airline maintenance task rescheduling in a disruptive environment. *European Journal of Operational Research*, *308*(2), 605–621.
27. Xu, H., Wang, D., Niu, G., Wang, X., Liu, R., & Hu, B. (2022). Service Oriented Profile Reliability Assessment of an Aviation Mechatronic Servo Actuation System. *Journal of Physics: Conference Series*, *2417*. https://api.semanticscholar.org/CorpusID:254996076
28. Zhou, H. (2024). Reliability-Centered Hierarchical Maintenance Policy for Maximizing Fleet Availability-A Study in the Aviation Maintenance, Repair, and Overhaul (MRO) Sector. *Repair, and Overhaul (MRO) Sector (November 01, 2024)*.