

MONITORING-DRIVEN DECISION SUPPORT FOR AVIATION SPARE PARTS LOGISTICS

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The increasing complexity of transport technologies, maintenance operations, and spare-parts logistics requires decision-support approaches that integrate monitoring, information quality assessment, and operational risk evaluation under capacity-constrained conditions. Although existing research has extensively addressed inventory optimization and maintenance scheduling, considerably less attention has been devoted to understanding how monitoring quality and information reliability influence logistics resilience and the continuity of transport systems. This paper proposes a monitoring-driven decision-support framework for integrated transport spare-parts logistics that combines qualitative system modelling with symbolic decision structures and logistics risk assessment. The proposed framework links monitoring processes, information quality, spare-parts availability, repair coordination, and human decision-making into a unified analytical architecture supporting modern transport technologies. Information deficiencies are interpreted as control deviations that propagate through logistics processes and increase the probability of transport asset downtime and service disruption. A conceptual monitoring-to-risk propagation model is introduced to describe the relationship between information quality, automation performance, operator intervention, and logistics resilience under degraded operating conditions. Furthermore, an illustrative multi-criteria decision formulation is presented to analyse trade-offs between transport availability, logistics costs, inventory policies, and expedited dispatch strategies. The proposed modelling approach is intended primarily for conceptual and qualitative analysis, rather than for precise operational prediction. It provides a structured foundation for analysing monitoring-driven logistics resilience, supporting risk-informed decision-making, and facilitating the future development of digital transport technologies, digital twins, and intelligent decision-support systems for integrated transport logistics.

KEYWORDS

Airport logistics, aviation industry, qualitative modelling, logistic dynamics, spare parts supply, decision support systems, monitoring and control, delay risk.

1 INTRODUCTION

The rapid digital transformation of aviation transport has fundamentally changed the requirements imposed on logistics support systems. Modern maintenance, repair and overhaul (MRO) organizations increasingly rely on integrated digital infrastructures capable of monitoring spare-parts availability, maintenance status, supplier performance and transport

operations in real time. As aircraft systems become more technologically advanced and global supply chains more interconnected, aviation logistics has evolved from a traditional inventory management function into an information-intensive decision-support system directly influencing aircraft availability, operational reliability and transport continuity [Ivanov 2020, Torralba-Carnerero 2024].

The availability of spare parts represents one of the most influential factors affecting aircraft operational readiness. Delays in spare-parts delivery, limited repair capacity, supplier uncertainty or inaccurate inventory information frequently result in aircraft-on-ground (AOG) events, prolonged maintenance cycles and increased operational costs [Kilpi 2004]. Consequently, aviation logistics must not only ensure the physical movement of components but also continuously evaluate information quality and coordinate corrective actions across multiple organizational levels.

Recent advances in Industry 4.0 technologies, digital twins, sensor networks and intelligent monitoring systems have significantly improved the capability of logistics organizations to collect operational data in real time [Murcinkova 2013]. Nevertheless, the availability of large amounts of data does not automatically guarantee effective logistics decision-making. In many practical situations, delayed, incomplete or inconsistent information may propagate through maintenance processes, leading to inappropriate inventory decisions, inefficient repair prioritization and reduced transport resilience [Christopher 2004].

Another important characteristic of aviation logistics is the increasing interaction between automated decision-support systems and human operators. While automation can substantially improve the efficiency of routine logistics processes, experienced logistics personnel remain essential when unexpected failures, supply-chain disruptions or degraded operating conditions occur [Parasuraman 2000, Hollnagel 2015]. Effective aviation logistics therefore requires a balanced integration of monitoring technologies, automation and human expertise capable of maintaining system performance despite uncertainty and capacity constraints. Most existing research focuses on inventory optimization, spare-parts allocation, maintenance scheduling or supply-chain optimization as separate problems [Costantino 2013, Ertogral 2019].

