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**A MODELING AND SIMULATION FRAMEWORK FOR  
SUPPORTING MILITARY AIR OPERATIONS: A  
HYBRID APPROACH**

Dissertation approved in its final version by signatories below:

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# A MODELING AND SIMULATION FRAMEWORK FOR SUPPORTING MILITARY AIR OPERATIONS: A HYBRID APPROACH

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I dedicate this work to my wife, Renata,  
and my daughter, Laís, my constant lift  
and compass. With you, every mission  
has meaning.

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*"Having the ability to improvise is essential,  
improvising as a rule is recklessness."*

— REIS JÚNIOR

# Resumo

Esta dissertação aborda o desafio da tomada de decisão em operações aéreas militares sob condições de incerteza, nas quais a limitada capacidade de antecipação do comportamento do sistema e as restrições de recursos podem degradar a efetividade operacional e a relação custo-benefício. Para apoiar a tomada de decisão nesse contexto, é desenvolvido um arcabouço de apoio à decisão baseado em simulação, integrando modelagem baseada em agentes do comportamento individual das aeronaves com simulação a eventos discretos dos processos operacionais, de manutenção e logísticos. O arcabouço incorpora representações estocásticas de falhas, tempos de reparo e atrasos no suprimento, e emprega experimentação de Monte Carlo para gerar indicadores probabilísticos relacionados ao sucesso das missões, disponibilidade das aeronaves, demandas de manutenção e restrições logísticas. A abordagem proposta é aplicada a um estudo de caso baseado em operações aéreas militares sustentadas, incluindo a calibração com dados da COMAO 2024 (Composite Air Operations – Training Phase) e a análise preditiva para a CRUZEX 2024 (Exercício Cruzeiro do Sul – exercício aéreo multinacional de grande escala). Esses cenários fornecem um ambiente operacional realista para avaliar a capacidade do arcabouço em representar a dinâmica do sistema e apoiar o planejamento sob incerteza. Os resultados demonstram que o arcabouço aprimora o apoio à decisão ao aumentar a precisão, a consciência situacional relativa ao suporte e a capacidade antecipatória, permitindo uma avaliação mais informada dos estados futuros do sistema e dos riscos associados. Em vez de prever resultados exatos, o arcabouço fornece uma visão probabilística do comportamento do sistema, contribuindo para uma tomada de decisão mais robusta e fundamentada em ambientes operacionais complexos.

# Abstract

This dissertation addresses the challenge of decision-making in military air operations under conditions of uncertainty, where limited foresight of system behavior and resource constraints can degrade operational effectiveness and cost–benefit performance. To support decision-making in this context, a simulation-based decision-support framework is developed, integrating agent-based modeling of individual aircraft behavior with discrete-event simulation of operational, maintenance, and logistics processes. The framework incorporates stochastic representations of failures, repair durations, and supply delays, and employs Monte Carlo experimentation to generate probabilistic indicators related to mission success, aircraft availability, maintenance workload, and logistics constraints. The proposed approach is applied to a case study based on sustained military air operations, including calibration with data from COMAO 2024 (Composite Air Operations – Training Phase) and forecasting analysis for CRUZEX 2024 (Cruzeiro do Sul Exercise – Large-Scale Multinational Air Exercise). These scenarios provide a realistic operational environment to evaluate the framework’s capability to represent system dynamics and support planning under uncertainty. Results demonstrate that the framework enhances decision-support by improving precision, support awareness, and anticipatory capability, enabling more informed assessment of future system states and risks. Rather than predicting exact outcomes, the framework provides probabilistic insight into system behavior, supporting more robust and informed decision-making in complex operational environments.

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# List of Acronyms

<b>ABS</b> Agent-Based Simulation. . . . .	25, 41–45, 54, 55, 64, 65, 70, 72, 79–82, 84, 88, 93, 101
<b>AOG</b> Aircraft on Ground. . . . .	32, 108
<b>BIT</b> Built-in Test. . . . .	70
<b>CDF</b> Cumulative Distribution Function. . . . .	112
<b>DES</b> Discrete-Event Simulation. . . . .	25, 39–41, 43–45, 54, 55, 76–82, 84, 88, 93, 101
<b>DSS</b> Decision Support Systems. . . . .	30, 31
<b>FC</b> Flight Cycles. . . . .	31
<b>FH</b> Flight Hours. . . . .	31
<b>ILS</b> Integrated Logistics Support. . . . .	20
<b>IPS</b> Integrated Product Support. . . . .	20
<b>M&amp;S</b> Modeling and Simulation. . . . .	36
<b>MDT</b> Mean Maintenance Downtime. . . . .	32
<b>MTBM</b> Mean Time Between Maintenance. . . . .	32
<b>MTBR</b> Mean Time Between Replacement. . . . .	32
<b>PHASE_1</b> COMAO – Composite Air Operations 2024 – Training Phase. . . . .	117–121, 124, 128
<b>PHASE_2</b> CRUZEX – Cruzeiro do Sul Exercise 2024 – Large-Scale Multinational Air Exercise. . . . .	117–125, 128
<b>PMF</b> Probability Mass Function. . . . .	96, 104, 112
<b>S.A.</b> Support Awareness. . . . .	25, 28, 30, 33–38, 40, 45, 48, 50–55, 84–87, 97, 107, 108, 110, 113, 114, 116, 123, 124, 126

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# 1 Introduction

## 1.1 Context and Motivation

Military air operations are conducted within complex socio-technical systems that require the coordinated interaction of operational execution, aircraft maintenance, and logistics support (LEVESON, 2011; BLANCHARD, 1998). In such systems, operational outcomes emerge from the dynamic interaction of technical components, organizational processes, and decision-making structures. This capability is commonly associated with the concept of supportability, understood as the system's capacity to maintain acceptable levels of operational and logistics effectiveness without disproportionate growth in cost (DAU, 2022).

In sustained air operations, increases in mission demand typically lead to higher aircraft utilization, accelerated component degradation, increased maintenance workload, and greater consumption of logistics resources. Studies in military logistics and reliability engineering indicate that higher operational tempo increases maintenance demand and spare parts consumption, thereby intensifying the stress on logistics support systems (BLANCHARD, 1998; SHERBROOKE, 2004). If not properly managed, these dynamics may result in a progressive degradation of the cost-benefit ratio, whereby additional expenditures yield diminishing operational returns. Although some degree of degradation is unavoidable, the inability to anticipate, understand, and manage this process represents a significant operational risk that affects the achievement of the mission (STACHEIRA *et al.*, 2024).

Historical experience in large-scale military operations also illustrates the challenges of sustainment planning under uncertainty. During Operation Desert Storm (1991), coalition forces deployed massive air and ground capabilities, generating unprecedented logistics demand. Although the campaign was operationally successful, planners faced significant difficulties forecasting spare parts requirements and positioning support resources across the theater. As a result, some items accumulated in excess while shortages emerged for others, revealing limitations in traditional planning approaches and motivating subsequent improvements in logistics forecasting and analytical decision-support tools (PAGONIS;

CRUIKSHANK, 1992; U.S. GOVERNMENT ACCOUNTABILITY OFFICE, 1991).

Managing logistics support in this context requires continuous and informed decision-making related to aircraft allocation, mission planning, maintenance scheduling, and logistics provisioning. However, these decisions are often made under conditions of uncertainty and incomplete information, as operational, maintenance, and logistics data are frequently fragmented across organizational and functional boundaries. In complex socio-technical systems, such fragmentation can limit the ability of decision-makers to understand system interactions and anticipate future states, thereby reducing the effectiveness of operational planning and resource allocation (LEVESON, 2011; ENDSLEY, 1995; HUNGER, 1996). As a consequence, decision-makers may struggle to understand how current actions affect future system states, limiting their ability to preserve operational effectiveness while controlling costs.

In addition to the inherent operational complexity, aircraft fleet management requires the integration of maintenance, logistics, and supportability considerations across multiple phases of the system life cycle. However, these aspects are frequently addressed in a fragmented manner, resulting in inconsistencies, delayed responses, and reduced operational effectiveness. As highlighted by Abrahão *et al.* (2019), the supportability of complex systems remains insufficiently integrated across life cycle phases, with limited knowledge dissemination and a lack of collaborative and comprehensive frameworks capable of supporting decision-making in an integrated manner. This gap is particularly critical in military aviation contexts, where operational readiness depends on the coordinated interaction between operational planning, maintenance processes, and logistics support.

From a systems engineering perspective, this challenge is closely related to the principles of Integrated Logistics Support (ILS) and Integrated Product Support (IPS), which emphasize the need for coordinated consideration of maintenance, logistics, and operational factors throughout the system life cycle.

## 1.2 Support and Decision-Making in Military Air Operations

Given these limitations in integrated support, the challenge of supporting military air operations is not solely technical but fundamentally decisional. Effective management of the cost-benefit ratio depends on the quality of decisions made throughout the operation, particularly in environments characterized by stochastic failures, variable repair times, and uncertain supply delays. In this setting, decision-makers require more than access to data; they require the ability to interpret system behavior and anticipate its evolution

over time.

In complex socio-technical systems, failures often emerge not from a single incorrect decision, but from the interaction of multiple locally rational decisions taken without full visibility of the system state. As noted by Leveson (2011), decentralized decision-making in complex socio-technical systems can produce undesirable outcomes even when individual decisions appear locally rational, because interactions among independently taken decisions may create dysfunctional system behavior.

Although Leveson (2011) discusses this phenomenon in the context of safety and accidents, the same systemic mechanisms may affect operational effectiveness in sustained military air operations. Decisions regarding flight tempo, maintenance prioritization, and logistics provisioning may individually appear reasonable but collectively produce unintended degradation of fleet availability and supportability when system-wide interactions are not fully understood.

The importance of structured forecasting in managerial decision-making has long been emphasized in logistics and management literature. Renfro and Morrison argue that “nothing is more important to accurate forecasting than developing a logical and consistent system which is responsive to the needs of managers and capable of being attuned to a changing environment” (Renfro and Morrison, apud (LAMBERT, 1993)). Forecasting methods are therefore fundamental to planning activities that must anticipate uncertain future conditions (WILSON; KEATING, 1994).

Furthermore, Lambert states that “forecasting is needed if management is to be able to approximate the future with some reasonable accuracy. Forecasting can provide a fairly accurate picture of the future; it is the driving force behind all forward planning activities within the firm” (LAMBERT, 1993).

In the context of sustained military air operations, this principle is particularly relevant: without structured and adaptive forecasting mechanisms, decisions regarding fleet allocation, maintenance exposure, and logistics provisioning remain vulnerable to reactive adjustments and experience-driven estimation rather than analytically grounded anticipation.

This requirement is closely related to the concept of situational awareness (or *support awareness*, for this dissertation context), which encompasses the perception of system elements, the comprehension of their interactions, and the projection of their future states (ENDSLEY, 1995; ENDSLEY; JONES, 2024). In fleet-level decision-making, support awareness extends beyond tactical considerations and includes understanding aircraft availability, maintenance status, logistics costs and constraints, and their combined impact on mission execution.

Static assessments, aggregated indicators, and deterministic assumptions may obscure

emerging constraints, such as clustered maintenance demands or impending logistics bottlenecks. In complex operational systems, overall performance is often constrained by a limited number of critical resources or processes, meaning that system-level performance may be determined by bottlenecks rather than by the local optimization of individual components (GOLDRATT, 1990). As a result, decisions intended to preserve effectiveness may inadvertently accelerate cost growth or reduce future mission decision-making capability.

### 1.3 Problem Statement

The sustainment of military air operations over extended periods requires decisions that balance operational effectiveness with the associated costs of maintenance and logistics support. In this context, supportability can be understood as the system's ability to maintain acceptable levels of effectiveness without excessive degradation of the cost-benefit relationship as operations evolve under uncertainty.

However, decision-making related to the support and sustainment of military air operations is constrained by limited precision, fragmented support awareness, and insufficient anticipatory capability. Operational execution, maintenance management, and logistics support are frequently addressed through separate tools and analyses, which restricts the decision-maker's ability to perceive the integrated system state, comprehend the interactions among its components, and anticipate future constraints arising from stochastic failures, repair delays, and supply limitations.

As a result, decisions affecting aircraft allocation, maintenance actions, and logistics provisioning are often based on static assessments or aggregated indicators that obscure dynamic behavior and uncertainty. These limitations reduce the ability to manage the *Support and Supportability Problem*, which is stated as the degradation of the cost-benefit ratio predicted during some life cycle phase of some system (STACHEIRA *et al.*, 2024). For sustained operations, these limitations increase the risk of reactive decision-making and inefficient use of available resources.

Therefore, the research problem can be stated as follows:

*Decision-making related to the supportability of military air operations is constrained by limited precision, fragmented support awareness, and insufficient anticipatory capability. These limitations reduce the ability to manage the degradation of the cost-benefit ratio during sustained operations conducted under uncertainty.*

## 1.4 Research Hypothesis

This research is based on the preliminary hypothesis that improving decision-support capabilities can mitigate the limitations identified in the problem statement. In particular, it is hypothesized that an integrated modeling approach can enhance the decision-maker's ability to understand system behavior and anticipate future constraints affecting supportability.

More specifically, the hypothesis of this work is that an integrated simulation-based decision-support framework, combining agent-based modeling of individual aircraft behavior with discrete-event modeling of operational, maintenance, and logistics processes, may enhance decision-making capability by improving precision, support awareness, and anticipatory capability, thereby supporting more effective management of logistics support and the cost-benefit ratio of military air operations within the defined scope of the study.

## 1.5 Objectives

The general objective of this research is to develop and evaluate a simulation-based decision-support framework that enhances precision, support awareness, and anticipatory capability in decisions related to the supportability and cost-benefit of sustained military air operations.

### 1.5.1 Specific Objectives

To achieve the general objective, the following specific objectives are pursued:

- To represent individual aircraft behavior and state evolution using agent-based modeling, using a tail-number approach, instead of a generic or uniform fleet approach.
- To model operational execution, maintenance workflows, and logistics support using discrete-event simulation.
- To incorporate stochastic representations of failures, repair times, and supply delays, in contrast to fixed values.
- To enable probabilistic analysis of operational outcomes through Monte Carlo experimentation, in contrast to single values.

- To evaluate how the proposed framework improves the quality of decision-support, particularly in terms of precision and support awareness, compared to fragmented or static planning approaches.

## 1.6 Scope and Limitations

This research focuses on decision support for military aviation fleet operations within a defined operational scope. The proposed framework is intended to support analysis at the operational and logistical decision-making level and does not aim to model detailed flight dynamics, human factors, or organizational behavior beyond their impact on support and sustainment, although the framework could be expanded for these other kinds of approaches in future works.

The emphasis of the study is on understanding system behavior and decision consequences under uncertainty, rather than on optimizing individual maintenance tasks or logistics processes. The limitations associated with modeling assumptions and abstraction choices are discussed in later chapters.

## 1.7 Structure of the Dissertation

This dissertation is organized as follows:

- Chapter 1 introduces the context and motivation of this dissertation. Then, it establishes the research problem, the preliminary hypothesis, the objectives, and the scope of this research.
- Chapter 2 reviews the literature on decision-making and support awareness in military aviation, modeling and simulation approaches, and their application to operations, maintenance, and logistics support.
- Chapter 3 presents the methodological framework adopted in this research, detailing the simulation architecture, modeling choices, and integration between agent-based and discrete-event simulation.
- Chapter 4 presents the simulation results and analyzes how the proposed framework supports decision-making and support awareness under different scenarios.
- Chapter 5 discusses the implications of the results, limitations of the study, and opportunities for future research.

## 2 Problem Research and Literature Review

This chapter reviews the theoretical and methodological foundations that support the development of the simulation-based decision-support model proposed in this dissertation. The review is structured to (i) establish the conceptual basis of decision-making and Support Awareness (S.A.) in military air operations contexts, and (ii) examine how modeling and simulation approaches have been used to represent the coupled dynamics of operations, maintenance, and logistics support.

First, the chapter discusses S.A. as a requirement for effective decision-making in socio-technical systems under uncertainty, emphasizing how fragmented information and static planning tools can limit the understanding of fleet readiness and mission feasibility over time. Next, it surveys the main classes of simulation approaches employed in aviation operations and sustainment studies, highlighting their typical scopes and limitations when applied in isolation.

The chapter then examines discrete-event simulation and agent-based simulation, discussing their respective strengths for representing process-driven dynamics and heterogeneous autonomous entities. Based on this discussion, hybrid approaches Agent-Based Simulation (ABS) - Discrete-Event Simulation (DES) are presented as a methodological direction capable of integrating aircraft-level behavior with structured operational and maintenance processes. Subsequently, the review addresses reliability, failures, maintenance workflows, and inventory modeling, emphasizing how stochastic demand and supply constraints affect availability and mission capability.

Finally, the chapter consolidates the findings of the literature and identifies the research gap addressed by this dissertation: the lack of transparent and integrated simulation frameworks that represent, within a unified environment, the interaction between operational demand, aircraft reliability, maintenance processes, and logistics support, while producing probabilistic outputs suitable for decision support and improved S.A.. This synthesis provides the foundation for Chapter 3, which presents the methodological approach and model architecture adopted in this research.

## 2.1 Definitions

### Support (Logistics Context)

In this dissertation, support refers to the set of maintenance, logistics, and resource-provisioning activities required to enable and sustain military air operations (BLANCHARD, 1998; DEFENSE ACQUISITION UNIVERSITY, 2024). This includes, but is not limited to, aircraft maintenance actions, spare parts provisioning, repair and inspection processes, logistics flows, and the allocation of support resources necessary to maintain aircraft in an operationally available condition. Support is therefore understood as an enabling function that directly influences operational availability and mission execution.

### Supportability

Supportability is defined as the ability of an aviation system to sustain operations over time while maintaining acceptable levels of operational effectiveness without excessive degradation of the cost–benefit relationship. In the context of military air operations, supportability emerges from the interaction between operational demand, aircraft reliability, maintenance capacity, and logistics support. It is not a static property, but a dynamic characteristic that evolves as operations progress under uncertainty and resource constraints (BLANCHARD, 1998; STACHEIRA *et al.*, 2024).

### Sustainability

Sustainability, within the scope of this dissertation, refers to the capacity to continue military air operations over extended periods without system collapse or unacceptable loss of capability. While sustainability is often used interchangeably with supportability in informal contexts, this work distinguishes the two concepts. Sustainability is treated as a broader operational condition, indicating whether operations can continue at all, whereas supportability focuses specifically on how effectively and efficiently those operations can be sustained in terms of cost and performance. Thus, supportability is considered a contributing dimension of sustainability.

### Uncertainty, Stochastic, and Probabilistic Concepts

Although the terms “uncertainty,” “stochastic,” and “probabilistic” are sometimes used interchangeably in informal contexts, this dissertation adopts a precise distinction consistent with modeling and simulation literature (LAW, 2015; TAYLOR, 2005).

*Uncertainty* refers to the epistemic condition in which the future state of the system cannot be predicted with certainty due to incomplete information, inherent variability, or system complexity. It characterizes the decision-making environment in which outcomes are not fully known in advance.

Uncertainty in complex systems may arise from different sources. In particular, it is commonly distinguished between *aleatory uncertainty*, which refers to inherent variability or randomness in system processes, and *epistemic uncertainty*, which refers to lack of knowledge or incomplete information about the system.

In the context of this dissertation, uncertainty is understood as encompassing both aspects. Aleatory uncertainty is represented through stochastic modeling of processes such as failures, repair durations, and supply delays, while epistemic uncertainty reflects limitations in forecasting, system visibility, and decision-making knowledge. The proposed framework does not explicitly separate these two types, but rather addresses their combined effect on system behavior and decision-support.

*Stochastic* refers to the modeling approach used to represent system processes whose behavior is governed by random variables. In this work, failures, repair durations, and supply delays are modeled as stochastic processes in order to capture variability in system dynamics.

*Probabilistic* refers to the form in which results are expressed and interpreted. Simulation outputs are analyzed probabilistically, typically as distributions, enabling the assessment of likelihoods, risks, and confidence levels associated with different outcomes.

Thus, uncertainty defines the problem context, stochastic modeling defines how system dynamics are represented, and probabilistic analysis defines how results are interpreted. In this sense, the proposed framework can be understood as transforming uncertainty into probabilistic insight through stochastic simulation.