Comparatively less attention has been devoted to integrated modelling approaches that explicitly connect logistics monitoring, information quality assessment, operational risk propagation and decision-support mechanisms within a unified analytical framework. Such integration is particularly important because deficiencies in monitoring frequently propagate through logistics processes before becoming visible as aircraft delays, maintenance bottlenecks or transport disruptions. Building upon the conceptual framework for integrated aviation logistics, this paper extends the analysis toward monitoring-driven logistics control and decision support. The emphasis is placed on understanding how monitoring information influences logistics resilience and how information degradation propagates into operational risk under capacity-constrained conditions [Liu 2021]. Unlike purely optimization-oriented approaches, the proposed methodology focuses on qualitative system behaviour and decision-support structures that remain applicable even when complete operational datasets are unavailable.

The primary objective of this paper is to develop a monitoring-driven framework for indirect aviation logistics support that integrates information quality assessment, logistics monitoring, operational risk propagation and symbolic decision-support modelling. To achieve this objective, the following research tasks are addressed:

- to analyse the role of monitoring and information quality in integrated aviation spare-parts logistics,
 - to develop a qualitative framework describing the propagation of monitoring deficiencies into logistics-induced operational risk,
 - to formulate symbolic decision-support structures linking monitoring outputs with inventory replenishment, repair prioritization and transport continuity,
 - to introduce an illustrative multi-criteria decision model representing trade-offs between aircraft availability, logistics costs and maintenance responsiveness,
 - to discuss the interaction between automation and human operators in maintaining logistics resilience under degraded operating conditions.
- The modelling approach presented in this paper is intended primarily for conceptual and qualitative analysis. It establishes a structured foundation for future quantitative calibration using operational aviation logistics data and supports the development of digital-twin-based monitoring systems and intelligent decision-support tools for resilient aviation logistics.

2 METHODOLOGICAL FRAMEWORK

The methodological workflow adopted in this paper consists of four consecutive analytical stages. The first stage focuses on monitoring logistics information throughout the spare-parts supply chain. The second stage evaluates the influence of monitoring quality on operator performance and automation reliability. Subsequently, monitoring outputs are propagated into a qualitative logistics-risk model describing disruption development under capacity constraints. Finally, symbolic multi-criteria decision modelling is introduced to support inventory management and maintenance prioritization. This sequential methodology establishes a consistent analytical framework linking information acquisition, risk assessment and operational decision-making. The first analytical stage focuses on monitoring because the quality of logistics information determines the effectiveness of all subsequent decision-support activities. Consequently, the following section examines how monitoring structures contribute to the overall performance of aviation spare-parts logistics.

3 INFORMATION QUALITY AND LOGISTICS CONTROL

Information quality is a critical determinant of indirect logistics performance. In practice, incomplete, delayed, or inaccurate information regarding inventory status, component condition, or transport progress significantly increases the likelihood of logistics-induced disruption [Torralba-Carnerero 2024]. Within the proposed framework, such information deficiencies are interpreted as control deviations that impair the effectiveness of logistics decisions.

The monitoring and control structure supporting indirect logistics is schematically illustrated in Figure 1, which depicts the spatial-temporal tracking of SP within the logistics chain. This representation highlights how delays or information losses at intermediate stages propagate through the system and affect the timeliness of repair and delivery activities [Gallego-Garcia 2021].

The dynamics of spare-part availability over delivery time, including natural saturation effects due to organizational and capacity constraints, are further illustrated in Figure 2. The logistic growth profile shown in this figure reflects typical behaviour observed in aviation supply chains, where initial ramp-up, accelerated delivery, and eventual saturation phases are influenced by supplier responsiveness, transport capacity,

and internal processing limits [Holmstrom 2010]. Although Figure 1 illustrates the structure of logistics monitoring, the resulting information must ultimately be translated into measurable logistics performance indicators [Zidek 2024]. For this reason, the temporal evolution of spare-parts availability is analysed in the following section using a qualitative logistics-growth model.

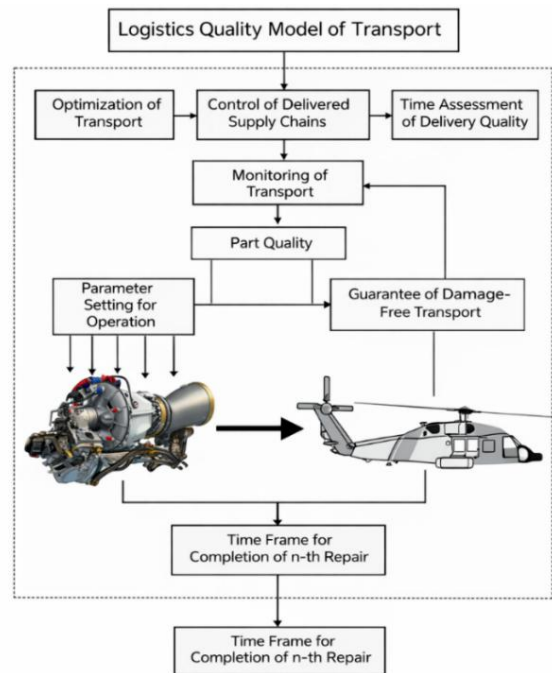


Figure 1. Spatial-temporal tracking of spare parts within the logistics model

3.1 Monitoring Quality Index

Effective monitoring in aviation spare-parts logistics depends on the quality of operational information available throughout the logistics process. From the perspective of logistics control, monitoring quality is primarily determined by three attributes: the completeness of collected information, its accuracy, and the timeliness with which information becomes available for decision-making. Since deficiencies in any of these attributes may significantly reduce the effectiveness of logistics support, an aggregated monitoring indicator is introduced.

The overall monitoring quality is expressed by the normalized Monitoring Quality Index:

$$M_Q = \omega_1 I + \omega_2 A + \omega_3 T \quad (1)$$

Where:

- M_Q – Monitoring Quality Index;
- I – information completeness;
- A – information accuracy;
- T – information timeliness;

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad (2)$$

where w_1, w_2, w_3 – weighting coefficients.

All three information-quality components are normalized to the interval [0,1], where 0 represents the lowest and 1 the highest information quality. The weighting coefficients are non-negative and sum to one. Their values may be selected according to the relative importance of completeness, accuracy, and timeliness for a particular logistics application; in the present conceptual framework, they are treated as model parameters rather than empirically calibrated quantities.

The Monitoring Quality Index provides an aggregated qualitative measure describing the effectiveness of information acquisition and processing within the aviation spare-parts logistics chain. High values of M_Q indicate reliable monitoring capable of supporting accurate inventory planning, maintenance coordination and transport scheduling. Conversely, decreasing monitoring quality increases uncertainty in logistics processes, resulting in delayed decision-making, reduced maintenance responsiveness and an increased probability of operational disruption. Although the proposed index is intentionally simplified, it provides a convenient analytical indicator for evaluating the influence of monitoring quality on subsequent logistics processes. Within the proposed framework, the Monitoring Quality Index represents the principal information input to the logistics resilience and risk-propagation models developed in the following sections. Figure 2 describes the temporal evolution of spare-part availability; therefore, the following section analyses this development using a qualitative logistics-growth model to illustrate how logistics performance evolves under finite transport and maintenance capacities.