Uncertainty  $\rightarrow$  (handled via) stochastic modeling  $\rightarrow$  (producing) probabilistic insight

This distinction is adopted to ensure terminological clarity throughout the dissertation and to avoid ambiguity in the interpretation of modeling assumptions and results.

### **Decision Sector**

In this dissertation, the Decision Sector refers to the decision-making function associated with the upper-level decision-maker responsible for defining the objectives, success criteria, and constraints of a military air operation, as well as for determining whether the operation should be executed, adapted, postponed, or canceled.

This sector precedes operational execution and logistics support and is primarily concerned with assessing mission feasibility, supportability, and risk, with particular emphasis on managing the cost-benefit of sustained operations under uncertainty. Decisions at this level are informed by the outputs of the proposed simulation framework, which provides probabilistic indicators related to mission success, aircraft availability, maintenance

workload, and logistics constraints, thereby enhancing precision, S.A., and anticipatory capability.

The term Decision Sector is deliberately adopted to avoid the use of hierarchical or doctrinal classifications such as operational, or tactical. These terms present well-known ambiguities due to differing interpretations in military doctrine and academic literature, particularly in contexts where alternative taxonomies coexist. By focusing on the decision-making function rather than hierarchical level, the adopted terminology ensures conceptual clarity and avoids misinterpretation regarding command authority, execution responsibilities, or planning scope.

### **Operations Sector**

In this dissertation, the Operations Sector refers to the functional domain responsible for translating the objectives and success criteria defined by the Decision Sector into executable operational actions. This sector governs the planning and execution of air operations, including the generation of the flight schedule, the allocation of aircraft to missions, and the management of mission execution over time.

The Operations Sector operates within the constraints imposed by aircraft availability, operational restrictions, and mission demand, interacting dynamically with the Logistics Sector through maintenance outcomes and resource availability. While it determines how approved missions are executed and adapts execution in response to system conditions, it does not define mission objectives or make authorization decisions.

Within the proposed simulation framework, the Operations Sector is represented by the operational logic that activates missions, assigns aircraft, manages operational tempo, and captures execution outcomes, thereby providing feedback to both the Logistics Sector and the Decision Sector regarding mission fulfillment, cancellations, and execution performance.

### **Logistics Sector**

Logistics may be understood as an integrated managerial function responsible for coordinating material flows, information, and resource availability in order to support organizational objectives efficiently and effectively (TAYLOR, 2005).

In this dissertation, the Logistics Sector refers to the functional domain responsible for sustaining air operations through maintenance activities and material support. This sector encompasses the management of aircraft condition, failure resolution, maintenance processes, and inventory support, including the availability and consumption of spare parts across the defined support structure.

The Logistics Sector governs the processes that determine aircraft availability over time, such as failure occurrence, maintenance evaluation, repair execution, and resource

waiting states. Its performance directly constrains the capacity of the Operations Sector to execute missions and informs the Decision Sector regarding supportability risks and sustainment limitations.

Within the simulation framework, the Logistics Sector is represented through discrete-event processes and agent-level behaviors that model maintenance workflows, repair durations, inventory dynamics, and logistics delays. By explicitly capturing stochastic failures and supply constraints, this sector enables the assessment of how sustainment performance influences operational availability and mission outcomes under uncertainty.

### **Cost–Benefit**

Cost–Benefit denotes the relationship between the resources expended to support military air operations and the operational outcomes achieved, such as aircraft availability, sortie generation, and mission accomplishment. In this dissertation, cost–Benefit is not treated as a single scalar metric, but as a relationship that may degrade over time as maintenance workload, logistics consumption, and operational disruptions accumulate. Managing this degradation is a central concern of supportability-related decision-making.

### **Precision**

Precision refers to the degree to which decision-support information is specific, consistent, and informative under uncertainty. In this context, precision does not denote statistical precision in the sense of low variance or repeatability, but rather the ability of a decision-support framework to improve the interpretability and consistency of information, providing actionable insight through structured, probabilistic, and time-dependent outputs. Thus, precision is associated with clarity of interpretation and usefulness for decision-making, rather than with deterministic accuracy or exact prediction of real-world outcomes (LAW, 2015; STACHEIRA et al., 2024). In this sense, precision reflects the capability of the framework to transform uncertainty into interpretable and decision-relevant information.

### **Situational Awareness**

Situational awareness is understood as the decision-maker’s ability to perceive the current state of the system, comprehend the relationships among its elements, and anticipate how the system is likely to evolve in the near future. In military aviation fleet management, situational awareness extends beyond the tactical level and includes visibility into aircraft states, maintenance processes, logistics constraints, and their dynamic interactions over time. (ENDSLEY, 1995; ENDSLEY; JONES, 2024; STACHEIRA *et al.*, 2024).

### **Support Awareness (S.A.)**

Situational Awareness is commonly defined, following Endsley (1995), as the per-

ception of elements in the environment, the comprehension of their meaning, and the projection of their future status. In the context of this research, the concept is extended to emphasize its application to logistics and supportability. Therefore, the term S.A. is introduced to describe the decision-maker's ability to perceive, understand, and anticipate the state and evolution of logistics support, maintenance processes, and resource constraints affecting fleet operations. S.A. can thus be understood as a domain-specific extension of situational awareness, focused on the sustainment dimension of military air operations.

### **Anticipatory Capability**

Anticipatory capability refers to the ability to identify emerging constraints, risks, or degradation trends before they manifest as operational shortfalls. This capability is closely related to S.A. but emphasizes forward-looking assessment rather than current-state understanding. Within this research, anticipatory capability is supported through time-dependent simulation outputs and probabilistic analysis, enabling evaluation of potential future system states under uncertainty (STACHEIRA *et al.*, 2024).

### **Military Air Operations**

Military air operations are defined as the set of planned and executed activities involving military aircraft to achieve operational objectives, including training, surveillance, transport, and combat missions. In this dissertation, military air operations are considered within a fleet-level perspective, focusing on the allocation, availability, and sustainment of aircraft over time rather than on individual mission tactics or flight dynamics.

### **Decision Support**

Decision support refers to the provision of structured information, analytical insight, and scenario-based evaluation to assist human decision-makers in understanding complex systems and evaluating alternative courses of action. In this dissertation, decision support is not equated with automated decision-making or optimization, but with enhancing the quality of human judgment through improved precision, S.A., and anticipatory capability.

### **Decision Support Systems (DSS)**

Combination of a database and tools for analysis, with the aid of the computer. It allows the user to interact directly with the database, to direct data to decisions models, and to visualize results in a convenient form (BALLOU, 1992).

Ballou (1992) say that a DSS has the following basic subsystems:

- Interactive capability, which enables the user to communicate directly with the system.
- A data manager that makes it possible to extract necessary information from both

internal and external databases.

- A modeling subsystem that permits the user to interact with management science models by inputting parameters and tailoring situations to specific decision-making needs.
- An output generator with graphics capability which provides the user with the capability to ask “what if” questions and obtain output in easily interpretable form.

Ballou (1992) describes two possibilities for a DSS:

- i - The system may provide an environment in which the decision maker may interact, but the final choice is substantially attributed to the decision maker. It is more typical when strategic planning is involved.
- ii - The system may give the solution which the decision maker is to implement. It is more characteristic of operational planning.

In the context of this dissertation, the framework is intended to serve as the foundation for a future DSS, although its primary current use is to verify the preliminary hypothesis within the proposed method. The framework is best classified as type (i), as the decision maker is responsible for the final scenario choice.

### **Simulation-Based Decision-Support Framework**

Simulation is particularly useful when a problem requires detailed representation of processes and interactions, when stochastic factors are present, and when experimentation with the real system is impractical or undesirable (BALLOU, 1992; LAW, 2015).

A simulation-based decision-support framework is defined as an integrated modeling environment that uses simulation to represent system behavior over time under uncertainty, with the explicit objective of supporting decision-making rather than predicting exact outcomes. In this research, such a framework integrates agent-based simulation and discrete-event simulation to represent individual aircraft behavior and structured operational, maintenance, and logistics processes within a unified analytical structure.

### **Scheduled Maintenance**

Blanchard (1998) explains that *preventive maintenance* is maintenance performed at predetermined intervals or according to prescribed criteria intended to reduce the probability of failure or degradation of system performance. Although *scheduled maintenance* may be more encompassing than *preventive maintenance*, for the purposes of this dissertation they will be considered synonymous. It covers inspections, periodic checks, and overhauls triggered by Flight Hours (FH), Flight Cycles (FC), or calendar limits.

### Unscheduled Maintenance

According to Blanchard (1998), *corrective maintenance (unscheduled maintenance)* involves maintenance actions performed after the occurrence of a failure to restore the system to an operational condition. It refers to failure-driven maintenance resulting in Aircraft on Ground (AOG) or reduced availability.

### Mean Time Between Maintenance (MTBM)

MTBM is the mean time between all maintenance actions. Include scheduled and unscheduled maintenance. It can also be used for each of those maintenance categories, scheduled ( $MTBM_s$ ) or unscheduled ( $MTBM_u$ ) (BLANCHARD, 1998).

### Mean Time Between Replacement (MTBR)

MTBR is a major parameter for the requirement of spare parts, as it denotes the mean time between item replacement. This parameter is relevant as, in contrast to MTBM, it exclusively considers maintenance events in which item replacement is required, which requires the availability of a spare part and an inventory requirement (BLANCHARD, 1998).

### Mean Maintenance Downtime (MDT)

MDT is the total time necessary to repair and restore a system or to retain a system in operational status. Include maintenance time and logistics and administrative delay times (BLANCHARD, 1998).

### Operational Availability ( $A_o$ )

$A_o$  reflects the probability that a system will be ready and able to perform its intended function when needed in an actual operational environment, under stated conditions. Although there are other types of system readiness measures,  $A_o$  was chosen because it is the preferred figure of merit for assessment purposes in a realistic operational environment (BLANCHARD, 1998).

Blanchard (1998) expresses mathematically as:

$$A_o = \frac{MTBM}{MTBM + MDT} \quad (2.1)$$

Alternatively, it means:

$$A_o = \frac{\text{Uptime}}{\text{Uptime} + \text{Downtime}} \quad (2.2)$$

Where:

Uptime: The average time the system is available for use.

Downtime: The average time the system is not available for use.

### **Monte Carlo Process**

When stochastic elements are introduced into a simulation model, a single execution is insufficient to characterize system behavior. Instead, the model must be executed multiple times with varying random inputs, allowing statistical analysis of the resulting outputs. This procedure corresponds to the Monte Carlo method, which evaluates system performance through repeated stochastic experimentation (TAYLOR, 2005).

### **Closing Remark**

The definitions presented in this section establish the conceptual foundation for the literature review and subsequent methodological development. They are used consistently throughout the dissertation to avoid ambiguity and to ensure alignment between the research problem, hypothesis, modeling approach, and analysis of results.

## **2.2 Decision-Making and S.A. in Military Air Operations**

Operational history also demonstrates how limitations in S.A. can affect sustainment decision-making during military operations. During Operation Desert Storm, logistics planners were required to support a rapidly expanding operational tempo while forecasting spare parts consumption and maintenance demand across a large deployment theater. Despite the overall success of the campaign, analyses conducted after the operation highlighted that forecasting difficulties and fragmented visibility of logistics flows contributed to imbalances between supply and actual operational demand. In several cases, large inventories of certain items accumulated while shortages occurred for others, indicating that decision-makers lacked integrated analytical tools capable of linking operational activity, maintenance requirements, and logistics provisioning (PAGONIS; CRUIKSHANK, 1992; U.S. GOVERNMENT ACCOUNTABILITY OFFICE, 1991). Such experiences illustrate the importance of improving S.A. in sustainment planning so that decision-makers can anticipate system behavior and align logistics resources with operational requirements.

Decision-making in military aviation occurs within complex socio-technical systems characterized by time pressure, uncertainty, and strong interdependence between operational and logistics elements (LEVESON, 2011). Effective decision-making in such environments depends not only on awareness of current conditions, but also on the precision and usability of the information available to decision-makers. In this dissertation, precision is understood as the degree to which decision-support outputs reduce ambiguity and support actionable interpretation under uncertainty. When information is imprecise, fragmented, or disconnected from future system behavior, decision-makers may be aware

of isolated indicators without being able to act effectively upon them. In supportability-related decisions, this limitation is particularly critical because uncertainty affects not only the current state of the fleet, but also its future ability to sustain operations over time (ENDSLEY; JONES, 2024; LAMBERT, 1993; WILSON; KEATING, 1994; DAU, 2022). In such environments, effective decision-making depends not only on the availability of data but also on the decision-maker's ability to perceive, interpret, and anticipate the state of the system as it evolves over time. This capability is commonly described in the literature as S.A. (ENDSLEY; JONES, 2024).

S.A. has been formally defined as the perception of elements in the environment, the comprehension of their meaning, and the projection of their status into the near future. According to the framework proposed by (ENDSLEY; JONES, 2024), S.A. comprises three hierarchical levels: (i) perception of relevant system elements, (ii) comprehension of their relationships and significance, and (iii) projection of future states based on current conditions. Deficiencies at any of these levels may compromise decision quality, even when large volumes of data are available.

In military air operations, S.A. extends beyond the tactical or cockpit level and encompasses operations and logistics dimensions. Decision-makers responsible for fleet management must continuously assess aircraft availability, maintenance status, mission demand, spare parts availability, and expected future constraints. These elements evolve dynamically and are influenced by stochastic factors such as failures, repair durations, and supply delays. As a result, S.A. in this context is inherently temporal and probabilistic, rather than static or deterministic.

A recurring challenge identified in the literature is that information relevant to S.A. is often fragmented across organizational and functional boundaries (CAMM, 2003). Operational planning, maintenance management, and logistics support are frequently supported by separate tools, databases, and reporting mechanisms. While each system may provide accurate local information, the lack of integration limits the ability to form a coherent global picture of system state and future behavior. Consequently, decision-makers may retain awareness of individual indicators, such as aircraft grounded for maintenance or low stock levels, without understanding how these elements interact and propagate over time.

This fragmentation contributes to a phenomenon in which decision-makers have data but lack system-level awareness. For example, a maintenance backlog may be visible, but its impact on future mission execution may not be readily apparent. Similarly, an acceptable current aircraft availability rate can mask an imminent degradation driven by accumulated flight hours, delayed resupply, or clustered scheduled maintenance. Such limitations are particularly critical during sustained or high-tempo operations, where small disruptions can cascade into significant operational shortfalls.

Another factor affecting S.A. in military aviation is the predominance of static or snapshot-based analyses. Traditional planning tools often rely on deterministic assumptions, average values, or point-in-time assessments that fail to capture the dynamic evolution of the system. While these tools may support routine planning, they are insufficient for exploring how uncertainty and variability influence future states. As a result, decision-makers may struggle to anticipate saturation effects, identify emerging bottlenecks, or evaluate the robustness of alternative strategies.

“Nothing is more important to accurate forecasting than developing a logical and consistent system which is responsive to the needs of managers and capable of being attuned to a changing environment” (LAMBERT, 1993).

The literature increasingly recognizes simulation as a means to enhance S.A. by enabling exploration of system behavior over time and under uncertainty. Rather than providing a single predicted outcome, simulation models can generate distributions of possible futures, reveal dependencies between system components, and expose emergent behaviors that are not obvious from static analyses. In this sense, simulation supports not only decision optimization, but also sense-making, allowing decision-makers to better understand how complex systems behave.

However, the effectiveness of simulation as a S.A. tool depends on its ability to represent relevant system components and their interactions in a transparent and interpretable manner. Models that focus exclusively on operational execution or logistics processes, without integrating both perspectives, may reproduce the same fragmentation observed in real-world decision environments. Similarly, overly aggregated models can obscure individual-level dynamics that are critical for understanding availability and maintenance behavior in aircraft fleets.

In summary, the literature indicates that lack of S.A. in military aviation fleet management arises not from insufficient data, but from limited integration, inadequate representation of dynamics and uncertainty, and insufficient visibility of system interactions over time. Addressing this gap requires modeling approaches capable of integrating operations and logistics dimensions, representing individual aircraft behavior, and supporting probabilistic analysis of future system states. These requirements motivate the simulation-based approach adopted in this research and inform the methodological choices discussed in the subsequent sections.

## 2.3 Modeling and Simulation (M&S) in Aviation Operations and Logistics

Simulation models differ from purely mathematical formulations because they attempt to reproduce the behavior of system components and their interactions rather than representing them solely through analytical equations (TAYLOR, 2005; BANKS *et al.*, 2010; LAW, 2015). This characteristic makes simulation particularly useful when relationships among system elements are complex or difficult to express mathematically.

M&S have been widely adopted as analytical tools for supporting decision-making in aviation systems, particularly in environments characterized by high complexity, uncertainty, and strong interdependence between operations and logistics elements (LAW, 2015; CONG *et al.*, 2021; VARENNA *et al.*, 2025). In both civil and military aviation, simulation enables the representation of time-dependent processes, stochastic behavior, and resource constraints, allowing analysts to explore system behavior under a variety of scenarios without disrupting real-world operations.

In the aviation domain, simulation has been applied to problems ranging from operational planning and fleet utilization to maintenance scheduling and logistics support (CONG *et al.*, 2021; KORCHAGIN; DENISKIN; POCEBNEVA; ALEKSANDROVSKIY, 2023; VARENNA *et al.*, 2025; FIGUEIREDO-PINTO, 2022). These applications share a common objective: to understand how aircraft, resources, and processes interact over time and how these interactions influence performance indicators such as availability, mission accomplishment, and system resilience. However, the literature also reveals that the scope, level of detail, and analytical intent of simulation models vary significantly depending on whether the focus is primarily operations or logistics.

A recurring limitation identified across many studies is the partial or fragmented representation of the aviation system, in which operational execution, maintenance activities, and logistics support are modeled separately or connected only through simplified assumptions. This fragmentation constrains the ability of simulation models to support holistic decision-making and to enhance S.A. at the system level (CONG *et al.*, 2021; VARENNA *et al.*, 2025; FIGUEIREDO-PINTO, 2022).

### 2.3.1 Simulation in Military Aviation

Simulation has been widely used to analyze fleet utilization, maintenance planning, and operational readiness in aviation systems (CONG *et al.*, 2021; VARENNA *et al.*, 2025). Simulation also has a long tradition in military aviation, where it has been employed to support mission planning, force structure analysis, readiness assessment, and operational

training (BANKS *et al.*, 2010; CONG *et al.*, 2021). In this context, simulation models are often used to evaluate the feasibility of missions, assess the impact of different operational tempos, and estimate aircraft availability under varying demand profiles.

Operationally oriented simulation models typically emphasize mission execution, sortie generation, and fleet utilization. Aircraft are frequently represented as resources assigned to missions according to predefined schedules or allocation rules. Such models are effective in analyzing operational capacity, identifying scheduling conflicts, and assessing the impact of mission demand on fleet usage. In some cases, simulation is also used to explore “what-if” scenarios, such as changes in mission tempo or fleet size (MUNHOZ *et al.*, 2024).

Despite their usefulness, many operational simulation models rely on simplified representations of maintenance and logistics. Aircraft availability is often treated as an exogenous input or derived from average availability rates, rather than being dynamically generated through failure occurrence, repair processes, and logistics constraints. As a result, these models may provide limited insight into how operational decisions influence maintenance workload, logistics demand, or future availability (VARENNA *et al.*, 2025; FIGUEIREDO-PINTO, 2022).

Another characteristic of many military aviation simulation studies is the use of deterministic or scenario-specific assumptions, particularly with respect to mission schedules and support resources. While this approach facilitates planning under nominal conditions, it may obscure the effects of uncertainty and variability that are intrinsic to real-world operations. Consequently, decision-makers may lack visibility into the range of possible outcomes associated with alternative operational strategies, limiting S.A. and risk assessment (LAW, 2015).

This research applies simulation to logistics support and sustainment of military air operations. Focus is on operational processes, maintenance operations, resource constraints, and logistical interactions that affect fleet availability and mission supportability, not high-fidelity aerodynamic or flight dynamics modeling.

### **2.3.2 Simulation for Maintenance and Logistics Support**

Simulation models often represent logistics constraints through stock levels, replenishment delays, and prioritization rules (SHERBROOKE, 2004; BLANCHARD, 1998). It has also been extensively applied to aviation maintenance and logistics support, where the primary objective is to analyze aircraft sustainment, maintenance workload, and spare parts provisioning. Maintenance-focused simulation models typically represent inspection routines, failure processes, repair activities, and turnaround times, enabling the estimation of aircraft downtime and maintenance capacity requirements.