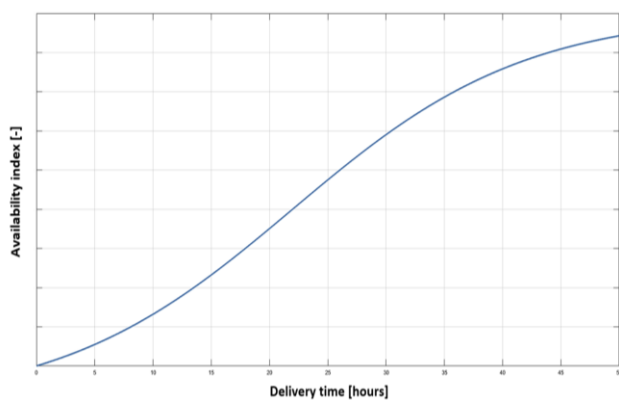


Figure 2. Logistic growth model of spare-part availability as a function of delivery time

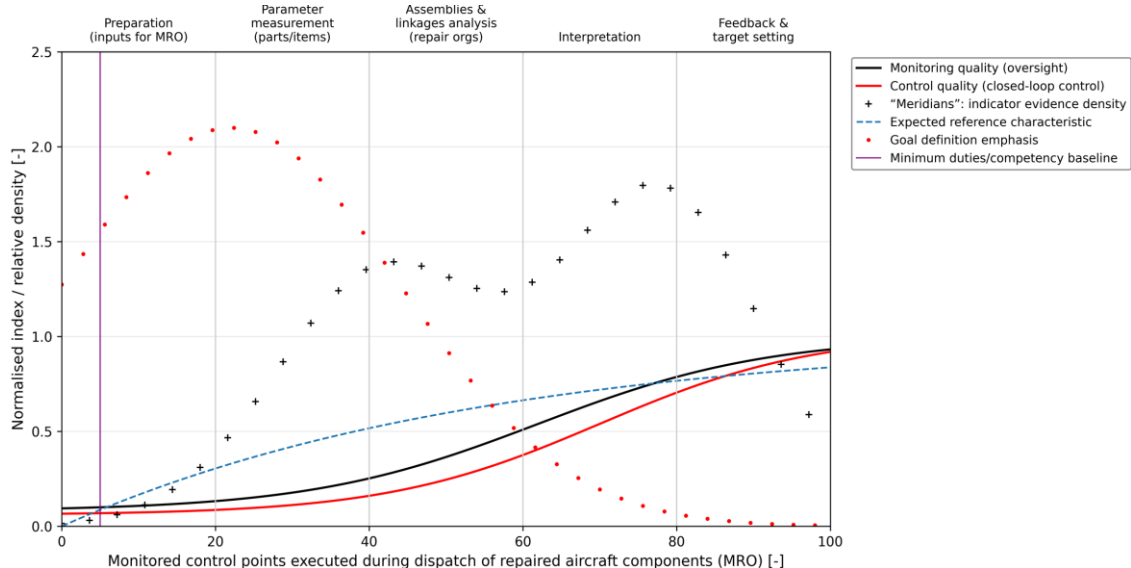


Figure 3. Evaluation of the logistics operator's quality (monitoring and control)

The capability of an aviation logistics system to maintain aircraft support under disturbances can be described using the concept of logistics resilience. Within the proposed framework, resilience is interpreted as the ability of the monitoring, decision-support and maintenance processes to preserve operational continuity despite spare-parts shortages, repair delays or degraded information quality:

The Monitoring Quality Index represents the primary information input of the proposed framework. The following sections demonstrate how monitoring quality propagates through operator performance and logistics resilience into operational decision support.

4 RESULTS

Despite increasing automation and digitalization in aviation logistics, the human operator remains an essential component of indirect logistics support [Hollnagel 2015]. This is particularly evident in non-standard or degraded operating conditions, where automated systems may provide incomplete, inconsistent, or delayed recommendations [Parasuraman 2000, Lee 2004].

Evaluation of logistics operator performance in monitoring and control is illustrated in Figure 3, which outlines a structured assessment of operator performance across goal definition, monitoring effectiveness, coordination of logistics sub-processes, and feedback management. This representation reflects the practical reality that logistics performance depends not only on system automation, but also on operator competence, workload, and decision quality.

Figure 4 further conceptualizes logistics operator resilience as the ability to sustain effective decision-making under degraded operating conditions. This figure highlights inferred operator capabilities related to adaptability, coordination, and corrective action, which contribute to the overall robustness of the logistics system in the presence of uncertainty and disruptions. Although operator performance represents an important component of indirect logistics support, its practical importance lies primarily in its influence on operational risk. Consequently, the following section investigates how monitoring deficiencies, automation limitations and human performance jointly determine the probability of logistics-induced disruption. Accordingly, resilience can be interpreted as an intermediate state variable connecting monitoring performance with operational logistics risk.

$$L_R = 1 - R_L \quad (3)$$

where:

- L_R — Logistics Resilience Index,
- R_L — normalized logistics disruption risk.

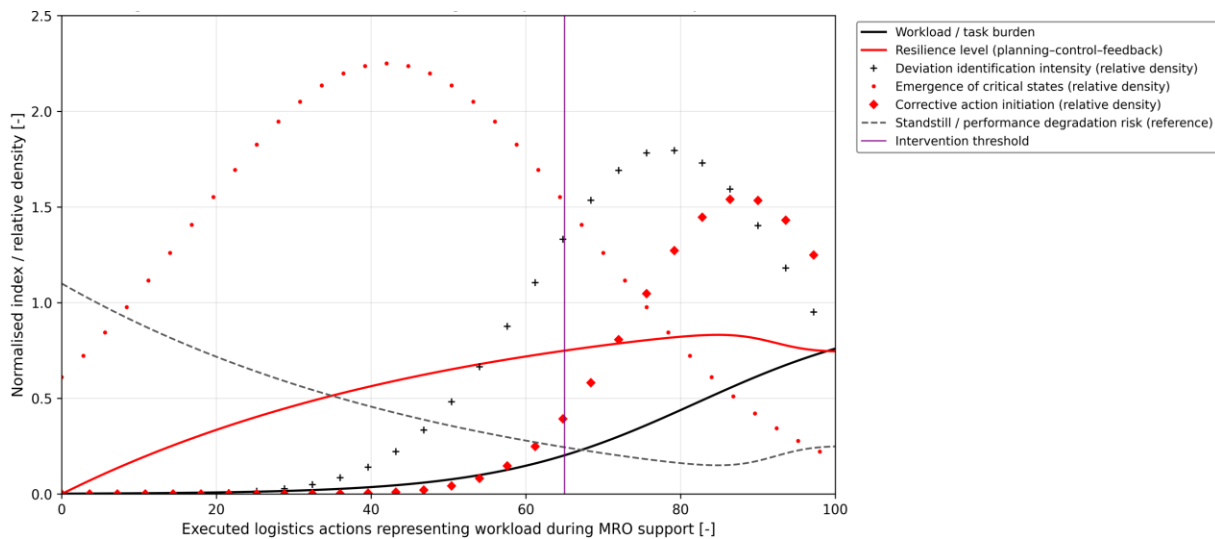


Figure 4. Resilience assessment of the logistics operator (inferred capabilities)

And the following condition applies: $0 \leq L_R \leq 1$

The Logistics Resilience Index is introduced here as a derived conceptual indicator based on the normalized logistics disruption risk, rather than as an independently calibrated or experimentally validated metric. Higher values of the Logistics Resilience Index indicate an increased capability of the logistics system to maintain aircraft operational readiness despite disturbances occurring within the spare-parts supply chain. Conversely, decreasing resilience reflects reduced robustness of logistics processes and an increasing probability of operational disruption. The resilience index provides the conceptual link between monitoring quality and operational risk. Consequently, the following section analyses how degradation of monitoring

effectiveness propagates into logistics-induced disruption under capacity-constrained operating conditions.

4.1 Monitoring-to-Risk Propagation in Logistics Operations

To analyze how deficiencies in monitoring and decision quality propagate into operational risk, an automated monitoring and evaluation structure is introduced in Figure 5. This model integrates input logistics effectiveness, the probability of problem occurrence, and process degradation into a unified assessment of logistics performance under uncertainty [Ivanov 2020, Demcak 2024, Hu 2026].