Logistics-oriented simulation models emphasize inventory management, spare parts consumption, and resupply processes. These models often incorporate multi-echelon inventory structures, representing the flow of materials across operational bases, depots, and industrial support levels. By simulating stochastic demand driven by failures, such models provide insight into stock-out risks, replenishment delays, and their impact on aircraft availability.

A key strength of maintenance and logistics simulation lies in its ability to represent process timing, queues, and resource contention. By modeling repair durations, waiting times, and inventory constraints explicitly, these models can identify bottlenecks and evaluate the effectiveness of different support strategies. As a result, simulation has become a valuable tool for analyzing sustainment performance and logistics resilience in aviation systems (LAW, 2015).

However, the literature also highlights important limitations. Maintenance and logistics simulation models frequently assume predefined or static operational demand, treating mission schedules as fixed inputs rather than as interacting components of the system. This separation limits the ability to capture feedback loops between mission execution, aircraft degradation, maintenance demand, and logistics consumption. In addition, aircraft are often modeled in an aggregated manner, reducing the ability to represent heterogeneity in usage history, condition, and reliability (CONG *et al.*, 2021; VARENNA *et al.*, 2025).

Such models may provide detailed insight into maintenance and logistics performance while offering limited visibility into how operational decisions influence future system states. Decision-makers may understand current stock levels or repair queues, yet lack a coherent picture of how these factors will affect mission execution over time.

### 2.3.3 Synthesis

The literature demonstrates that modeling and simulation are well-established and valuable approaches for analyzing both military aviation operations and aviation maintenance and logistics support. Operational models provide insight into mission execution and fleet utilization, while maintenance and logistics models offer detailed representations of sustainment processes and resource constraints. Nevertheless, these approaches are often developed in isolation, leading to fragmented analyses that limit system-level understanding.

This fragmentation constrains S.A. by preventing decision-makers from perceiving, comprehending, and projecting the combined effects of operational demand, aircraft reliability, maintenance processes, and logistics support. These limitations motivate the

development of integrated simulation frameworks capable of representing individual aircraft behavior, structured processes, and stochastic interactions within a unified modeling environment. Such considerations form the basis for the discussion of discrete-event simulation, agent-based simulation, and hybrid approaches presented in the subsequent sections.

## 2.4 DES in Maintenance and Logistics Systems

DES is one of the most widely adopted modeling paradigms for the analysis of complex systems in which state changes occur at discrete points in time as a result of specific events. In DES models, system behavior is represented through a sequence of events that modify the state of entities, resources, or queues, with time advancing according to the occurrence of these events rather than in fixed increments. This paradigm is particularly well suited for systems characterized by structured processes, temporal dependencies, and resource constraints (LAW, 2015; KELTON; SADOWSKI; ZUPICK, 2024).

In aviation operations and logistics, DES has been extensively applied to model maintenance workflows, inspection procedures, repair processes, ground operations, and supply chain activities. Typical DES representations include queues for maintenance tasks, processing times for inspections and repairs, transportation or resupply delays, and resource utilization constraints. These characteristics make DES a natural choice for analyzing system performance indicators such as aircraft turnaround time, maintenance backlog, repair capacity, and logistics throughput (KORCHAGIN; DENISKIN; POCEBNEVA; VASILYEVA, 2022; KORCHAGIN; DENISKIN; POCEBNEVA; ALEKSANDROVSKIY, 2023; VARENNA *et al.*, 2025; TORRES; BARBIERI; MUÑOZ, 2024).

One of the principal strengths of DES lies in its ability to represent process-oriented behavior with temporal accuracy. Maintenance activities in aviation are governed by well-defined sequences of actions, such as evaluation, repair, inspection, and release to service, each associated with stochastic or deterministic durations. DES enables the explicit modeling of these sequences, allowing analysts to capture waiting times, bottlenecks, and delays resulting from limited resources or competing demands. As a result, DES has become a standard tool in maintenance engineering and logistics analysis.

Another important advantage of DES is its compatibility with queueing theory and resource-based analysis. In logistics and maintenance systems, aircraft, components, or work orders often compete for shared resources such as hangars, tooling, or spare parts. DES provides a consistent framework for representing such competition and for evaluating the impact of capacity constraints on system performance. This capability is particularly relevant in aviation contexts, where resource saturation can significantly degrade opera-

tional availability.

Despite these strengths, the literature also identifies important limitations associated with the exclusive use of DES in aviation operations and fleet management. A recurring limitation is the tendency to represent aircraft and other system entities in an aggregated or homogeneous manner. In many DES models, aircraft are treated as identical units flowing through maintenance or operational processes, characterized by average failure rates or mean processing times. While this abstraction simplifies model structure, it restricts the ability to represent heterogeneity among aircraft, such as differences in accumulated flight hours, maintenance history, or reliability behavior (VARENNA *et al.*, 2025; FIGUEIREDO-PINTO, 2022).

Furthermore, DES models typically emphasize process logic over autonomous decision-making. Events and transitions are often triggered by predefined rules or schedules, leaving limited room for entities to exhibit adaptive or state-dependent behavior. In operational contexts where individual aircraft respond differently to failures, restrictions, or mission assignments, this limitation can reduce the model's ability to capture emergent behavior arising from local interactions.

Another challenge associated with DES concerns the representation of dynamic operational demand. While DES excels at modeling internal processes, operational demand, such as mission schedules or sortie requirements, is frequently treated as an external input rather than as an interacting component of the system. As a result, feedback loops between mission execution, aircraft degradation, and maintenance demand may be simplified or overlooked, limiting the model's ability to support holistic decision-making.

From the perspective of S.A., DES models provide valuable insight into process performance and resource utilization but may offer limited visibility into the evolving state of individual system elements. Decision-makers may observe indicators such as queue lengths or average downtime without being able to trace these outcomes to the behavior of specific aircraft or to anticipate future states resulting from accumulated conditions. This limitation is particularly relevant in military aviation, where understanding the condition and trajectory of each aircraft is critical for mission planning.

In summary, discrete-event simulation constitutes a powerful and well-established methodology for modeling maintenance and logistics processes in aviation systems. Its strengths in representing structured workflows, timing, and resource constraints make it indispensable for analyzing operational support activities. However, when used in isolation, DES may fall short in representing individual-level autonomy, heterogeneity, and adaptive behavior, as well as in providing comprehensive S.A. of fleet dynamics (LAW, 2015; KELTON; SADOWSKI; ZUPICK, 2024). These limitations motivate the integration of DES with complementary modeling paradigms, such as agent-based simulation, as

discussed in the subsequent sections.

## 2.5 ABS in Operational and Logistics Contexts

In simulation modeling, system components are represented as objects within a computational environment. These objects emulate real entities and processes, allowing their interactions to be executed and observed under simulated conditions, thereby providing insights into system behavior and performance (TAYLOR, 2005).

ABS is a modeling paradigm in which systems are represented as collections of autonomous entities, referred to as agents, each endowed with individual states, attributes, and decision rules. System behavior emerges from the interactions among agents and between agents and their environment, rather than being imposed through aggregate equations or centralized control logic. This paradigm has gained prominence in the analysis of complex systems where heterogeneity, adaptation, and local interactions play a central role (MACAL; NORTH, 2010; CONG *et al.*, 2021; CUI *et al.*, 2021; LORENTE *et al.*, 2022; SALA *et al.*, 2024).

From an implementation perspective, some agent-based models can be developed within discrete-event simulation environments because both paradigms represent state changes at discrete points in time. Nevertheless, the conceptual focus of ABS differs from DES, as it emphasizes autonomous entities and emergent behavior rather than process flow alone (LAW, 2015; ANYLOGIC, 2026).

In operational and logistics contexts, ABS has been applied to domains such as transportation systems, supply networks, military operations, and fleet management (CONG *et al.*, 2021; CUI *et al.*, 2021; LORENTE *et al.*, 2022; SALA *et al.*, 2024; LUO *et al.*, 2022). These applications exploit the ability of agents to represent decision-making units, such as vehicles, platforms, organizations, or personnel, that operate under local information and constraints. By modeling such entities individually, ABS enables the explicit representation of diversity in behavior, condition, and history, which is often critical for understanding system-level outcomes.

One of the principal strengths of ABS lies in its capacity to represent heterogeneous entities and state-dependent behavior. In aviation and logistics systems, aircraft, components, and support elements rarely behave identically over time. Differences in accumulated usage, maintenance history, operational restrictions, and exposure to stochastic events can lead to divergent trajectories among otherwise similar assets. ABS provides a natural mechanism to capture these differences, allowing each agent to evolve according to its own state and interaction history (FIGUEIREDO-PINTO; ABRAHÃO; FAN, 2021; FIGUEIREDO-PINTO, 2022; SALA *et al.*, 2024).

Another advantage of ABS is its ability to support the analysis of emergent phenomena. In fleet operations, system-level patterns, such as availability fluctuations, maintenance bottlenecks, or mission cancellations, often arise from the interaction of multiple localized decisions and events. These patterns may not be apparent from aggregate or deterministic models. By simulating interactions at the agent level, ABS allows such phenomena to emerge organically, supporting exploratory analysis and system-level understanding (CONG *et al.*, 2021; LORENTE *et al.*, 2022; LUO *et al.*, 2022).

ABS has also been recognized as a useful tool for representing adaptive and decentralized decision-making. In many operational settings, decisions are not made by a single centralized authority but emerge from the interaction of multiple actors responding to local conditions. ABS can incorporate such decentralized logic, enabling agents to respond dynamically to changes in their environment, such as failures, restrictions, or competing demands (LORENTE *et al.*, 2022; LUO *et al.*, 2022).

Despite these strengths, the literature also identifies significant challenges associated with the exclusive use of ABS in operational and logistics modeling. A primary limitation concerns the representation of structured processes and precise timing. While agents can be programmed to follow procedural logic, ABS does not inherently provide the formal constructs for modeling queues, resource contention, or process flows with the same clarity and rigor as discrete-event simulation. As a result, models relying solely on ABS may struggle to accurately represent maintenance workflows, inspection sequences, or logistics delays.

Another challenge relates to computational complexity and scalability. As the number of agents and interactions increases, ABS models may incur significant computational overhead, particularly when detailed behavior and frequent interactions are modeled. This limitation can constrain the scope of scenarios that can be explored or the number of Monte Carlo replications that can be performed within reasonable time frames (LAW, 2015; ANYLOGIC, 2026).

From a methodological perspective, ABS models may also pose difficulties in terms of verification and transparency. Because system behavior emerges from the interaction of numerous local rules, tracing the causal chain between inputs and outputs can be challenging, particularly when agent logic is complex or poorly documented. Without careful design and explicit specification of behaviors, ABS models risk becoming opaque, limiting their usefulness as decision-support tools.

ABS offers clear advantages by enabling the explicit tracking of individual entities and their evolving states. Decision-makers can, in principle, observe the condition, status, and trajectory of each asset, supporting a more granular understanding of system behavior. However, if not complemented by appropriate process modeling and temporal

control, ABS alone may provide limited insight into the timing, sequencing, and resource dependencies that shape operational outcomes.

In summary, agent-based simulation provides a powerful framework for representing heterogeneity, autonomy, and emergent behavior in operational and logistics systems. Its strengths make it particularly suitable for modeling individual aircraft behavior, reliability dynamics, and adaptive decision-making. Nevertheless, when applied in isolation, ABS may be insufficient to represent the structured, time-driven processes characteristic of aviation maintenance and logistics. These observations reinforce the need for hybrid approaches that integrate ABS with complementary paradigms, such as discrete-event simulation, in order to achieve both behavioral richness and temporal rigor.

## 2.6 Hybrid Simulation Approaches (ABS–DES)

The increasing complexity of socio-technical systems has motivated the development of hybrid simulation approaches that combine different modeling paradigms within a single framework. In aviation operations and logistics, where autonomous entities interact through structured processes over time, hybrid models have emerged as a means to overcome the limitations associated with the isolated use of a single simulation technique (ANYLOGIC, 2026; FIGUEIREDO-PINTO, 2022; VARENNA *et al.*, 2025).

Among the most prominent hybrid approaches is the integration of ABS and DES. Each paradigm addresses complementary aspects of system behavior (FIGUEIREDO-PINTO, 2022; CONG *et al.*, 2021; VARENNA *et al.*, 2025). DES is well suited for modeling structured processes characterized by queues, resources, and time-dependent events, such as maintenance workflows, inspections, and logistics delays. ABS, in contrast, excels at representing autonomous entities with individual states, decision rules, and interaction patterns, enabling the emergence of system-level behavior from local dynamics.

The literature indicates that problems involving both individual-level autonomy and process-level structure are poorly represented when modeled exclusively through either ABS or DES. In aviation contexts, aircraft exhibit autonomous behavior in the sense that each unit accumulates flight hours, experiences failures, and transitions between operational states independently. At the same time, aircraft are embedded within highly structured operations and logistics processes governed by temporal constraints, procedural rules, and resource availability. Capturing both aspects simultaneously requires a modeling approach that can accommodate autonomy and structure without forcing excessive abstraction.

Hybrid ABS–DES models typically adopt architectures in which agents represent the primary decision-making or state-holding entities, while DES components govern the exe-

cution of processes triggered by agent behavior. In such architectures, agents may initiate events, such as mission execution or maintenance requests, that activate DES process flows. Conversely, DES processes generate time-dependent events and messages that influence agent state transitions. This bidirectional interaction allows the model to preserve logical consistency while maintaining temporal accuracy (FIGUEIREDO-PINTO, 2022; ANYLOGIC, 2026).

In the context of aviation operations and logistics, hybrid approaches have been applied to domains such as transportation systems, supply chains, maintenance networks, and fleet management. These applications demonstrate that hybrid models can represent heterogeneous entities, asynchronous events, and feedback loops more effectively than single-paradigm models. However, the literature also highlights several challenges associated with hybrid simulation, including increased model complexity, difficulties in verification and validation, and reduced transparency when integration mechanisms are poorly defined.

A critical observation emerging from prior studies is that the benefits of hybrid simulation depend strongly on clear separation of responsibilities between paradigms. When the roles of ABS and DES are not explicitly defined, hybrid models risk becoming unnecessarily complex or conceptually ambiguous. Successful implementations typically assign decision-making, state management, and heterogeneity to agents, while reserving DES for process timing, sequencing, and resource flow. This separation enhances interpretability and supports systematic verification.

Another recurring theme in the literature concerns the use of hybrid simulation as a decision-support and sense-making tool, rather than as a pure optimization engine. Hybrid models are particularly effective at revealing emergent behavior arising from the interaction of individual entities and structured processes, such as bottlenecks, saturation effects, and cascading delays. These phenomena are often difficult to anticipate through analytical or aggregated models, yet they are central to understanding system resilience and operational risk (LORENTE *et al.*, 2022; LUO *et al.*, 2022; FIGUEIREDO-PINTO, 2022).

Despite these advantages, many published hybrid ABS–DES models remain either conceptual or application-specific, with limited methodological transparency. Detailed descriptions of agent logic, process flows, integration mechanisms, and verification procedures are frequently omitted, limiting reproducibility and practical adoption (LAW, 2015; ANDERSON *et al.*, 2014). This observation reinforces the importance of explicitly documenting model architecture, assumptions, and interaction logic when hybrid simulation is employed in academic research.

In summary, the literature supports hybrid ABS–DES simulation as a suitable and

increasingly necessary approach for modeling complex systems that combine autonomous entities and structured processes, such as military aviation operations and logistics. The integration of ABS and DES enables the simultaneous representation of individual aircraft behavior, operational execution, and logistics support dynamics within a unified framework. These characteristics directly address the limitations identified in single-paradigm models and provide a methodological foundation for enhancing system-level understanding and S.A.. The hybrid approach adopted in this research builds upon these insights, emphasizing transparency, modularity, and explicit integration mechanisms to support robust decision-oriented analysis.

## 2.7 Modeling Aircraft Reliability, Failures, and Maintenance

Aircraft reliability and maintenance are central determinants of operational availability and mission success in aviation systems. The literature on aviation sustainment consistently emphasizes that failures, maintenance actions, and repair delays are not isolated phenomena, but elements of a coupled system in which operational usage, component degradation, and logistics support interact dynamically over time. As a result, the modeling of reliability and maintenance plays a critical role in simulation-based analyses of fleet performance (BLANCHARD, 1998; FIGUEIREDO-PINTO; ABRAHÃO; FAN, 2021; FIGUEIREDO-PINTO, 2022; MARTINS, 2023).

### 2.7.1 Reliability Modeling in Aviation Systems

An important advantage of simulation models is their ability to incorporate variability in system parameters and inputs. Instead of relying on fixed values, simulations allow variables to fluctuate around expected values, reflecting the stochastic nature of real operational systems (TAYLOR, 2005).

Reliability modeling in aviation commonly relies on probabilistic representations of component failure behavior (BLANCHARD, 1998; FIGUEIREDO-PINTO; ABRAHÃO; FAN, 2021; MARTINS, 2023).

Variability in operational parameters, as failure processes, can be represented through probability distributions, typically characterized by statistical measures such as mean and standard deviation. Incorporating such distributions allows simulation models to reproduce stochastic fluctuations observed in real systems (TAYLOR, 2005). These representations aim to capture the inherent uncertainty associated with component degradation and operational stress, while remaining compatible with available historical data.

In many studies, failures are modeled as stochastic events triggered by accumulated

flight hours, cycles, or mission profiles (FIGUEIREDO-PINTO; ABRAHÃO; FAN, 2021; FIGUEIREDO-PINTO, 2022; BLANCHARD, 1998). This approach reflects the operational reality that aircraft components are subject to wear and fatigue driven by usage rather than by calendar time alone. Reliability models often distinguish between failures that impose operational restrictions and those that require immediate maintenance action, enabling the assessment of different levels of impact on aircraft availability.

While detailed physics-based reliability models exist for specific components, simulation studies focused on operations and logistics analysis typically adopt simplified probabilistic representations. Such simplifications are justified when the objective is to evaluate system-level behavior, such as availability trends or maintenance workload, rather than to predict the exact failure mechanism of individual components.

### 2.7.2 Representation of Failures in Simulation Models

In simulation-based analyses, failures serve as primary triggers for maintenance demand and logistics consumption. The literature indicates that failures are often modeled at discrete points in the operational cycle, such as during pre-operation checks or post-operation inspections. This abstraction reflects the fact that, from an operational planning perspective, the precise moment of failure occurrence during a mission is often less relevant than the resulting impact on aircraft availability and maintenance requirements.

Simulation models commonly differentiate between scheduled and unscheduled maintenance. Scheduled maintenance is typically triggered by accumulated usage thresholds, such as flight hours or cycles, and follows predefined procedures. Unscheduled maintenance arises from stochastic failures and introduces variability into maintenance workload and downtime. The interaction between these two types of maintenance is a recurring focus in the literature, as clustering effects may significantly affect fleet availability during sustained operations (BLANCHARD, 1998; FIGUEIREDO-PINTO; ABRAHÃO; FAN, 2021; MARTINS, 2023).

A further distinction frequently adopted is between failures that require component replacement and those that can be resolved through inspection, adjustment, or minor repair. This distinction is particularly relevant for logistics modeling, as replacement-driven failures generate demand for spare parts, while non-replacement failures primarily consume maintenance time.

### 2.7.3 Maintenance Process Modeling

Maintenance process modeling seeks to represent the sequence of actions required to return an aircraft to an operational state following a failure or scheduled intervention.

Typical maintenance models include stages such as fault confirmation, procedure selection, repair execution, inspection, and release to service (KORCHAGIN; DENISKIN; POCEBNEVA; VASILYEVA, 2022; KORCHAGIN; DENISKIN; POCEBNEVA; ALEK-SANDROVSKIY, 2023; CONG *et al.*, 2021). Each stage may be associated with stochastic or deterministic durations, reflecting uncertainty in diagnosis, repair complexity, or resource availability.

Discrete-event simulation is frequently employed to model maintenance workflows due to its ability to represent queues, delays, and resource contention. However, the literature also highlights that maintenance processes are often simplified in system-level models to maintain tractability. Common simplifications include aggregated repair times, binary feasibility decisions, and the exclusion of detailed task-level scheduling.