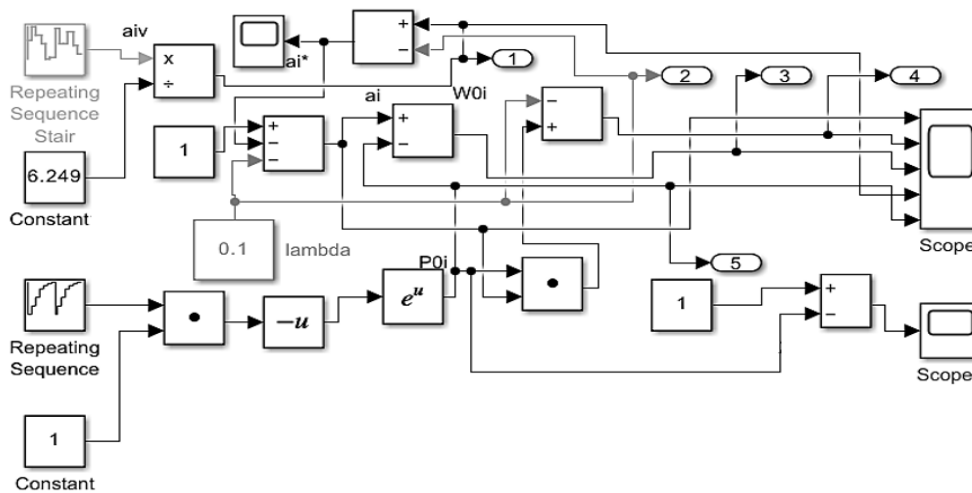


Figure 5. Automated monitoring model for complex logistics processes

Legend: aiv – level of input efficiency of the logistics process (order quality, SP availability, supplier reliability); λ (lambda) – intensity of problem occurrence in the supply process; a_i – current process efficiency after accounting for the impact of failures; w_{0i} – weighting coefficient representing the importance of input efficiency; p_{0i} – probability of a problem arising at a given step of the process.

Figure 6 illustrates how degradation in process effectiveness propagates into disruption risk over time. The illustrative model indicates a non-linear relationship between monitoring quality and the probability of logistics-induced disruption, suggesting that relatively small degradations in information quality or response effectiveness may lead to disproportionate increases in aircraft downtime and transport delays [Parasuraman 2000]. From a transport-system perspective, this monitoring-to-risk propagation framework provides a qualitative basis for assessing logistics resilience and for comparing alternative organizational

and technological configurations with respect to their ability to mitigate disruption under capacity-constrained conditions. Although the monitoring-to-risk model quantifies the likelihood of logistics disruption, the obtained risk estimate alone does not improve logistics performance. Operational improvements are achieved only after the estimated risk is incorporated into inventory planning, repair prioritization and dispatch decisions. Consequently, the following section introduces a symbolic decision-support formulation linking logistics risk with operational optimization.

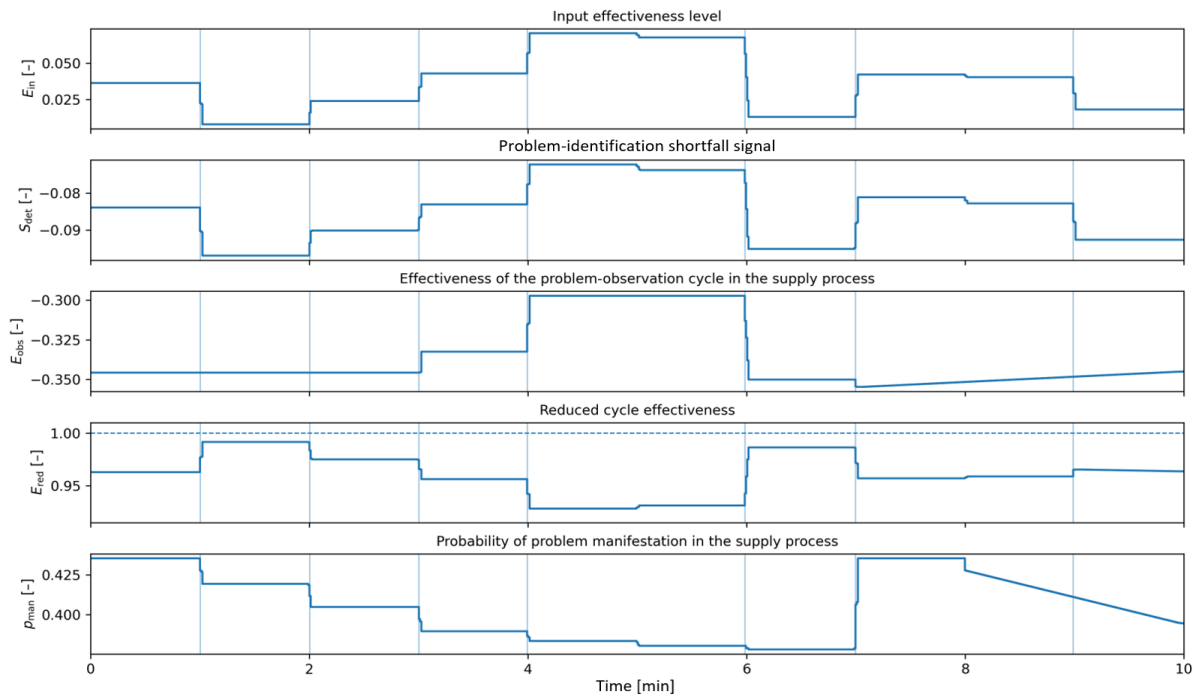


Figure 6. Supply-process effectiveness to risk propagation (time histories)

Legend: Vertical markers (in subplot number 4) indicate scenario-change instants in E_{in} .

Decision-making in indirect aviation logistics often involves trade-offs among competing objectives, particularly between minimizing aircraft downtime and controlling logistics-related costs. From a transport-system perspective, these trade-offs directly affect delay risk, schedule reliability, and service continuity. To illustrate how such decisions may be formally represented within the proposed conceptual framework, an illustrative symbolic optimization formulation is introduced. Let the aggregated decision objective be expressed as:

$$\min_{SS_L, x_{AOG}} J = w_D \mathbb{E}[D] + w_C \mathbb{E}[C], \quad (4)$$

where $\mathbb{E}[D]$ – is the expected time loss associated with logistics-induced aircraft downtime or delay,
 $\mathbb{E}[C]$ – is the corresponding logistics cost indicator,
 w_T, w_C – are weighting coefficients reflecting the operator's preference between time availability and cost efficiency. The estimated logistics risk therefore becomes an input variable for operational decision-making, linking monitoring performance directly with inventory policies and transport continuity. The expected time loss may be expressed as:

$$\mathbb{E}[D] = \lambda_d p_{so}(SS_L) ((1 - x_{AOG}) L_{std} + x_{AOG} L_{AOG}), \quad (5)$$

where λ is the average demand intensity,
 $p_{so}(SS_L)$ is the probability of a shortage event as a function of the local service stock level SS_L ,
 x_{AOG} – is a binary variable indicating the dispatch mode ($x_{AOG} = 1$: AOG/expedite; $x_{AOG} = 0$: standard dispatch),
 L_{std} and L_{AOG} – are the lead-times for standard and expedited dispatch, respectively [h].
The cost function is defined as:

$$\mathbb{E}[C] = c_h SS_L + c_{AOG} \lambda_d p_{so}(SS_L) x_{AOG}, \quad (6)$$

where c_h – is the holding-cost coefficient per stocked unit [cost units per unit-month],
 c_{AOG} – is the expedite-cost coefficient per expedited shortage event [cost units per event].
The decision variables are subject to operational constraints:

$$0 \leq SS_L \leq SS_{max}, x_{AOG} \in \{0, 1\}. \quad (7)$$

This formulation does not aim to provide a fully calibrated optimization solution, but rather to demonstrate how indirect logistics decisions may be structured symbolically within a multi-criteria framework. Table 1 summarizes illustrative trade-offs among service stock level, dispatch mode, expected time loss, and logistics cost.