From an analytical perspective, such simplifications are acceptable when the objective is to assess the impact of maintenance on operational availability rather than to optimize maintenance procedures themselves. Nevertheless, the choice of abstraction level must be consistent with the intended scope of the analysis and clearly documented to avoid misinterpretation of results.

#### **2.7.4 Interaction Between Maintenance and Logistics Support**

The interaction between maintenance and logistics support is a critical aspect of aircraft sustainment modeling. Maintenance actions that require component replacement generate demand for spare parts, linking reliability behavior directly to inventory consumption and resupply processes. The literature consistently reports that shortages in spare parts can significantly increase aircraft downtime, even when maintenance capacity is otherwise sufficient (SHERBROOKE, 2004; BLANCHARD, 1998; FIGUEIREDO-PINTO, 2022).

Simulation models often represent logistics constraints through stock levels, replenishment delays, and prioritization rules. Multi-echelon inventory structures are commonly adopted to reflect operational bases, depots, and higher-level support organizations. By coupling maintenance demand with inventory availability, such models enable the assessment of how logistics performance influences aircraft readiness.

A key insight from the literature is that maintenance and logistics interactions introduce non-linear effects into the system. For example, moderate increases in failure rates may lead to disproportionate increases in downtime when inventory levels are low or replenishment times are long. Capturing these effects requires modeling approaches capable of representing both stochastic demand and process-level delays.

### **2.7.5 Implications of S.A.**

From the perspective of S.A., the modeling of reliability, failures, and maintenance is essential for understanding not only the current state of the fleet, but also its likely future evolution. Models that rely solely on average failure rates or static availability assumptions provide limited insight into how accumulated conditions and pending maintenance actions may affect future mission capability.

By explicitly representing failures, maintenance decisions, and logistics constraints, simulation models can support the perception of system state, the comprehension of dependencies between operational and support elements, and the projection of future availability. These capabilities are particularly relevant in military aviation contexts, where decision-makers must anticipate the effects of uncertainty and resource limitations over extended operational periods.

### **2.7.6 Synthesis**

The literature demonstrates that probabilistic modeling of reliability, explicit representation of failures, and abstraction of maintenance processes are well-established practices in aviation simulation. However, effectively integrating these elements with operational execution and logistics support remains a methodological challenge. Addressing this challenge requires modeling approaches capable of representing individual aircraft behavior, maintenance workflows, and inventory interactions within a unified framework. These considerations directly inform the hybrid simulation approach adopted in this research and the modeling choices detailed in Chapter 3.

## **2.8 Logistics Support and Inventory Modeling in Aviation**

Logistics support is a fundamental component of aviation systems, directly influencing aircraft availability, maintenance effectiveness, and mission execution. In military aviation, logistics support encompasses the provisioning, storage, distribution, and replenishment of spare parts and consumables required to sustain operations over time. The literature consistently emphasizes that, even when maintenance procedures and technical expertise are available, insufficient or delayed logistics support may become the dominant constraint on operational readiness (SHERBROOKE, 2004; BLANCHARD, 1998; DEFENSE ACQUISITION UNIVERSITY, 2024).

### 2.8.1 Inventory Modeling in Aviation Systems

Inventory modeling in aviation traditionally focuses on determining appropriate stock levels to balance availability, cost, and risk of shortages. Classical approaches often rely on analytical or optimization-based methods, such as multi-echelon inventory models, which aim to position spare parts across different support levels: operational bases, depots, and industrial facilities; in order to meet stochastic demand generated by failures (SHERBROOKE, 2004).

These models typically characterize demand using probabilistic failure processes and seek to minimize expected downtime or lifecycle cost subject to service level constraints. While such approaches provide valuable insight into long-term inventory policies, they frequently rely on steady-state assumptions or average demand rates. As a result, their ability to represent transient behaviors, time-dependent interactions, and operational contingencies is limited.

Simulation-based inventory models have emerged as a complementary approach, enabling the explicit representation of time-varying demand, replenishment delays, and consumption dynamics (SHERBROOKE, 2004; VARENNA *et al.*, 2025; CONG *et al.*, 2021). By simulating the interaction between failures, maintenance actions, and stock availability, these models allow analysts to explore how inventory policies perform under different operational scenarios, including periods of high mission tempo or disrupted supply chains.

### 2.8.2 Multi-Echelon Logistics Support Structures

Military aviation logistics is inherently multi-echelon in nature. Spare parts and repairable items are distributed across hierarchical support levels, which may include deployed locations, operational bases, regional depots, and industrial or manufacturer-level facilities. Each echelon is characterized by distinct stock levels, replenishment times, and access constraints (SHERBROOKE, 2004; DEFENSE ACQUISITION UNIVERSITY, 2024).

The literature highlights that the effectiveness of a logistics support system depends not only on total inventory levels, but also on how inventory is distributed across echelons and how resupply flows are managed. Delays at higher echelons may propagate downstream, increasing aircraft downtime at operational bases even when total system inventory is sufficient. Consequently, modeling approaches that neglect echelon interactions may underestimate the operational impact of logistics constraints.

Simulation models frequently adopt simplified representations of multi-echelon systems, focusing on key echelons relevant to the operational context under study. Such abstractions are generally acceptable when the objective is to analyze system-level behav-

ior and identify dominant bottlenecks, provided that the assumptions and limitations are clearly stated.

### 2.8.3 Interaction Between Inventory Availability and Aircraft Operations

A central theme in the literature is the strong coupling between inventory availability and aircraft operational performance. When spare parts required for maintenance are unavailable, aircraft may remain grounded despite the presence of maintenance capacity and completed diagnostics. This interaction introduces non-linear effects into the system, as relatively small changes in inventory levels or replenishment times may lead to disproportionate increases in downtime and mission cancellations (SHERBROOKE, 2004; CONG *et al.*, 2021; VARENNA *et al.*, 2025).

Simulation-based studies have shown that logistics constraints often become more pronounced under sustained operations, where cumulative demand and replenishment delays interact with mission schedules. In such scenarios, static or average-based inventory assessments may fail to anticipate periods of operational saturation, leading to reduced S.A. and reactive decision-making.

By explicitly modeling the consumption of spare parts, waiting states for resource availability, and resupply delays, simulation approaches enable the analysis of how logistics support influences both current and future aircraft availability. This capability is particularly relevant for decision-makers tasked with evaluating the resilience of logistics configurations under uncertainty.

### 2.8.4 Inventory Modeling and S.A.

From a S.A. perspective, logistics and inventory models play a critical role in supporting the perception and comprehension of system state. Knowledge of current stock levels alone is insufficient if decision-makers cannot assess how inventory availability will affect maintenance outcomes and mission execution over time. Effective S.A. requires visibility into how logistics constraints interact with operational demand and reliability behavior (ENDSLEY; JONES, 2024; TAYLOR, 2005).

Simulation-based inventory modeling contributes to S.A. by enabling the projection of future states under alternative scenarios. By generating time-dependent indicators, such as expected waiting times for parts, likelihood of stock-outs, and projected downtime, simulation models provide decision-makers with a more comprehensive understanding of system behavior than static reports or point estimates.

However, the literature also cautions that inventory models must be integrated with operational and maintenance representations to fully support S.A.. Isolated logistics simulations may accurately represent stock dynamics while failing to capture their operational consequences. This observation reinforces the need for integrated modeling frameworks that combine inventory dynamics with aircraft behavior and maintenance processes.

### 2.8.5 Synthesis

The literature demonstrates that logistics support and inventory modeling are essential components of aviation sustainment analysis. Simulation-based approaches offer significant advantages over static or purely analytical models by enabling the explicit representation of stochastic demand, replenishment delays, and time-dependent interactions. Nevertheless, the effectiveness of such models in supporting decision-making and S.A. depends on their integration with operational execution and maintenance dynamics. These considerations further motivate the development of unified simulation frameworks capable of representing aircraft operations, maintenance processes, and logistics support within a coherent analytical structure, as pursued in this research.

## 2.9 Simulation-Based Decision Support and S.A.

Decision support in complex socio-technical systems requires more than the provision of data or the optimization of isolated performance indicators. In operational environments characterized by uncertainty, time pressure, and interdependent processes, such as military aviation, decision-makers must be able to perceive the current state of the system, comprehend the interactions among its components, and anticipate how the system is likely to evolve under different conditions (BALLOU, 1992; ENDSLEY; JONES, 2024; LEVESON, 2011). These capabilities correspond directly to the concept of S.A. discussed earlier in this chapter.

The literature increasingly recognizes simulation as a powerful decision-support instrument precisely because of its capacity to represent system dynamics over time and under uncertainty. Unlike static analytical tools, simulation enables the exploration of cause-and-effect relationships, the identification of emergent behaviors, and the evaluation of alternative courses of action before they are implemented in real operations. In this sense, simulation supports not only decision-making, but also sense-making, helping decision-makers understand why certain outcomes occur and how they may change under different assumptions (LAW, 2015; BALLOU, 1992; TORRES; BARBIERI; MUÑOZ, 2024; LORENTE *et al.*, 2022).

In aviation operations and logistics, simulation-based decision support has been applied to assess fleet readiness, maintenance capacity, inventory policies, and mission feasibility (CONG *et al.*, 2021; VARENNA *et al.*, 2025; FIGUEIREDO-PINTO, 2022; TORRES; BARBIERI; MUÑOZ, 2024). These applications demonstrate that simulation can enhance decision quality by exposing trade-offs between operational objectives and support constraints. However, the literature also reveals that the effectiveness of simulation as a decision-support tool depends strongly on the scope and integration of the modeled system. Models that focus narrowly on a single domain, such as operations, maintenance, or logistics, may improve local understanding while failing to provide a coherent picture of system-wide behavior.

A recurring limitation identified in prior studies is the persistence of fragmented S.A., even when simulation is employed. Operational models may provide detailed insight into mission execution but rely on simplified or exogenous representations of maintenance and logistics. Conversely, sustainment models may accurately represent maintenance and inventory dynamics without capturing how operational demand influences future system states. In both cases, decision-makers may retain partial awareness of subsystem performance while lacking an integrated understanding of how these subsystems interact and constrain one another over time.

Simulation-based decision support aimed at improving S.A. must therefore satisfy several requirements identified in the literature. First, it must enable the perception of relevant system elements by making the state of individual assets, resources, and processes visible and traceable. Second, it must support comprehension by explicitly representing dependencies and feedback loops between operational execution, reliability behavior, maintenance processes, and logistics support. Third, it must facilitate projection by allowing the exploration of future system states through scenario analysis and probabilistic experimentation (ENDSLEY, 1995; ENDSLEY; JONES, 2024).

Hybrid simulation approaches are particularly well suited to meeting these requirements. By combining detailed representations of individual entities with explicit process modeling and stochastic behavior, such approaches allow decision-makers to observe how local events propagate through the system and influence global performance indicators. Moreover, simulation outputs expressed as distributions rather than point estimates provide a more informative basis for decision-making under uncertainty, enabling the assessment of risk, robustness, and resilience (FIGUEIREDO-PINTO, 2022; LORENTE *et al.*, 2022; VARENNA *et al.*, 2025).

Visualization and interaction capabilities further enhance the contribution of simulation to S.A.. Although visualization alone does not guarantee understanding, the literature indicates that well-designed simulation environments can improve cognitive integration by linking quantitative indicators to system behavior over time. Time series,

state occupancy plots, and scenario comparisons allow decision-makers to relate abstract performance metrics to underlying processes and asset states, supporting more informed judgments (ENDSLEY; JONES, 2024; LUO *et al.*, 2022).

Despite these advantages, the literature also cautions that simulation-based decision-support systems must be designed with transparency and interpretability in mind. Excessive model complexity, opaque logic, or insufficient documentation may undermine trust and limit practical adoption. As a result, several authors emphasize the importance of clear model structure, explicit assumptions, and systematic verification when simulation is used to support high-stakes decisions (LAW, 2015; ANDERSON *et al.*, 2014).

In summary, the literature supports simulation as a valuable tool for enhancing decision support and S.A. in aviation operations and logistics, provided that models are sufficiently integrated, transparent, and aligned with decision-maker needs. Improving S.A. requires moving beyond isolated analyses toward unified frameworks that reveal system states, interactions, and future trajectories under uncertainty. These insights directly motivate the integrated, hybrid simulation approach proposed in this research, which seeks to consolidate operational, maintenance, and logistics perspectives within a coherent decision-support environment.

## 2.10 Verification and Validation in Simulation Studies

Verification and validation constitute fundamental steps in any simulation study, as the usefulness of simulation results depends on the degree to which the model accurately represents the system being analyzed. Verification refers to the process of ensuring that the simulation model has been correctly implemented from a computational perspective. In practice, this involves confirming that the program logic, algorithms, and stochastic inputs operate as intended, often through debugging procedures, simplified test cases, or comparisons with independent calculations (LAW, 2015; ANDERSON *et al.*, 2014).

Validation, in contrast, concerns the adequacy of the model as a representation of the real system. It involves evaluating whether the assumptions, logic, and structural relationships embedded in the model faithfully capture the relevant dynamics of the system under study. Validation may include comparisons between simulation outputs and observed system behavior, or expert assessment of whether the simulated results are consistent with expected operational patterns. Together, verification and validation aim to establish confidence that the simulation model is both correctly implemented and sufficiently representative of the real system to support meaningful analysis and decision-making (LAW, 2015; ANDERSON *et al.*, 2014).

Anderson *et al.* (2014) emphasizes that verification and validation are duties that

should not be underestimated. These are essential phases in any simulation study, necessary to guarantee that judgments and conclusions derived from the simulation results are suitable for the actual system.

## 2.11 Synthesis of the Literature and Research Gap

The literature reviewed in this chapter demonstrates that modeling and simulation are well-established and widely recognized approaches for analyzing aviation operations, maintenance, and logistics systems. DES has been extensively applied to represent structured processes, queues, and resource constraints, particularly in maintenance and logistics support. ABS, in turn, has been employed to capture heterogeneity, autonomy, and emergent behavior in operational and logistics contexts. Hybrid simulation approaches combining these paradigms have increasingly been proposed as a means to address the complexity of socio-technical systems.

In parallel, the literature on decision-making and S.A. highlights that effective management of complex systems requires more than isolated performance indicators or static assessments. In military aviation, S.A. depends on the ability to perceive the evolving state of individual assets, comprehend the interdependencies between operational execution and support functions, and anticipate future system behavior under uncertainty. Fragmented information, static planning tools, and excessive reliance on aggregated indicators have been identified as persistent obstacles to achieving this awareness.

Despite the maturity of simulation methods in aviation-related domains, the reviewed studies reveal several recurring limitations. First, many simulation models adopt fragmented perspectives, focusing either on operational execution or on maintenance and logistics support, without explicitly integrating these domains within a unified framework. As a consequence, feedback loops between mission demand, aircraft degradation, maintenance workload, and logistics consumption are often simplified or overlooked.

Second, a significant portion of the literature relies on aggregated representations of aircraft fleets, treating aircraft as homogeneous resources characterized by average availability or utilization rates. While such abstractions facilitate model tractability, they limit the ability to represent individual aircraft behavior, heterogeneous reliability profiles, and state-dependent constraints, which are critical for understanding availability dynamics in sustained operations.

Third, although uncertainty is widely acknowledged in reliability and maintenance modeling, its integration with operational planning and logistics support remains limited. Deterministic mission schedules and average-based assumptions are frequently combined with stochastic failure models, reducing the ability of simulation outputs to support prob-

abilistic S.A. and risk-informed decision-making.

Finally, while hybrid ABS–DES approaches have been proposed to address some of these challenges, many existing models lack methodological transparency. Detailed descriptions of agent logic, process flows, integration mechanisms, and verification procedures are often insufficient, limiting reproducibility, extension, and practical adoption as decision-support tools.

Taken together, these observations indicate a clear research gap. There is a lack of integrated, transparent simulation frameworks capable of representing military aviation operations as a coupled system in which individual aircraft behavior, maintenance processes, and logistics support interact dynamically under uncertainty. More specifically, the literature lacks models that simultaneously:

- represent aircraft as autonomous entities with explicit state logic and heterogeneous behavior;
- integrate operational execution, maintenance workflows, and logistics support within a single modeling environment;
- incorporate stochastic representations of failures, repair durations, and supply delays;
- support probabilistic analysis through Monte Carlo experimentation; and
- enhance S.A. by revealing system states, dependencies, and future trajectories.

This dissertation addresses this gap by proposing a hybrid simulation framework that integrates agent-based simulation and discrete-event simulation to model military aircraft fleet operations and logistics support in a unified and transparent manner. By consolidating operational, maintenance, and logistics perspectives, the proposed approach seeks to improve S.A. and support informed decision-making under uncertainty. The methodological framework developed to achieve this objective is presented in Chapter 3.

Summarizing the literature review, (CONG *et al.*, 2021) and (FIGUEIREDO-PINTO, 2022) represent the closest references to the present research. Cong *et al.* (CONG *et al.*, 2021) demonstrate that a goal-driven, agent-based modeling approach is viable for the analysis of aviation maintenance support systems, providing an important methodological foundation. Figueiredo (FIGUEIREDO-PINTO, 2022) advances this line of research by adopting a hybrid ABS-DES architecture and integrating predictive and scheduled maintenance under uncertainty, offering a comprehensive maintenance-centric decision-support framework.

TABLE 2.1 – Comparison of methodological and functional coverage between literature and the proposed dissertation

Study	Aspects covered in the study									
	I	II	III	IV	V	VI	VII	VIII	IX	X
Cong et al. (2021)	X			X	X	X	X			
Torres et al. (2024)		X						X	X	
Sala et al. (2024)	X				X				X	
Varenna et al. (2025)		X			X				X	
Korchagin et al. (2023)					X				X	
Korchagin et al. (2022)		X			X				X	
Lorente et al. (2022)	X				X				X	
Martins (2023)					X	X			X	
Figueiredo-Pinto (2021)				X	X	X		X	X	
Figueiredo-Pinto (2022)	X	X	X	X	X	X		X	X	
This Dissertation	X	X	X	X	X	X	X	X	X	X

An “X” indicates that the aspect is explicitly modeled and operationalized in the study; blank cells indicate absence or only implicit consideration.

**I.** ABM

**II.** DES

**III.** Hybrid ABS-DES

**IV.** Goal-driven kpi

**V.** Maintenance Processes

**VI.** Failure Modeling

**VII.** Spare Parts & Inventory

**VIII.** Monte Carlo / Risk

**IX.** Decision Support System

**X.** Integrated Maintenance–Inventory Coupling

However, both studies treat spare parts availability either implicitly or as an exogenous assumption. As highlighted in Column X of Table 2.1, the present dissertation advances by explicitly coupling inventory dynamics with maintenance processes, such that maintenance execution and aircraft availability are intrinsically limited by the availability and replenishment of spare parts within a multi-echelon logistics system. This coupling is particularly relevant to deployed air operations, where aircraft operate from dispersed locations and maintenance outcomes are directly affected by forward-positioned stocks, resupply delays, and support aircraft constraints rather than by centralized base-level assumptions. In addition, the proposed framework incorporates Monte Carlo-based risk analysis and implements an operational decision-support system aimed at real-world, resource-limited environments, thus extending existing approaches both methodologically and functionally.

## 3 Method and Modeling

This chapter presents the methodological approach adopted for the development of the simulation model proposed in this research. The method was designed to represent the interactions between upper-level planning, operational execution, and logistical support in military aviation, translating real-world decision-making processes into a structured and dynamic simulation environment.

The approach combines agent-based and discrete-event simulation techniques, enabling the representation of both autonomous entities, such as aircraft and the items that compose them, and the sequential flow of operational and logistical processes. This hybrid modeling structure allows the simulation to capture complex interdependencies between mission planning, aircraft availability, and resource utilization while maintaining flexibility for scenario variation and experimentation.

The model's development follows a structured framework organized into three interdependent sectors: decision, operations, and logistics; which together define the flow of information and decision-making across hierarchical levels.

These sectors are defined in section 2.1. In practical terms, their contributions for modeling are as follows:

- The Decision Sector establishes the mission objectives and defines the performance indicators used to assess mission success.
- The Operations Sector converts these objectives into a flight schedule, which influences aircraft employment and mission pace.
- The Logistics Sector provides fleet characteristics, item data, and stock information that define the model's scope and determine the system's capacity to sustain operations.