Option	SS_L [pcs]	Dispatch mode	Assumed $p_{so}(SS_L)$	$\mathbb{E}[D]$ [h/month]	$\mathbb{E}[C]$ [cost index]
A	0	Standard	0.8	76.8	0.0
B	0	AOG/expedite	0.8	25.6	8.0
C	1	Standard	0.3	28.8	1.0
D	1	AOG/expedite	0.3	9.6	4.0
E	2	Standard	0.1	9.6	2.0
F	2	AOG/expedite	0.1	3.2	3.0

Table 1. Illustrative trade-off between service stock and expedited dispatch

Note: Assume $L_{std} = 48$ h; $L_{AOG} = 16$ h; $\lambda_d = 2$ events/month. For the cost index, assume $c_h = 1$ cost unit per stocked unit/month and $c_{AOG} = 5$ cost units per expedited shortage event. Increasing SS_L reduces expected time-loss by lowering the probability of shortage, while expedited dispatch reduces the time-loss per shortage event at a higher cost. For example, option E ($SS_L = 2$, standard) yields a similar $\mathbb{E}[D]$ as option D ($SS_L = 1$, AOG), but with a different cost profile, illustrating the multi-criteria nature of the decision. The illustrative scenarios demonstrate that different inventory policies may achieve similar operational availability while requiring substantially different logistics expenditures. Consequently, optimization should be interpreted as a decision-support process balancing transport continuity, maintenance responsiveness and economic efficiency rather than minimizing a single objective function. From a transport-system perspective, the formulation highlights that different combinations of inventory and dispatch policies may yield comparable time-loss outcomes at different cost levels, or vice versa. This reinforces the role of human decision-making in selecting acceptable compromise solutions

under capacity constraints and uncertainty, consistent with the conceptual framework presented in Figure 1. Unlike conventional spare-parts inventory models that primarily optimize stock levels, the proposed framework integrates monitoring quality, operator performance and logistics resilience into a unified analytical structure. This systems-oriented perspective enables qualitative assessment of logistics behaviour even when complete operational datasets are unavailable. Consequently, the methodology may support preliminary logistics system design, airport maintenance planning and future implementation of digital-twin-based decision-support systems.

5 CONCLUSIONS

This paper proposes a monitoring-driven decision-support framework for transport spare-parts logistics under capacity-constrained conditions. The framework integrates logistics monitoring, information quality assessment, operational risk propagation, and symbolic decision modelling into a unified conceptual architecture supporting resilient transport operations. The proposed approach illustrates how monitoring quality may influence logistics resilience and transport continuity. Information deficiencies propagate through logistics processes, increasing the probability of spare-parts shortages, maintenance delays, and transport disruptions. The introduced Monitoring Quality Index, Logistics Resilience Index, and monitoring-to-risk propagation model provide qualitative tools for analysing these relationships. An illustrative multi-criteria decision formulation further shows how trade-offs between transport availability, logistics costs, inventory policies, and dispatch strategies can be systematically evaluated. The analysis also highlights that effective logistics performance depends on the complementary roles of automation and human operators, particularly under degraded operating conditions. Although the presented methodology is intended primarily for conceptual and qualitative analysis, it establishes a structured basis for future quantitative calibration using operational logistics data. Future research will focus on validating the proposed framework with real transport data, integrating digital-twin technologies, and developing intelligent decision-support systems for resilient transport logistics.

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