The construction process is iterative, involving the definition of model logic, parameterization, and validation steps to ensure consistency with operational and logistic realities. Stochastic elements, such as aircraft failures, repair times, and resource constraints,

are incorporated to reflect the uncertainty inherent in real-world operations. To quantify these uncertainties, a Monte Carlo process is applied, producing probability distributions of the selected performance indicators. These indicators may include, for example, mission success rates, maintenance workload, or any other metric defined by the user and provided by the model.

This methodological framework guides the progressive development of the simulation model, from conceptualization and data structuring to scenario testing and result analysis. Figure 3.1 illustrates a basic depiction of the method, beginning with the input data of the scenario (Figure 3.1 - 01) - including the setup parameters to be evaluated, followed by the simulation model (Figure 3.1 - 02) that incorporates the hybrid logic of the model. The simulation runs many times in a Monte Carlo process (Figure 3.1 - 03) to obtain the probabilistic results as scenario output data (Figure 3.1 - 04). These results are compared with other scenarios' results (Figure 3.1 - 05). The following sections describe in detail the contribution of each sector, the simulation configuration, and the general flow of information that supports the execution of the model.

The model represents uncertainty through stochastic processes and enables its interpretation through probabilistic outputs obtained via Monte Carlo simulation.

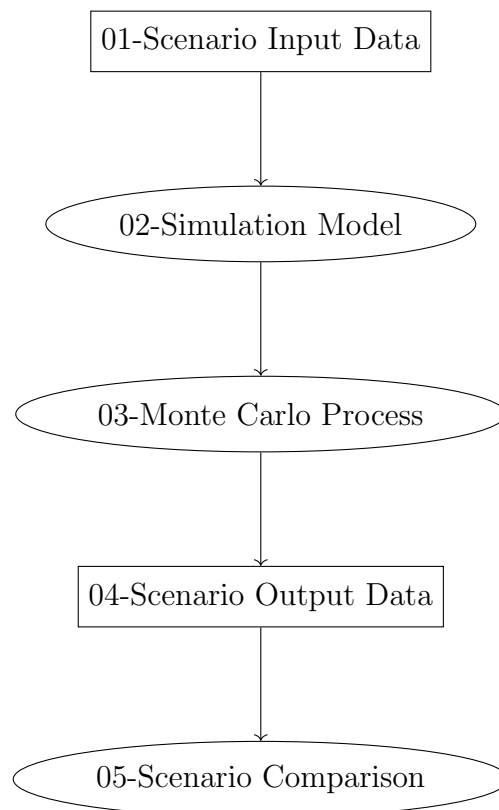
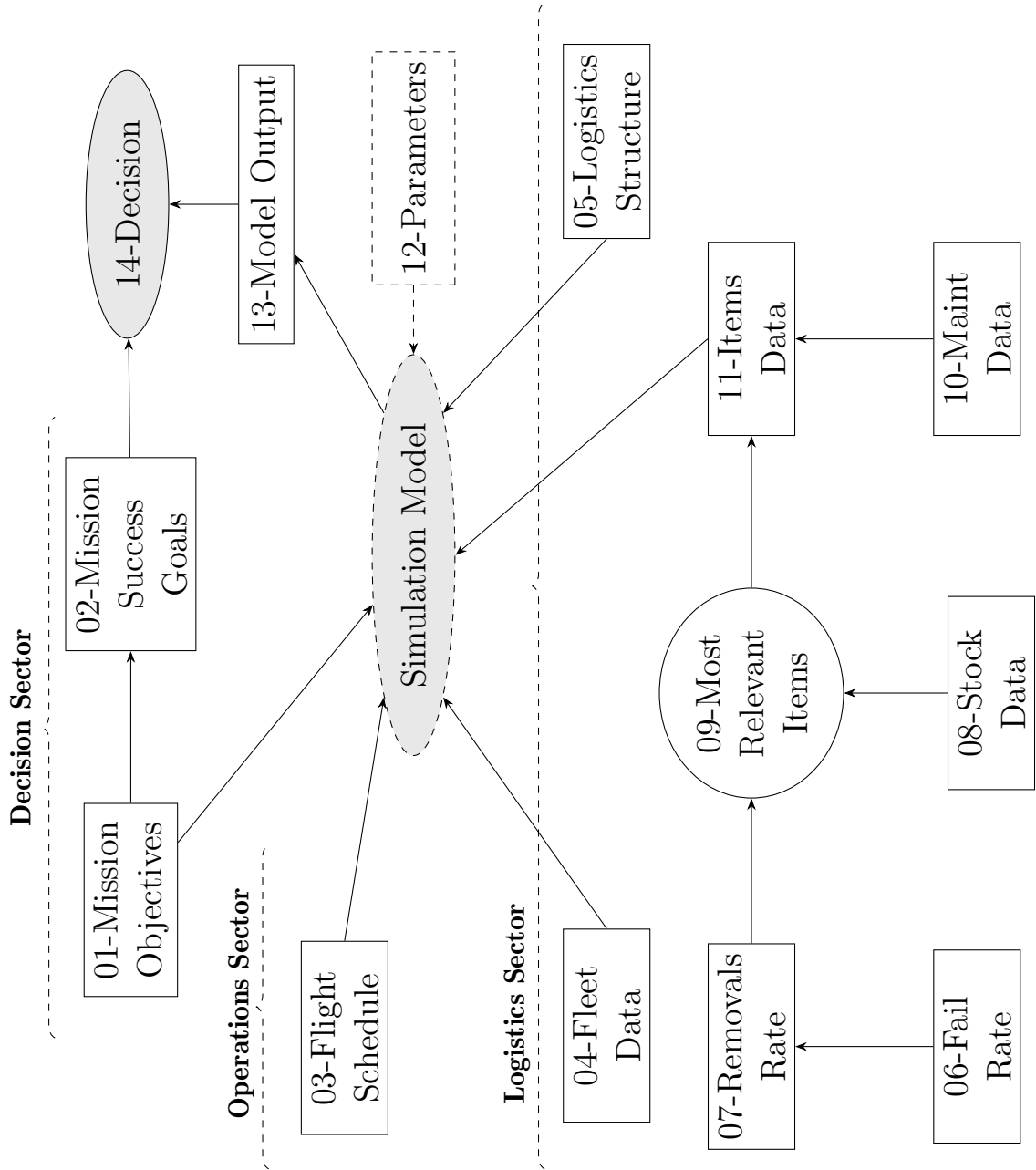


FIGURE 3.1 – Framework for Simulation-Based Decision Support Integrating Hybrid Modeling and Monte Carlo Process for Scenario Comparison in Aircraft Fleet Operations.

### **3.1 Sectors Involved and Their Contribution**

Figure 3.2 illustrates the contribution of each sector about the information incorporated into the model. The expected goals (Figure 3.2 - 02) are utilized to evaluate scenario success by comparing them with the kpi obtained from the method's application. The diagram includes aspects that were fixed at the end of the model development, as well as elements that can be updated for each simulation.

FIGURE 3.2 – Model Inputs by Sector Contribution



### 3.1.1 Decision Sector

The Decision Sector involves high-level decisions and, in this way, is responsible for determining what mission the fleet must operate and what is expected as a result of this operation. This sector defines the formulation of the mission, defines its objectives (Figure 3.2 - 01), and sets the goals (Figure 3.2 - 02). This information is communicated to the other sectors involved, which will undertake the mission, since it is feasible and suitable. Occasionally, the mission proves infeasible due to certain limitations that were not taken into account previously. In other cases, the mission may also require adjustments to improve its effectiveness and efficiency. Therefore, the decision sector must understand the achievable outcomes and the potential consequences of proceeding with the selected scenario. Based on this, decision-makers can choose to adapt the proposed mission or even consider canceling it. This decision (Figure 3.2 - 14) is based on the goals, comparing then with the model output (Figure 3.2 - 13), which shows the risk of the decision.

### 3.1.2 Operations Sector

The Operations Sector assimilates the demands emanating from the decision sector and plans the best way to execute them. Several considerations are made, such as the analysis of operational requirements, crew allocation, and contingency analysis. As a product of this planning, the flight schedule (Figure 3.2 - 03) is generated, which encompasses each sortie to be performed in fulfillment of the mission. The flight schedule contains information such as the date and time of takeoff, flight time, mission profile, and information about the allocated crew (the crew will not be the subject of analysis in this work).

### 3.1.3 Logistics Support Sector

The Logistics Sector, in turn, will have a dual role in the development of this method. Firstly, with regard to its usual responsibilities, the sector is responsible for planning the allocation of aircraft and seeking effectiveness and efficiency in the accomplishment of the mission. To this end, it gathers fleet data (Figure 3.2 - 04) such as flight hour availability, maintenance to be performed (before, during, and even after the mission period), and available supplies. It also carries out any necessary logistical coordination for mission success.

Furthermore, the sector is important in the building of the aircraft model and the logistical structure (Figure 3.2 - 05), since it has the necessary understanding (and data available) for this. Initially, the sector assists in understanding the fleet environment and

defining the scope by analyzing the relevance and criticality of both the logistical structure and the aircraft components. This approach aims to restrict resource allocation solely to elements that significantly influence scenario analysis.

Finally, this sector will provide the logistical data that feed the model (aggregated in Figure 3.2 - 11), such as item stock (Figure 3.2 - 08) and maintenance data (Figure 3.2 - 10). The items included in the model's scope are those considered most relevant (Figure 3.2 - 09) in terms of representativeness, taking into account failure (Figure 3.2 - 06) and removal (Figure 3.2 - 07) rates.

## 3.2 Simulation Model

After figuring out how each sector contributes, let's focus on the model itself. Figure 3.3 shows what this research considers important enough to include in this model. The main idea is to make a model that is as detailed as it needs to be but as simple as it can be while still being a useful model of how an actual military fleet would work during a medium-length operation. The algorithm in Figure 3.4 is the pseudo-code of what is expected when an aircraft is declared unavailable and enters the Evaluation process of Figure 3.3. Scheduled maintenance or a failure can start the evaluation process, which can be verified before or after the flight. As a simplification, failures that occurred during the flight are considered "post-flight failures" since no maintenance action is taken during the flight.

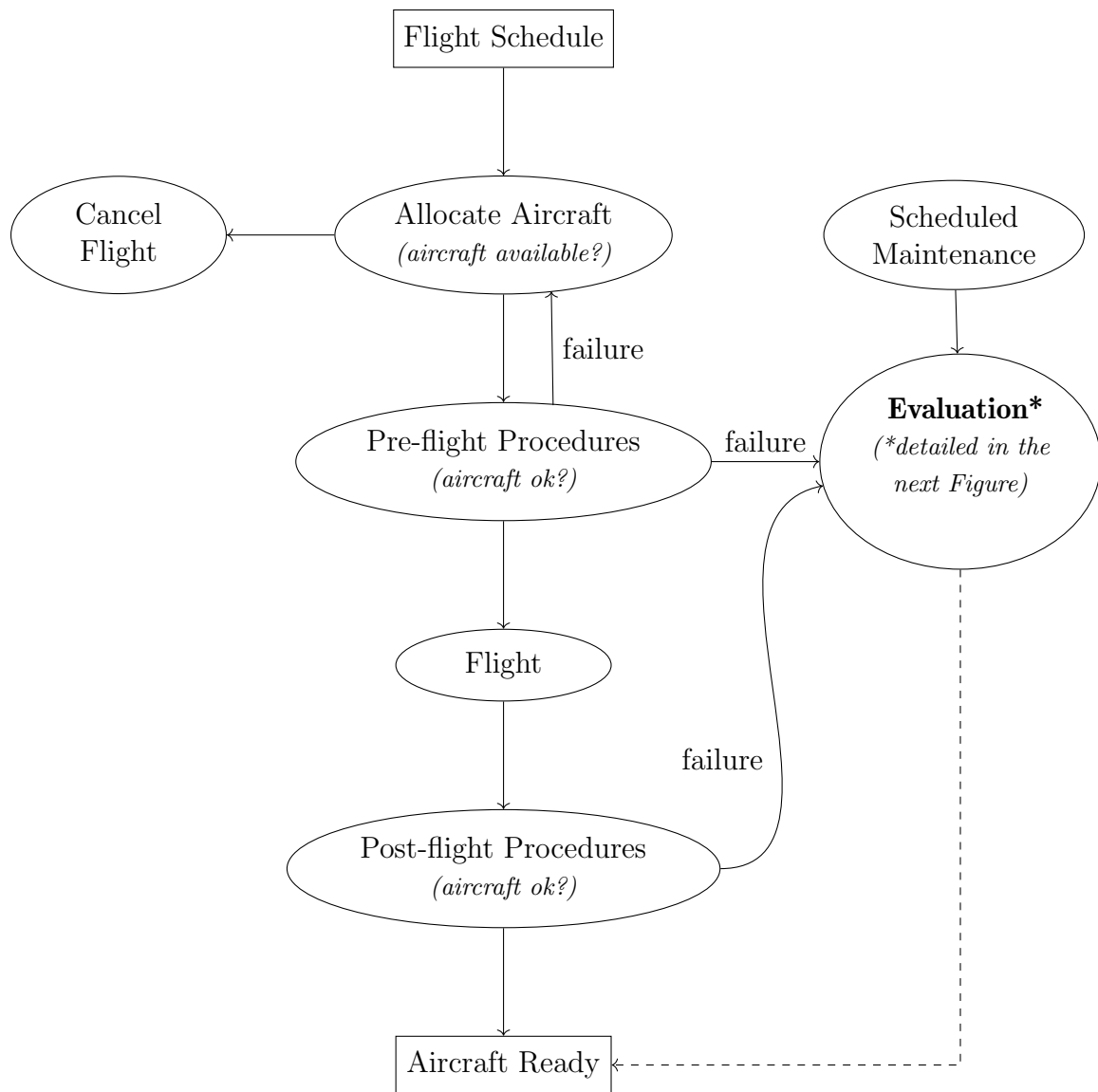


FIGURE 3.3 – Integrated Simulation Model Architecture Illustrating the Intended Model Logic Based on Fleet Availability and Maintenance Requirements.

```

1: Input: startProcedureOutcome, flightOutcome,
           scheduledMaintenanceData, aircraftData, maintenanceData, items-
           Data
2:
3: aircraft.status ← Unavailable
4: if failureConfirmed() then
5:   if knownSolutionExists(maintenanceData) then
6:     solution ← retrieveKnownSolution()
7:   else
8:     openManufacturerCase()
9:     solution ← waitForManufacturerResponse()
10:  end if
11:  if itemReplacementRequired(solution) then
12:    if itemInStock(itemsData) then
13:      reserveItem()
14:    else
15:      requestSupply()
16:      waitForItemDelivery()
17:      reserveItem()
18:    end if
19:  end if
20:  if solutionFeasible(solution, aircraftData, maintenanceData ) then
21:    performMaintenance(solution)
22:  else
23:    scheduleAdditionalMaintenance()
24:  return
25:  end if
26: end if
27: aircraft.status ← Available
28: updateAircraftData()
29: updateMaintenanceLogs()
30: updateItemsData()

```

FIGURE 3.4 – Evaluation and Maintenance Decision Logic Triggered by Aircraft Unavailability, Including Failure Diagnosis, Resource Allocation, and Repair Execution.

### 3.3 Agent-Based Simulation (ABS)

The ABS approach has been used to represent each aircraft in the fleet’s autonomous behavior and interaction with the operational and logistical environments. In this modeling approach, each aircraft is represented as an autonomous agent capable of changing states, making decisions depending on internal and external variables, and influencing overall system performance.

The ABS approach was chosen because it enables the simulation to reflect varied behaviors and unpredictable occurrences resulting from individual aircraft operations. This level of representation allows for the investigation of fleet-level emergent features such

as availability patterns, mission accomplishment rates, and maintenance requirements, which arise from the interplay of individual agents acting under common restrictions.

In the model, aircraft agents interact with entities that represent the flight schedule (which assigns missions) and the logistics subsystem (which provides data about item failures, stock levels, and repair times). Each aircraft's behavior follows a state-based logic, enabling the simulation of operational cycles, inspection procedures, and the consequences of failures or maintenance events.

This agent-based representation has a flexible framework that may be developed to accommodate more decision layers, such as crew allocation, base logistics, or support aircraft, without jeopardizing model integrity. It also allows for experimentation with different fleet compositions and operating techniques, letting the user to evaluate the influence of policy changes or logistical constraints on mission outcomes.

### 3.3.1 Agents

In an ABS, agents are autonomous entities that possess individual states, attributes, and decision rules. They interact with one another and with the environment according to predefined behaviors, influencing the dynamics of the system as a whole. Each agent can perceive changes, update its internal state, and execute actions independently. This approach enables the representation of heterogeneous actors, local interactions, and emergent system-level patterns that are difficult to capture using aggregated or purely deterministic models.

The simulation developed in this research comprises four main types of agents: Failure, Flight, Item, and Aircraft. Each category encompasses domain-specific parameters and behaviors crucial for representing the operational, logistical, and reliability aspects of a military aviation context.

#### 3.3.1.1 Failure Agent

The Failure agent represents an equipment malfunction or degradation event that may affect an aircraft's ability to operate. It stores descriptive and technical information about each failure mode, as well as the resources required for its correction. Its parameters are:

- *f\_code* – Unique identifier for the failure mode;
- *f\_pn* – Part number associated with the failed component;
- *f\_description* – Textual description of the failure;

- *f\_category* – Classification of the failure (e.g., critical, non-critical);
- *f\_restrictionType* – Operational restriction imposed while the failure remains unresolved; and
- *f\_timeToRepair* – Estimated time to return the aircraft to service.

These agents allow the model to generate failure events and propagate their consequences to aircraft availability.

### 3.3.1.2 Flight Agent

The Flight agent represents an individual mission or sortie. It includes both temporal and operational attributes used to determine aircraft demand, as well as mission scheduling. Its parameters include:

- *fl\_departureDateTime* – Scheduled departure date and time;
- *fl\_duration* – Planned duration of the mission;
- *fl\_departsAt* – Location or aerodrome from which the mission begins;
- *fl\_destination* – Destination or recovery location; and
- *fl\_profile* – Mission profile, used to determine flight intensity or operational requirements.

These agents provide the demand structure to which the aircraft fleet responds, enabling the simulation of operational tempo and mission allocation.

### 3.3.1.3 Item Agent

The Item agent represents a logistical component required for maintenance actions. Each item includes reliability characteristics, repair constraints, and stock availability at multiple support echelons. The relevant parameters are:

- *i\_pn* – Part number of the item;
- *i\_description* – Description of the component;
- *i\_failRate* – Failure rate associated with the item;
- *i\_stopRate* – The rate at which the item causes the aircraft to require maintenance, including circumstances where the item does not need to be replaced;

- *i\_category* – Category or functional grouping;
- *i\_restrictionType* – Operational restriction associated with the item’s failure;
- *i\_timeToRepair* – Duration required to return the aircraft to operational status following the repair of this item;
- *i\_stockLevelBase* – Quantity available at the operational base;
- *i\_stockLevelDepot* – Quantity available at the maintenance depot;
- *i\_stockLevelIndustry* – Quantity available at the industrial support level; and
- *i\_stockLevelDeployed* – Quantity available at the deployed location.

These agents enable the simulation to assess the impact of inventory levels on operational continuity, allowing shortages, stock movements, and consumption to affect aircraft readiness.

#### 3.3.1.4 Aircraft Agent

The Aircraft agent is the central operational entity of the simulation. It represents an individual aircraft tracked throughout the study period, with detailed state variables reflecting its health, limitations, and initial status. Its parameters are:

- *a\_gate* – Current physical or operational location of the aircraft;
- *a\_initialFh* – Initial flight hours at the start of the simulation;
- *a\_tailNumber* – Unique aircraft identifier;
- *a\_healthFactor* – Numerical indicator of aircraft historical reliability;
- *a\_limitToFly* – Operational limit beyond which the aircraft must be removed from service;
- *a\_status* – Current operational state (e.g., ready, under evaluation, waiting resource);
- *a\_statusChange* – Forecast of status change; and
- *a\_initialCode* – Initial failure or scheduled maintenance code. Code used in model initialization.

Aircraft agents interact with failures, maintenance actions (when applicable), and flight demands. Their combined behavior determines mission availability, fleet capacity, and the emergent operational performance indicators studied in this dissertation.

### 3.3.2 Aircraft State Chart

The Aircraft agent, being the most complex and crucial component of this model, required a more elaborate framework of states and transitional logics to accurately reflect real-world actions of the fleet. This framework is the Aircraft State Chart, shown in Figure 3.5.

In the model, each aircraft can be in one of two primary conditions: *available* or *unavailable*. These conditions encompass the various internal states an aircraft may assume during its operational lifecycle. The states that an aircraft can assume are shown schematically in Figure 3.5.

When an aircraft is *available*, it may assume several operational states:

- The default state is *ready*, indicating that the aircraft is fit to be scheduled for a mission.
- Once selected by the flight schedule, it transitions to the *startProcedure* state, where pre-flight inspections are conducted.
- If no issues are detected, the aircraft proceeds to the *flight* state and performs its assigned mission.
- If any issue is detected during checks, the aircraft transitions to the *evaluation* state in the *unavailable* condition. In this case, another aircraft in the ready state may be assigned to the mission if available.
- Upon completing the mission in the *flight* state, the aircraft enters the *powerDown* state. Here, post-flight inspections are conducted, and operational and logistics data are updated.
- Based on these results, the aircraft may return to the *ready* state or transition to the *unavailable* condition for scheduled or unscheduled maintenance.

About the unavailable condition, the already mentioned *evaluation* state is the initial destiny of every aircraft that leave the available condition. In this state, some functions are executed to determine:

- 1 Whether the reported fault actually requires maintenance, or whether it turns out to be a false alarm dismissed by the maintenance team;
- 2 Whether appropriate maintenance procedures have been defined for the fault;
- 3 Whether any components need to be replaced; and

4 Whether the required spare parts are available in stock.

Based on these evaluations, the aircraft may follow different paths:

- If it was a false alarm, the aircraft returns to *available* condition, in the *ready* state;
- If a maintenance procedure is not yet defined, the aircraft transitions to the *waitingProcedure* state, remaining idle until the procedure becomes available;
- If the required parts are temporarily unavailable, the aircraft enters the *waitingResources* state, awaiting the allocation of resources;
- Once all conditions are met, the aircraft proceeds to the *repair* state, where maintenance actions are performed.
- After repair completion the aircraft returns to the *ready* state, rejoining the pool of *available* aircraft.

An additional state, *outOfService*, is included in the model to represent aircraft that are temporarily or permanently removed from the fleet. This state is useful for scenarios such as simulating a dispatched mission where not all aircraft are allocated, or when an aircraft is withdrawn due to long-term unavailability or retirement.

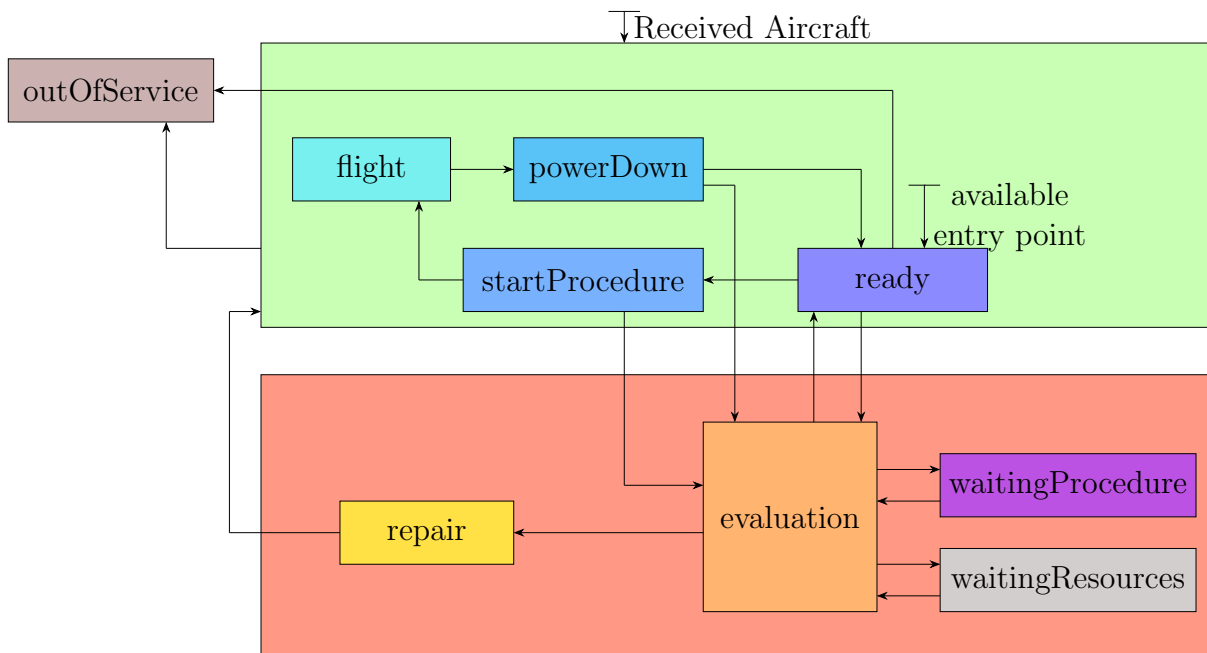


FIGURE 3.5 – Aircraft Statechart Diagram Representing Available and Unavailable States and the Possible Transitions.

### 3.3.2.1 Behaviors

In an ABS, behaviors represent the rules, decision processes, and state transitions that govern how each agent acts over time. Behaviors determine how entities respond to events, interact with other agents, and contribute to the emergent properties of the system. In this model, behaviors are structured to reflect operational dynamics, reliability events, inventory variation, and mission scheduling.

#### Failure Agent Behavior

Every time an aircraft is required for flight during the simulation, all its items are tested in a procedure similar to a power-on Built-in Test (BIT), in the *startProcedure* state. This test is executed by a function that verifies whether a failure has been activated. The same procedure is performed after each flight, in the *powerDown* state.

ACTIVATION: A Failure agent becomes active when the associated probability or condition is met, based on the failure rate of the item (*i\_failRate* or *i\_stopRate*), the accumulation of cycles and flight hours, and randomness. Failures are modeled as independent stochastic events across aircraft and components. This assumption implies that the occurrence of a failure in one system does not influence the probability of failure in another, allowing the use of independent random sampling in the simulation.

PROPAGATION: Once active, the failure imposes restrictions on the aircraft, potentially grounding it or limiting its mission eligibility. The Aircraft agent which was grounded due to this failure transits to the *evaluation* state.

REPAIR CYCLE: If the failure is confirmed and all the previous analyses of conditions necessary for repair are reached, such as maintenance procedure and stock available, the failure enters a repair sequence, consuming resources (if necessary) and time to restore the aircraft to service. The duration required to execute a repair takes into account its corresponding *timeToRepair* as the mean of a stochastic distribution.

RESOLUTION: After the repair time has elapsed, the failure agent is deactivated and frees the aircraft of its restrictions.

Failure agents operate as triggers for maintenance demand and parametrize the consequences. Failure agents directly impact fleet availability by constraining operational status.

#### Flight Agent Behavior

Flight agents do not evolve autonomously but act as scheduled demands that activate at predetermined times. Their behaviors include:

MISSION INITIALIZATION: When the departure time arrives, the flight becomes active and requests an aircraft assignment.

**ASSIGNMENT LOGIC:** The system evaluates the available aircraft in the *ready* state and allocates one that is suitable, following the priority function. This function analyzes the status of each aircraft, the limit of flight hours to fly, and the accumulated flight hours. The assignment function also introduces an element of randomness, leading to a non-strict adherence to the priority choice. The strict adherence rate is controlled by a user-defined parameter (*randomAllocation*). If there is no aircraft available, the flight is canceled. If the aircraft fails before takeoff, the same previously described routine is executed to assign another aircraft to the mission if a spare aircraft is available.

Through these behaviors, flight agents drive the operational workload imposed on the fleet.

### **Item Agent Behavior**

Item agents evolve according to the consumption, replenishment, and stock interactions across the support echelons. Their behaviors include:

**DEMAND GENERATION:** When a failure occurs that requires a specific item, the corresponding Item agent receives a demand event.

**STOCK VERIFICATION:** The system checks availability across stock levels. If the item is immediately available, it is used and the stock is updated. Otherwise, the replenishment function is triggered by the item lack event, and the aircraft must wait for resupply.

**CONSUMPTION:** If stock is available at some level, following the hierarchical logistic echelon structure, one unit is consumed and deducted from the appropriate level.

**REPLENISHMENT AND DELAY:** If local stock is unavailable, the repair delays until inventory becomes available, influencing the downtime of the affected aircraft. The aircraft waits for its turn to receive the respective item in the queue. This queue represents waiting for stock availability, not maintenance personnel, which are not constrained in this version of the model.

**RELIABILITY INTEGRATION:** Item failure rates contribute to the generation of new Failure agents, linking item behavior to operational reliability.

The behaviors of the Item agent integrate logistics constraints into the operational cycle, allowing the model to capture the influence of supply availability on mission readiness.

### **Aircraft Agent Behavior**

Aircraft agents exhibit the most complex behavior in the system, serving as the central entities whose states and interactions define fleet performance. Key behavioral components include:

**STATUS TRANSITIONS:** The aircraft transitions between states such as *ready*, *flight*, in *evaluation*, or *repair*, depending on failures, restrictions, and flight schedules.

**FAILURE INTEGRATION:** Active failures modify the aircraft's operational status, potentially grounding it or restricting mission types.

**RESTORATION:** After the active failure is repaired, the aircraft switches back to the *ready* state.

**MOVEMENT AND ASSIGNMENT:** The aircraft proceeds to departure, executes missions, lands at its destination, and conducts ground movement to the gate or hangar, in accordance with the events and interactions related to this aircraft.

Together, these behaviors represent the operational lifecycle of an aircraft, from mission execution to reliability degradation and recovery.

### 3.3.2.2 Interactions

In ABS, system behavior emerges from the interactions among autonomous agents rather than from predefined aggregate equations. These interactions define how operational demands influence aircraft availability, how failures propagate into maintenance workload, and how logistics constraints affect mission fulfillment. In this model, interactions occur primarily through events, state transitions, data exchanges, and resource dependencies.

#### **Aircraft and Flight Agents**

Aircraft and Flight agents interact through mission assignment processes:

- When a Flight agent becomes active at its scheduled departure time, it requests an aircraft that is both available and eligible to perform the mission.
- The Aircraft agent responds by either accepting the assignment, transitioning from *ready* to *startProcedure*, or being bypassed if its status or restrictions prevent participation.

This interaction couples operational demand with the dynamic availability of the fleet.

#### **Aircraft and Failure Agents**

Failure agents directly modify the operational status of aircraft:

- When a failure is activated, the Aircraft agent transitions to the evaluation state.
- Active failures may impose restrictions that limit mission eligibility or ground the aircraft entirely.

- When the failure is resolved, the Failure agent communicates the resolution, allowing the aircraft to return to a ready state.

This interaction captures the feedback loop between reliability events and fleet readiness.

### **Failure and Item Agents**

The very first interaction is to assess the necessity of item replacement. If replacement is unnecessary, stock is not required, and the failure can proceed to repair.

Failures requiring item replacement:

- Upon activation, each failure queries the corresponding Item agent to verify stock availability.
- If the item is available, the repair can proceed immediately, consuming one unit of stock.
- If not, an order is made for the item and the aircraft changes to the *waitingResources* state until the replenishment occurs.

This interaction embeds logistics constraints directly into operational outcomes, allowing stock shortages to affect mission capability.

### **Interactions Among Aircraft Agents**

Aircraft agents typically don't interact directly, except in terms of minimal mission criteria; however, they compete for shared system resources:

- Multiple aircraft may require the same item or maintenance capacity, influencing each other's availability.
- Flights compete for aircraft allocation, and an aircraft assigned to one mission cannot be used for another simultaneously.
- Depending on the mission profile and its requirements, a single aircraft cannot operate alone without the support of one or more other aircraft.

These indirect interactions contribute to emergent system-level behavior, including bottlenecks and waiting times.

### **Interactions with Global Parameters**

Agents are also influenced by scenario-level parameters, such as:

- failure probabilities,
- time-to-repair distributions,
- ground movements delays,
- administrative delays,
- stock replenishment policies.

These parameters serve as global inputs affecting all agents and enabling systematic scenario exploration.

### 3.3.2.3 Environment

Prior to elaborating on the specific elements of the Environment, it is essential to highlight the importance of it inside an agent-based simulation. In this model, the environment defines the structural and contextual conditions under which all agents operate, shaping their behavior, interactions, and the emergent dynamics of the system. By explicitly describing the temporal, operational, logistical, and data environments, this subsection clarifies the assumptions, boundaries, and constraints that govern the simulation. This enhances the transparency and reproducibility of the model, ensures that the reader comprehends the representation of real-world processes, and establishes the foundation for analyzing the results presented in subsequent chapters.

The environment defines the structural and contextual boundaries within which all agents operate. It specifies the temporal progression, operational rules, logistical constraints, and spatial representation that together form the foundation of the simulation. By clearly establishing these elements, the environment delineates what is included within the scope of the model and what is intentionally excluded, ensuring analytical transparency and enabling the correct interpretation of emergent system behavior.

#### **Temporal Environment**

The simulation operates within a discrete temporal framework that structures the sequencing of all events. Mission departures, failure activations, repair cycles, and stock consumption occur at specific time points or intervals defined by this temporal environment. Time progression governs causality, ensuring that operational effects, such as the accumulation of flight hours, the duration of downtime, or delays due to resource shortages, are traced accurately throughout the simulated timeframe.

#### **Operational Environment**

The operational environment establishes the rules that manage aircraft participation in missions. It includes the mission schedule, the criteria for aircraft assignment, and

the conditions determining eligibility for flight. This environment controls how operational demand interacts with aircraft availability and status, shaping the fleet's ability to fulfill assigned missions. By defining this structure explicitly, the model can assess how differences in mission cadence or assignment logic affect overall performance.

### **Logistics Environment**

The logistics environment defines the material support structure that supports fleet operations. It includes stock levels for each item across different support echelons: base, depot, industrial level, and deployed site; and the rules for item consumption and replenishment. The logistics environment directly constrains the system: shortages delay repairs, influence downtime, and indirectly affect mission completion rates. Its explicit definition ensures that logistical limitations remain within the intended scope of the model, allowing the user to evaluate how inventory configuration impacts operational resilience.

### **Data and Parameter Environment**

The environment also incorporates the data inputs and parameters that define the scenario under analysis. These include failure rates, removal rates, aircraft initial conditions, mission profiles, item characteristics, and stock quantities. Each of these elements shapes agent behavior and determines the boundaries of the scenario. By importing and controlling these data structures, the environment provides a flexible but well-defined basis for scenario variation, sensitivity studies, and Monte Carlo analysis.

### **Spatial Environment**

Although the model does not implement full geographic mobility or detailed aeronautical navigation, it provides a structured spatial representation that supports visualization, operational interpretation, and scenario awareness. This spatial environment includes:

Aircraft movement sequences, such as gate–takeoff–landing–gate cycles, which allow the visualization of operational flows.

Ground transitions, including gate–hangar–gate movements, which represent aircraft displacement during inspection or maintenance sequences.

Simplified flight phases, enabling the visualization of aircraft leaving, traversing, and returning to operational areas.

Tactical scenario representation, offering a high-level spatial depiction of aircraft distribution and mission execution within a simplified operational theater.

Georeferenced visualization, which positions missions or movements onto a geographic reference, improving interpretability and allowing users to relate simulated events to real-world spatial contexts.

This spatial component improves the model's explanatory power while remaining

within a defined scope: provides visualization and contextual awareness, but does not simulate aerodynamics, detailed trajectories, or real-time flight physics. The spatial environment is therefore intentionally abstracted to support decision-making and scenario comprehension without exceeding the intended level of model complexity.

## 3.4 DES

The DES component structures the operational and maintenance processes of the model by representing them as sequences of events that occur at specific points in time. While the agent-based structure defines the autonomy and state transitions of each aircraft, DES provides the process logic, timing, delays, and resource flows that govern how agents move through operational and logistical activities. In this model, DES is responsible for orchestrating three major flows: the Evaluation Process, the Repair Process, and the Flight Process. These flows determine how aircraft transition between states, how failures propagate into maintenance activities, and how missions are executed.

### 3.4.1 Evaluation Process

The Evaluation Process is activated whenever an aircraft transitions into the *evaluation* state on its statechart. At the moment of entry into this state, the aircraft saves the relevant failure information, such as the failed item code or the scheduled maintenance code, the associated mean *timeToRepair*, and the linked stock data. Following this initialization, the DES process is triggered, which also occurs during the state's entry action.

The flow begins with the aircraft performing a ground movement from the gate to the hangar, introducing a realistic delay and reflecting the physical repositioning required for assessment. Once in the hangar, the process evaluates whether the event corresponds to scheduled maintenance or unscheduled maintenance:

- If scheduled, the aircraft is immediately sent to the Repair Process.
- If unscheduled, the system executes a structured sequence of checks:
  1. Failure confirmation: verifies whether the reported fault is valid.
  2. Maintenance procedure availability: ensures that a defined procedure exists for the failure.
  3. Component replacement requirement: determines whether a replacement part is needed.
  4. Stock availability: verifies stock levels when replacement is required.

Depending on the outcome of these checks, the aircraft follows one of several paths:

- returns to the *ready* state, if false alarm (statechart),
- enters *waitingProcedure* state (statechart),
- enters *waitingResources* state (statechart),
- or continues to the Repair Process (DES).

This process captures the core logic connecting reliability events, procedural constraints, and logistical limitations.

### 3.4.2 Repair Process

The Repair Process represents the sequence of actions required to restore an aircraft to operational condition. Once triggered, the aircraft undergoes:

- Preparation for maintenance, including the necessary movements and delay.
- Execution of the maintenance action, using the *timeToRepair* associated with the failure or scheduled event.
- The model incorporates stochastic variation around this mean repair time to reflect real-world uncertainty.
- Post-maintenance inspection, ensuring that the repair was successful and that the aircraft meets operational criteria.
- Ground movement back to the gate, completing the maintenance cycle.

Upon returning to the gate, the DES process sends the appropriate message to the statechart, enabling the aircraft to transit back to the *available* condition, on the *ready* state.

### 3.4.3 Flight Process

The Flight Process controls the operational flow of missions and incorporates simplified spatial representation. When a mission begins, the DES sequence guides the aircraft through:

1. Taxi from gate to takeoff point

2. Takeoff and initial climb
3. Mission execution, using the predefined mission duration
4. Descent and landing phases
5. Taxi back to the gate

After the takeoff phase, aircraft visualization may be split across multiple spatial environments, enabling:

- a simplified representation of the flight phase in an abstract spatial space,
- a top-level tactical scenario view,
- and a georeferenced visualization linked to mission routes or operational areas.

This structure maintains operational realism while avoiding unnecessary aerodynamic and performance details.

#### 3.4.4 State Transitions Using DES Events

The interaction between the DES flows and the aircraft statechart is central to the model. DES processes send messages that trigger state transitions such as:

- *flight* → *powerDown*;
- *evaluation* → *ready*;
- *evaluation* → *repair*;
- *evaluation* → *waitingProcedure*;
- *evaluation* → *waitingResources*;
- *repair* → *ready*.

Some transitions are activated through functions rather than DES events, including:

- mission initiation through a *FlightOrder* message sent by a Flight agent, resulting in a transition from *ready* to *startProcedure* state;
- *failureFunction* that activates transitions from *powerDown* to *evaluation* or *ready* states, according to the result of the function;

- *failureFunctionStart*, in case of failure during *startProcedure*, send the aircraft to *evaluation* state;
- scheduled-maintenance triggers based on accumulated flight hours send the aircraft from *ready* to *evaluation* state;
- *timeout* that activates transitions from *waitingProcedure* back to *evaluation* state;
- *resupply* function that returns the aircraft from *waitingResources* back to *evaluation* state;
- The transition from *available* condition to *outOfService* state can be activated soon after initialization, involving the discontinuation of unassigned aircraft, or through the *outOfService* function, which is triggered when the aircraft has surpassed the predetermined limit of operating hours.

This integration ensures that DES governs all time-based sequences, while the statechart governs the logic-based decision structure.

## 3.5 Integration Between DES and ABS

The simulation model relies on a tight integration between ABS and DES. ABS governs the autonomy, state transitions, and decision-making of each aircraft, while DES governs the timing, process logic, and sequencing of operational and maintenance events. The interaction between these two paradigms allows the model to represent both individual-level behavior and system-level process flows.

### 3.5.1 ABS as the decision layer

Each aircraft behaves as an autonomous agent with its own statechart. State changes are triggered by:

- internal conditions (failures, accumulated flight hours),
- external requests (mission assignment),
- or messages received from DES processes.

This ensures that aircraft react individually to reliability events and availability constraints.

### 3.5.2 DES as the process layer

DES structures the execution of real-world processes such as:

- mission execution,
- evaluation for faults,
- repair activities,
- ground movements and delays,
- stock consumption and replenishment order.

These processes generate timed events that update each aircraft's state.

### 3.5.3 Message and Function Coupling

Communication between ABS and DES occurs through:

- Messages sent from DES to ABS, triggering statechart transitions (e.g., repair completed, fail confirmed, return to gate).
- Functions executed in ABS, triggering DES processes (e.g., start flight, failure activation, scheduled maintenance activation).
- Timeouts in ABS, that are independent of DES and represent waiting conditions (e.g., *waitingProcedure* used as the mean time waiting manufacturer's reply to a solicitation).

### 3.5.4 Benefits of the integrated approach

This hybrid architecture provides several advantages:

- **Temporal accuracy:** DES ensures correct sequencing of maintenance and operational tasks.
- **Behavioral flexibility:** ABS allows heterogeneous aircraft behavior and emergent patterns.
- **Realistic delays:** DES models ground movements, inspections, and repair times.

- **Scenario adaptability:** ABS–DES integration enables testing different strategies and logistical constraints without redesigning the model.

Together, ABS and DES form a coherent simulation framework capable of capturing the complexity of fleet operations while remaining computationally manageable.

## 3.6 Assumptions and Simplifications

Like any simulation, the implementation relies on a set of assumptions and simplifications that shape the scope and applicability of the results. These assumptions are necessary to balance model realism with computational efficiency and to maintain a manageable level of detail.

### 3.6.1 Simplified Maintenance Workflow

The maintenance process is represented through a single evaluation flow followed by a single repair flow. Real-world maintenance may involve:

- specialized crews,
- simultaneous tasks,
- phased inspections,
- tooling constraints.

These were intentionally abstracted to maintain focus on failure confirmation, repair time, stock availability, and operational impact.

### 3.6.2 Stochastic Repair Times Based on Mean Values

Repair duration is modeled using a stochastic distribution centered around a mean *timeToRepair* of the failed item. This simplifies:

- technician variability,
- procedural differences,
- availability of tools or diagnosis duration.

The focus remains on capturing uncertainty, not replicating full maintenance engineering processes.

### 3.6.3 Binary Maintenance Decisions

Decisions such as “Is the maintenance procedure available?” or “Does the item need replacement?” are modeled as binary outcomes. Real-world scenarios involve conditional checks, safety assessments, and expert judgment. The simplified logic preserves the causal structure without overcomplicating the decision tree.

### 3.6.4 Abstracted Movements

The runway was always considered available. Taxiing, towing, and hangar movements are modeled as delays with simplified spatial transitions. These movements do not include:

- runway saturation,
- air traffic control restrictions,
- taxi route congestion,
- ramp operational conflicts,
- real airport geometry.

This keeps ground operations realistic enough for timing analysis without transforming the model into an airport simulation.

### 3.6.5 No Queuing for Maintenance Personnel

The current DES does not include a constraint for maintenance crews. All maintenance events are conducted once the materials are available. This assumption simplifies the model but can be expanded in future versions.

### 3.6.6 Instantaneous Task Switching

State transitions from ABS triggered by DES messages occur immediately, except when explicitly modeled (timeouts or transitions with delays). This abstraction avoids introducing micro-delays that would not meaningfully affect scenario-level outcomes.

### 3.6.7 No Degradation During Flight Phases

Failures occur at the start or end of the mission, not dynamically during flight. This simplification avoids the complexity of mid-flight failures while still capturing the operational impact of reliability. This assumption simplifies the model but can be expanded in future versions.

### 3.6.8 Summary

These assumptions aims to keep the model:

- computationally efficient,
- transparent,
- aligned with available data, and
- consistent with the methodological scope of this dissertation.

They also ensure that model results reflect decisional and logistical insights, rather than attempting to replicate engineering-level maintenance or flight physics.

## 3.7 Tests and Evaluation Framework

This section defines the structured testing and evaluation approach adopted to assess the functional correctness, robustness, and decision-support capability of the proposed simulation framework. While Chapter 4 presents the detailed execution and results of these tests, the present section establishes their conceptual rationale, sequencing, and relationship to the research hypothesis.

The evaluation strategy follows a progressive logic. It begins by ensuring structural consistency and computational robustness of the model, proceeds to assess behavioral coherence under parameter variation and stress conditions, and culminates in the application of the framework to a representative operational case study. The purpose of this progression is to demonstrate not only that the model functions correctly, but also that it meaningfully supports decision-making related to supportability under uncertainty.

### 3.7.1 Evaluation Logic and Relation to the Hypothesis

The central hypothesis of this dissertation states that:

*An integrated ABS and DES framework can improve precision, S.A., and anticipatory capability in decision-making related to the support of military air operations under uncertainty.*

To evaluate this hypothesis, the testing structure must demonstrate that the framework:

- Produces logically consistent and stable behavior (structural validity),
- Responds coherently to variations in operational and logistics parameters (behavioral validity),
- Generates probabilistic and time-dependent indicators relevant to supportability decisions (decision-support relevance),
- Provides actionable information that can influence upper-level decisions (case study demonstration).

Each test stage therefore contributes to one or more components of the hypothesis.

### **3.7.2 Robustness Analysis**

The first stage of testing consists of robustness analysis. Its purpose is to verify that the hybrid ABS–DES architecture remains logically consistent and computationally stable under variability and extreme conditions.

Robustness testing includes:

- Verification of valid state transitions across the aircraft statechart,
- Confirmation that DES flows activate and terminate as designed,
- Assessment of system behavior under extreme parameter values (e.g., zero stock, high failure rates, high operational tempo),
- Inspection for infinite loops, dead states, or contradictory transitions.

This stage ensures that the framework does not produce illogical or unstable outcomes when subjected to stress conditions. Robustness is a prerequisite for credible decision-support analysis.

The detailed execution and outcomes of robustness tests are presented in Chapter 4.

### 3.7.3 Sensitivity and Parameter Variation Tests

Following structural robustness, the model is subjected to systematic variation of key parameters. The objective is to evaluate whether changes in failure rates, repair times, inventory levels, replenishment delays, and operational tempo produce proportional and interpretable changes in system performance indicators.

This stage assesses:

- Coherence of cause-effect relationships,
- Stability of probabilistic outputs across Monte Carlo replications,
- Logical propagation of operational and logistics constraints.

Sensitivity analysis supports the hypothesis component related to precision, by verifying that the model responds consistently to quantified parameter changes.

Chapter 4 details the experimental design and observed system behavior under these variations.

### 3.7.4 Decision-Support Evaluation

Beyond structural correctness, the framework must demonstrate its capacity to enhance S.A. and anticipatory capability.

This stage evaluates whether the model outputs:

- Reveal time-dependent interactions between operations and logistics,
- Provide probabilistic distributions rather than deterministic snapshots,
- Allow projection of future degradation in availability and cost-benefit,
- Support comparison between alternative operational scenarios.

The focus here is not optimization, but interpretability and informational richness. The evaluation examines whether the framework enables the Decision Sector to perceive system state, comprehend dependencies, and anticipate future constraints.

Chapter 4 presents the corresponding experimental evidence.

### 3.7.5 Case Study Application

The final stage of evaluation consists of applying the framework to a representative operational scenario designed to reflect sustained military air operations.

The case study integrates:

- Defined mission objectives,
- Operational tempo,
- Aircraft configuration,
- Maintenance parameters,
- Inventory constraints.

Through Monte Carlo experimentation, the case study generates probabilistic indicators of mission success, availability evolution, maintenance workload, and logistics bottlenecks.

This stage demonstrates how the Decision Sector can use simulation outputs to assess supportability and cost-benefit trade-offs under uncertainty. It constitutes the final empirical demonstration of the dissertation hypothesis.

Detailed implementation and analysis of the case study are presented in Chapter 4.

### 3.7.6 Summary of the Testing Structure

The testing framework follows a structured progression:

1. Robustness Analysis → ensures structural and logical integrity.
2. Sensitivity Tests → ensures behavioral coherence and precision.
3. Decision-Support Evaluation → assesses informational quality and S.A. enhancement.
4. Case Study → demonstrates applicability in a realistic operational context.

This structured evaluation ensures that the proposed simulation framework is not only technically functional, but also methodologically aligned with the objective of improving decision-making related to supportability in military air operations.

Chapter 4 presents the detailed execution, results, and interpretation of each stage.

# 4 Results Presentation, Analysis and Discussion

## 4.1 Introduction

This chapter presents, analyzes, and discusses the results obtained from the implementation and experimental evaluation of the proposed hybrid simulation framework. The objective of this chapter is not merely to report numerical outputs, but to examine the behavior of the model under controlled experimental conditions and to assess, based on empirical evidence, whether the framework fulfills the requirements established in Chapter 3.

As defined in Section 3.7, the evaluation strategy was structured to test the robustness, behavioral coherence, and decision-support capabilities of the proposed model. The analyses presented here follow that structure. First, the robustness of the framework is examined to verify structural consistency, logical stability, and computational reliability under boundary and stress conditions. Subsequently, sensitivity analyses are conducted to evaluate how variations in key parameters, such as failure rates, repair durations, inventory levels, and operational tempo, affect system behavior and performance indicators.

Beyond structural and parametric validation, particular attention is devoted to evaluating whether the model enhances three core attributes associated with improved decision-making in logistics support management: precision, S.A., and anticipatory capability. These attributes derive directly from the research problem defined in Chapter 1, which states that decision-making related to the support of military air operations can be improved by increasing precision, S.A., and anticipatory capability in order to better manage the cost–benefit of sustained operations under uncertainty. Accordingly, this chapter examines whether the outputs generated by the framework provide clearer probabilistic information, greater visibility of system dynamics, and improved ability to project future operational states.

The results are organized into four major analytical blocks. The first addresses robustness and structural integrity. The second evaluates sensitivity and behavioral response

patterns. The third examines the framework’s effectiveness as a decision-support instrument across the Decision, Operations, and Logistics sectors. The fourth presents an integrated case study, demonstrating system behavior under sustained operational conditions and assessing its implications for support management.

Throughout this chapter, results are interpreted within the defined modeling scope and experimental configuration. The discussion focuses on internal coherence, causal consistency, and interpretability of outputs, avoiding extrapolations beyond the validated domain of the model. The broader implications and contributions of these findings are reserved for Chapter 5, where the results are contextualized within the academic and practical landscape of military aviation supportability.

This structure ensures that the evaluation proceeds systematically from model verification to hypothesis assessment, providing a transparent and evidence-based foundation for the conclusions that follow.

## 4.2 Robustness Assessment of the Proposed Framework

The first stage of the empirical evaluation focuses on the structural and computational robustness of the proposed hybrid simulation framework. Before analyzing its decision-support capabilities, it is necessary to demonstrate that the model operates consistently under boundary conditions, extreme parameter configurations, and repeated stochastic experimentation. Robustness, in this context, refers to the stability, logical coherence, and numerical reliability of the model when subjected to stress conditions that challenge its internal structure.

This section presents the results of three complementary robustness tests: (i) structural consistency verification, (ii) extreme-condition stress testing, and (iii) Monte Carlo computational stability analysis.

### 4.2.1 Structural Consistency and State Logic Verification

The first robustness test evaluates whether the integration between the ABS and DES components preserves logical consistency across all aircraft state transitions and process flows. The objective is to verify that no dead states, unreachable transitions, or contradictory process activations emerge during simulation execution.

To support this analysis, Table 4.1 summarizes the state transitions observed during a full simulation cycle, including:

- Available states: *ready*, *startProcedure*, *flight*, *powerDown*;

- Unavailable states: *evaluation*, *waitingProcedure*, *waitingResources*, *repair*; and
- *outOfService* state.

The table identifies, for each state, the triggering events, subsequent transitions, and what I checked for each transition and how I verified it was working properly. Some checks were executed using logs, to certify the logic being applied as necessary. The main logs are listed below.

TABLE 4.1 – Observed aircraft state transitions and structural verification checks during simulation cycles.

State	Trigger / Entry event	Allowed next transition(s)	Verification check(s)
<i>Available states</i>			
<i>ready</i>	Aircraft returned after completed cycle; repair finalized; false alarm cleared	→ <i>startProcedure</i> ( <i>FlightOrder</i> ); → <i>evaluation</i> (scheduled trigger); → <i>outOfService</i> ( <i>a_limitToFly</i> reached)	Verified that every successful cycle returns to <i>ready</i> ; confirmed no direct transition to <i>flight</i> ; audited transition logs to ensure scheduled maintenance and out-of-service trigger functions correctly; dashboard visual evidences: ground movement and colored state flag

*Continued on next page*

State	Trigger / Entry event	Allowed next transition(s)	Verification check
<i>startProcedure</i>	FlightOrder issued by schedule and allocation logic	→ <i>flight</i> (cleared); → <i>evaluation</i> (pre-flight failure)	Confirmed entry only after FlightOrder; validated branching based on failure flags; compared number of <i>startProcedure</i> entries with scheduled departures and abort log; dashboard visual evidences: ground movement and colored state flag
<i>flight</i>	<i>StartProcedure</i> cleared and take-off authorized	→ <i>powerDown</i> (mission completed)	Validated increment of flight hours and cycles; confirmed mission success metric increments at take-off; verified no maintenance resolution occurs during <i>flight</i> ; dashboard visual evidences: ground movement and colored state flag
<i>powerDown</i>	Flight completed; post-flight inspection initiated	→ <i>ready</i> (no failure); → <i>evaluation</i> (failure detected)	Checked post-flight failure sampling; validated correct routing to <i>evaluation</i> when failure flag activated; ensured successful missions counted independently of post-flight failure; dashboard visual evidences: ground movement and colored state flag

*Continued on next page*

State	Trigger / Entry event	Allowed next transition(s)	Verification check
<i>Unavailable states</i>			
<i>evaluation</i>	Scheduled maintenance trigger; pre-flight failure; post-flight failure	→ <i>ready</i> ; → <i>waitingProcedure</i> ; → <i>waitingResources</i> ; → <i>repair</i>	Verified mutual exclusivity of exit paths; confirmed spare requirement generation; validated no unintended state loops; audited counts against failure occurrence rates; dashboard visual evidences: stock map values, ground movement, failure label, and colored state flag
<i>waitingProcedure</i>	Procedure unavailable; case opened with industry	→ <i>evaluation</i> (procedure released)	Compared dwell-time distribution with configured delay parameter; verified return to <i>evaluation</i> preserves decision logic sequence; dashboard visual evidences: failure label, and colored state flag
<i>waitingResources</i>	Required spare unavailable at time of evaluation	→ <i>evaluation</i> (resupply completed)	Validated inventory cannot become negative; confirmed aircraft remains blocked until stock replenishment event; checked release timing against replenishment delay; dashboard visual evidences: stock map values, failure label, and colored state flag

*Continued on next page*

State	Trigger / Entry event	Allowed next transition(s)	Verification check
<i>repair</i>	Evaluation confirmed repair feasible and prerequisites satisfied	→ <i>ready</i> (repair completed)	Verified repair duration behavior; confirmed spare consumption occurs once; ensured repair clears failure flags before transition to <i>ready</i> ; dashboard visual evidences: stock map values, ground movement, failure label, and colored state flag
<i>Absorbing state</i>			
<i>outOfService</i>	limitToFly threshold reached; campaign removal policy	No transition during campaign window	Validated deterministic transition at threshold; confirmed aircraft does not re-enter operational cycle; cross-checked removal timing with input parameters; dashboard visual evidences: aircraft position and colored state flag

#### List of main logs:

- Scheduled Maintenance - “xx (*tailNumber*), goToMaintenance: xxx (*hrsMtceInterval*) hrs”;
- Reach *a\_limitToFly* - “xx (*tailNumber*), retired: xxx (*hrsFlown*)”;
- Failure at start procedure - “xx (*tailNumber*), goToMaintenance, failure xx (*code*)”;
- Lack of spare aircraft - “There is no spare acft”;
- Allocate spare aircraft - “Spare acft - Flight Order to: xx (*tailNumber*), day: xx”;
- Failure post-flight - “xx (*tailNumber*), goToMaintenanceLand, failure xx (*code*)”;
- Evaluation entry - “Evaluation: xx (*tailNumber*), failure xx (*code*)”;

- Waiting Procedure - “xx (*tailNumber*), waiting Procedure”;
- Waiting Resource - “xx (*tailNumber*), waiting Resource”;
- Lack of spare parts - “Missing item: xx (*code*), aircraft: xx (*tailNumber*)”;
- Stock update - “stockItem before resupply: xx”;
- Stock update - “stockItem after resupply base stock decrease: yy”;
- Flight - “xx (*tailNumber*), goToFlight”;
- Landing, logbook update - “xx (*tailNumber*), landed. xx (*hrsFlown*, *flightTime*)”;
- Landing, check scheduled maintenance - “xx (*tailNumber*), hrsToMtce(x, y, ..., z): [xx, yy, ..., zz]”;
- Replace item or not - “(don’t need) replace item *code*”;
- Lack of item at first level - “noStock xx (*code*)”;
- False alarm - “xx (*tailNumber*) NFF”;

The results confirm that all defined states were reachable under at least one experimental configuration and that all transitions were triggered exclusively by valid conditions (e.g., failure occurrence, scheduled maintenance threshold, spare availability). No unintended cyclic behavior or logically inconsistent state persistence was detected.

Furthermore, process synchronization between ABS state logic and DES maintenance flows remained stable. When an aircraft agent entered a maintenance-related state, the corresponding DES process was correctly instantiated, and completion events returned control to the agent statechart without deadlock or duplication.

These findings indicate that the structural coupling between autonomous aircraft agents and event-driven maintenance processes is logically sound within the defined modeling scope.

## 4.2.2 Extreme-Condition Stress Testing

The second robustness test evaluates system behavior under extreme and boundary parameter configurations. The purpose of this analysis is to determine whether the model produces coherent and interpretable responses when exposed to stress scenarios that significantly deviate from baseline conditions.

Three stress configurations were analyzed:

- High Failure Rate Scenario: failure rates increased by a defined multiplier relative to baseline;
- Zero-Stock Scenario: critical spare parts stock reduced to near depletion;

- High Operational Tempo Scenario: mission demand increased beyond nominal capacity.

The dynamic behavior of fleet availability under these scenarios is presented below. These graphics show availability trajectories over time and mission success results for baseline and stress configurations.

Figure 4.1 illustrates how an extreme high failure rate scenario impacts operational availability. Although availability does not drop to zero, the mission success rate in this case is zero, as no aircraft took off. The average availability was around 33%, and this is due to available aircraft waiting to be scheduled, but which always experienced malfunctions during pre-flight procedures. The high inventory level and the low simulated repair time prevented the availability from dropping to zero definitively.

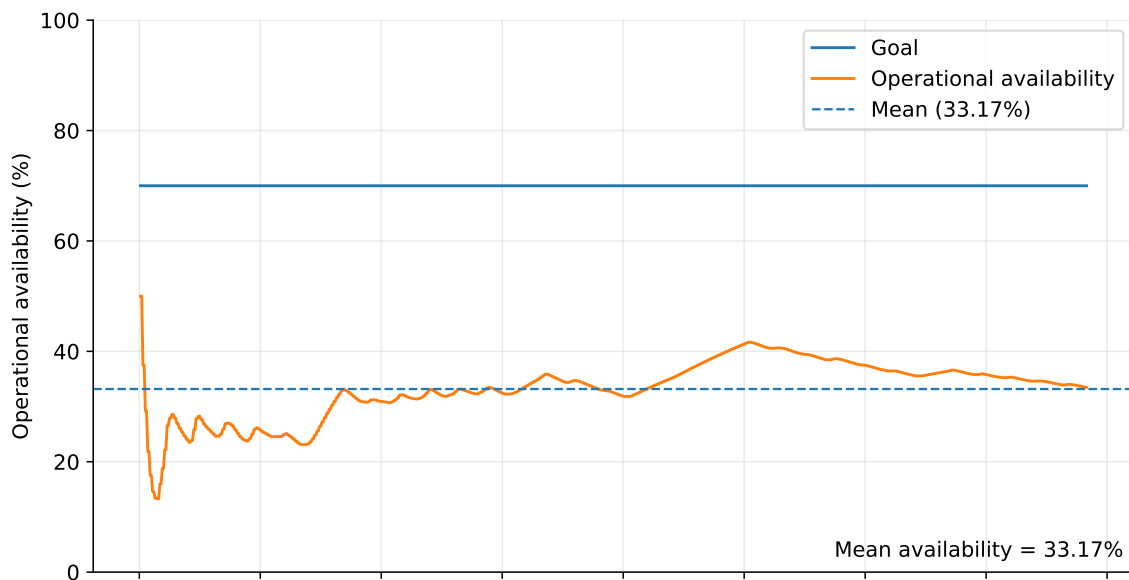


FIGURE 4.1 – Mean Fleet Availability Under an Extreme Failure Rate Scenario Obtained from Monte Carlo Simulation.

Figure 4.2 illustrates how a zero-stock scenario impacts operational availability. The availability drops step-by-step until it reaches zero, when all aircraft demand their first item replacement. The mission success rate in this case was 21%, as some flights could be executed prior to replacement demand. The graphic presents a quick upward tendency prior to the definite zero availability (stable curve at the end), which could sound like an error, since there are no spare parts. It could be a false alarm, or even a failure that demands maintenance but does not need to be replaced. It could be a false alarm or even a failure that demands maintenance but does not need to be replaced.

Figure 4.3 represents mission success over time at an extremely high tempo. In this graphic, it is possible to observe how the high intensity of aircraft use leads to fleet depletion, drastically reducing the mission success rate in the final phase of the campaign. In this scenario, the mission success rate at the end of the simulation was 27%, and half of the fleet reached the *a\_LimitToFly* parameter.

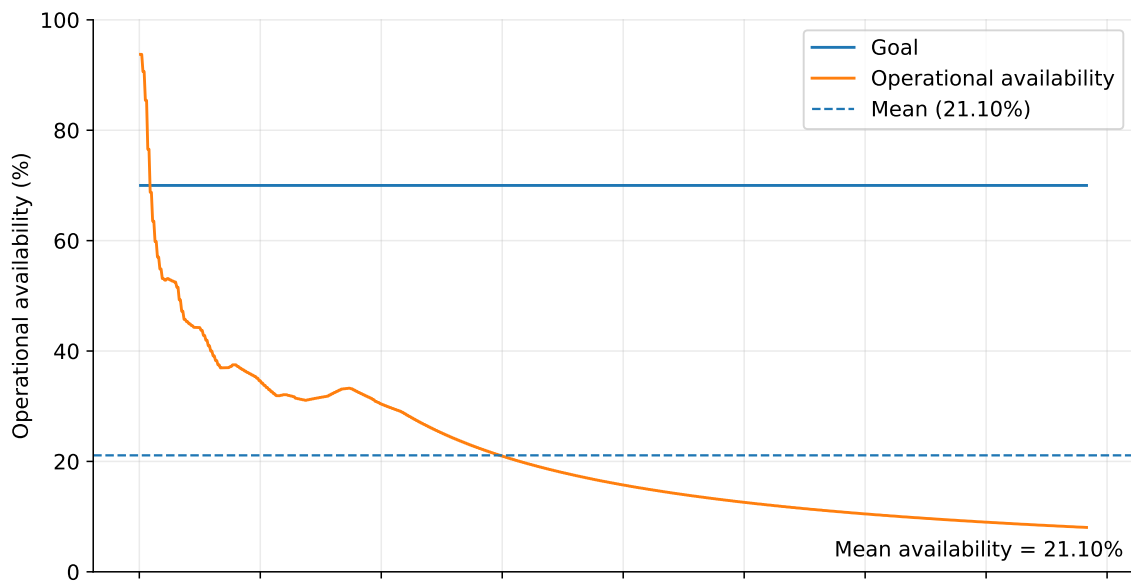


FIGURE 4.2 – Mean Fleet Availability Under a Zero-Stock Scenario, Highlighting the Impact of Supply Constraints on Operational Readiness.

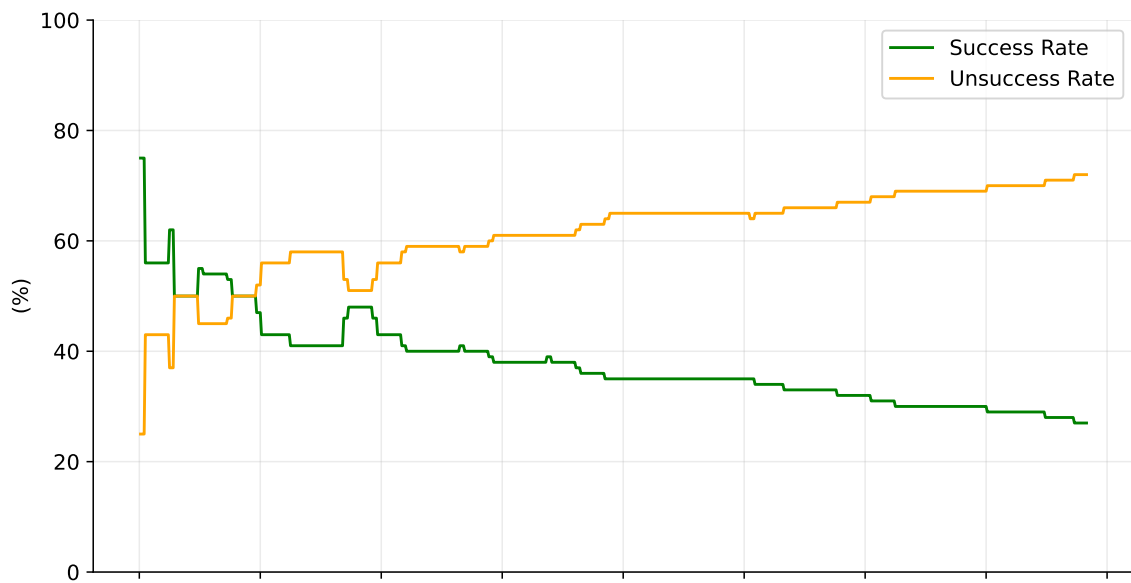


FIGURE 4.3 – Mission Success Rate Under a High Operational Tempo Scenario, Reflecting Increased Demand on Aircraft, Maintenance, and Logistics Resources.

The results exhibit expected degradation patterns. In the high failure rate scenario, maintenance demand increases proportionally, leading to extended downtime and reduced availability. In the minimal inventory configuration, aircraft increasingly transition into *waitingResources* states, producing availability decay even when maintenance capacity remains available. Under elevated operational tempo, availability initially stabilizes but gradually deteriorates as cumulative flight hours accelerate failure incidence.

Importantly, no numerical instability, oscillatory divergence, or non-physical behavior was observed in any configuration. Degradation trajectories remain continuous and causally interpretable, reflecting consistent interaction between operational usage, reliability behavior, and logistics constraints.

These outcomes suggest that the model preserves structural coherence under stress and that its internal logic remains stable even when parameter values are pushed toward operational limits.

### 4.2.3 Computational Stability and Monte Carlo Convergence Behavior

The third robustness dimension concerns stochastic stability. Because the framework relies on probabilistic representations of failures, repair durations, and supply delays, its outputs must demonstrate convergence behavior under repeated Monte Carlo experimentation.

To evaluate convergence, multiple independent simulation replications were executed under identical baseline conditions. For each replication set, mean success rate and associated standard deviation were computed as a function of the number of iterations.

The convergence behavior is illustrated in Figure 4.4, which demonstrates the stabilization of both the mean number of executed flights and the corresponding success rate as the number of Monte Carlo replications increases. Results indicate that convergence is effectively achieved between 1,000 and 3,000 iterations, with subsequent increases producing only marginal fluctuations (<0.3% in mean success rate), thereby confirming the statistical robustness of the simulation outputs and demonstrating that the stochastic sampling process produces statistically consistent results. The y-axis of the histogram is Probability Mass Function (PMF), since each bar represents the probability that the result falls within a one-bar width interval, and the total sum of probabilities is equal to one.

The convergence analysis also supports a rational trade-off between computational cost and statistical precision. Although increasing the number of Monte Carlo replications reduces the sampling error of the estimators proportionally to  $1/\sqrt{N}$ , the results indicate that both the mean executed flights and the associated success rate stabilize after approximately 1,000–3,000 iterations, with variations below 0.3% beyond this range. Additional replications therefore yield diminishing returns in precision while proportionally increasing computational time. Considering this balance, 5,000 iterations were selected for the comparative analyses presented in this dissertation, as this configuration ensures estimator stability and robustness while maintaining

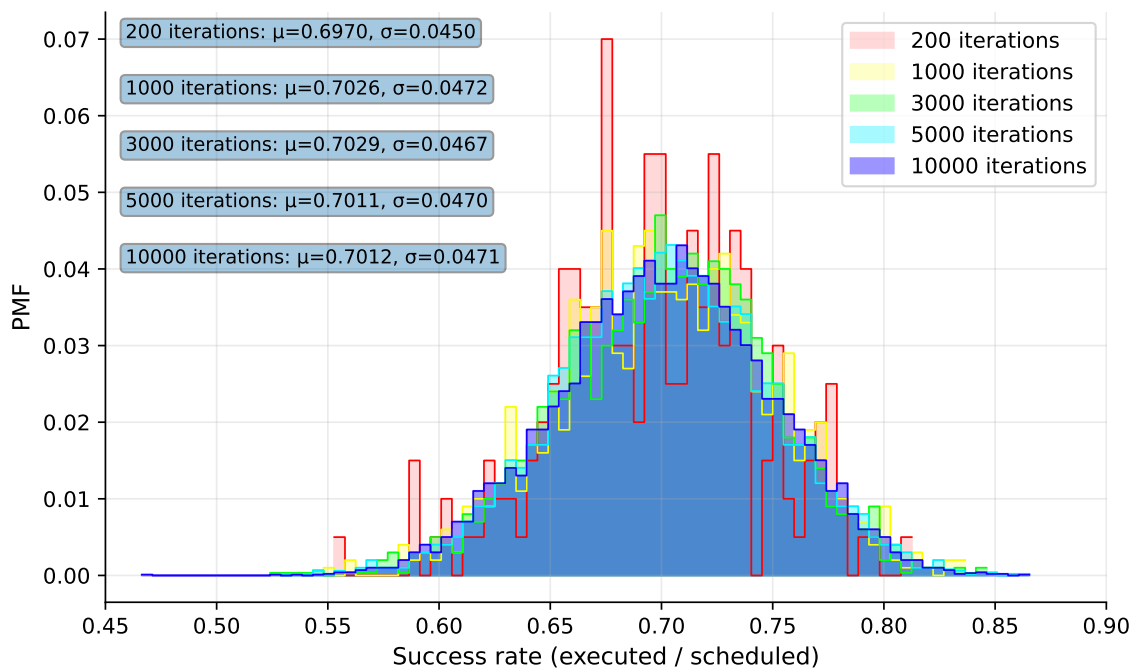


FIGURE 4.4 – Convergence of the Mean Mission Success Rate as a Function of the Number of Monte Carlo Iterations Under Baseline Conditions.

computational efficiency.

No evidence of distributional drift or numerical instability was observed as replication count increased. The resulting probability distributions exhibit smooth density shapes without artificial clustering or discontinuities.

This stability is critical because the framework’s capacity to enhance precision and anticipatory capability depends on reliable probabilistic outputs. The observed convergence behavior indicates that the stochastic components of the model are implemented consistently and produce reproducible statistical patterns.

#### 4.2.4 Discussion of Robustness Findings

Taken together, the robustness analyses demonstrate that the proposed hybrid simulation framework is structurally consistent, behaviorally coherent under extreme conditions, and computationally stable under repeated stochastic experimentation.

The structural verification confirms that the integration between agent-level state logic and process-driven maintenance flows does not introduce unintended transitions or deadlocks. The stress tests reveal degradation patterns that align with theoretical expectations derived from reliability and queueing behavior. The Monte Carlo convergence analysis confirms statistical reliability of probabilistic outputs.

From the perspective of the research problem, these findings establish a necessary foundation for subsequent evaluation of precision, S.A., and anticipatory capability. A decision-support

framework cannot enhance support management if its internal behavior is unstable or logically inconsistent. The robustness results presented in this section therefore provide empirical assurance that the model operates within coherent structural and numerical boundaries.

Having established robustness, the next section examines how the system responds to controlled parameter variations and whether these responses are proportionate, interpretable, and analytically meaningful.

### 4.3 Sensitivity and Behavioral Response Analysis

Following the robustness assessment presented in Section 4.2, this section evaluates the behavioral coherence of the framework under systematic parameter variation. While robustness testing verified structural stability and logical consistency, sensitivity analysis examines whether the model responds proportionately and causally to controlled changes in key variables that affect supportability.

In this research, degradation in operational performance is not driven by maintenance workforce limitations or processing congestion. Instead, performance deterioration emerges from material support constraints, particularly spare part availability across echelons. Therefore, the analysis explicitly interprets system behavior in terms of supportability dynamics rather than maintenance capacity saturation.

The parameters varied in this section include:

- i failure rates,
- ii repair durations,
- iii inventory levels, and
- iv operational tempo.

For each parameter group, variations were introduced relative to baseline conditions while maintaining all other variables constant. The primary indicators analyzed are:

- Fleet availability
- Mission success probability
- Proportion of aircraft in *waitingResources* state
- Spare part consumption rate

These indicators allow direct observation of how operational demand and stochastic reliability interact with logistics constraints.

### 4.3.1 Impact of Failure Rate Variations

Failure rates constitute the primary stochastic driver of maintenance demand and spare part consumption. To evaluate sensitivity to reliability assumptions, failure rates were varied by defined multipliers relative to baseline values.

Figure 4.5 presents fleet operational availability as functions of the failure rate multiplier. The data are the mean values obtained by Monte Carlo Process, and use relative values (compared to baseline scenario A:  $x/A$ ).

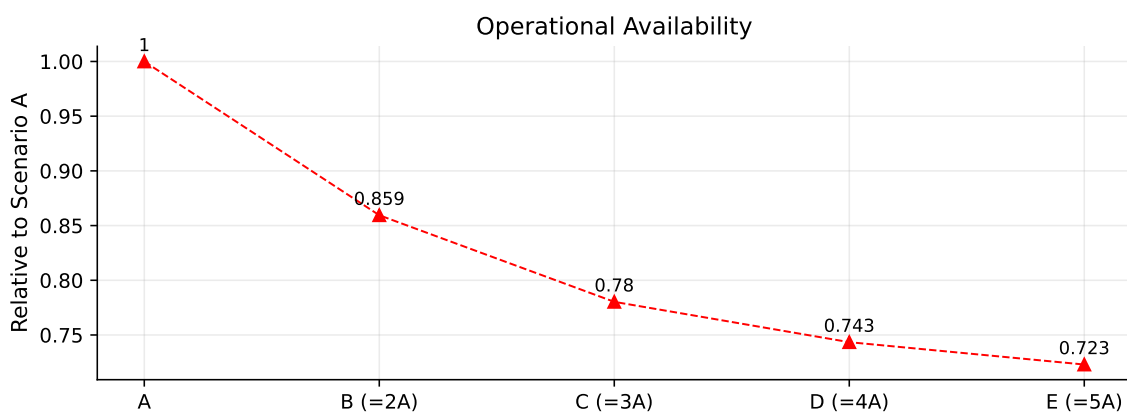


FIGURE 4.5 – Impact of Failure Rate Variation on Operational Availability.

As failure rates increase, the model exhibits a monotonic reduction in fleet availability. This degradation is not caused by repair congestion or maintenance queue buildup due to labor constraints. Instead, the dominant mechanism is accelerated depletion of spare parts.

The causal chain observed is:

- Failure rate  $\uparrow$
- $\rightarrow$  Item demand  $\uparrow$
- $\rightarrow$  Stock depletion  $\uparrow$
- $\rightarrow$  time in *waitingResources*  $\uparrow$
- $\rightarrow$  Aircraft downtime  $\uparrow$
- $\rightarrow$  Availability  $\downarrow$
- $\rightarrow$  Mission Success  $\downarrow$

At moderate failure multipliers, the system absorbs additional demand without significant availability degradation, provided that stock levels remain sufficient. However, beyond a threshold, inventory depletion accelerates and aircraft increasingly remain unavailable while awaiting material resupply.

The non-linear behavior observed at higher multipliers reflects logistics-driven saturation

effects. As stock levels approach critical thresholds, small increases in failure demand produce disproportionately larger increases in waiting time. This behavior is consistent with supportability theory and indicates that the model captures material bottlenecks rather than artificial numerical artifacts.

These results confirm that reliability variation propagates coherently through the logistics subsystem, reinforcing the internal consistency of the integrated architecture.

### 4.3.2 Impact of Repair Duration Variations

Repair duration affects aircraft downtime directly but does not generate congestion due to workforce constraints in this model. Maintenance activities are assumed to occur once material support is available. Therefore, repair duration influences availability primarily through time-dependent exposure to new failure risk and extended unavailability periods.

Figure 4.6 presents mission success rate under variations in repair duration.

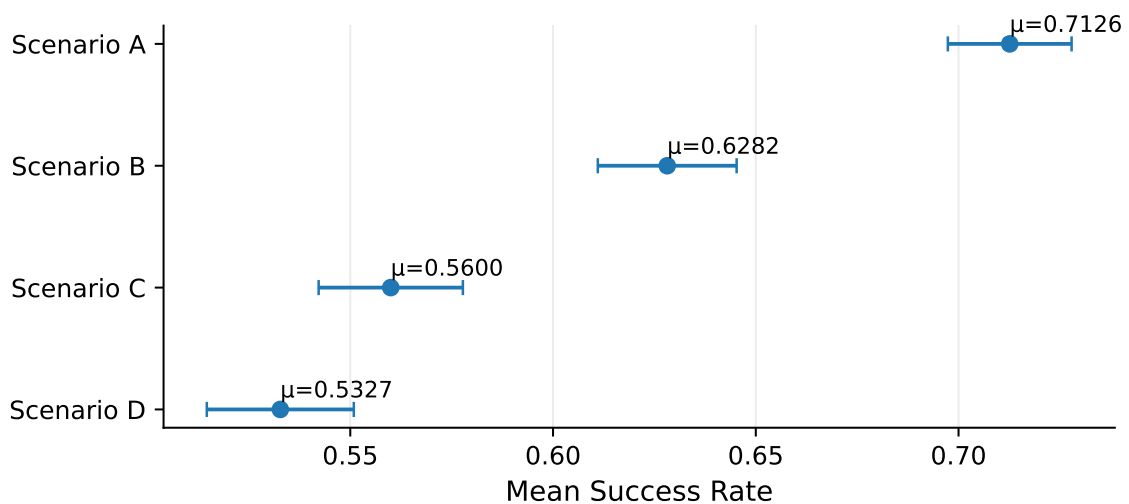


FIGURE 4.6 – Impact of Repair Duration Variation on Mission Success.

As repair duration increases, aircraft remain unavailable longer once material support is secured. This extends operational cycles and reduces fleet readiness. However, unlike workforce-limited systems, no repair queue accumulates independently of logistics availability.

The observed behavior demonstrates:

Repair duration  $\uparrow$

$\rightarrow$  Downtime per event  $\uparrow$

$\rightarrow$  Availability  $\downarrow$

$\rightarrow$  Mission Success  $\downarrow$

The relationship remains proportional and continuous, indicating correct synchronization

between statechart transitions and DES process timing.

Importantly, the absence of artificial oscillations or unstable patterns confirms that the DES timing layer interacts consistently with the ABS state logic.

### 4.3.3 Impact of Stock Level Adjustments

Stock configuration is the central driver of supportability performance in the proposed framework. To evaluate the sensitivity of the system to stock configuration, initial inventory levels of critical items were varied across defined ranges.

Figure 4.7 illustrates the mission success rate influenced by the fluctuations in availability as the stock allocation scenario varies. The baseline scenario considers an unrestricted stock (Full) as the optimal hypothetical condition. Subsequently, it is compared with a zero-stock scenario and five further scenarios. Those scenarios are also unconstrained scenarios, but allocations occur at varying distances, accompanied by delays (ranging from 24 to 240 hours) in receiving parts not available in local stock. The results align with expectations, since the mission success rate declines as there are greater delays, particularly in the zero-stock case.

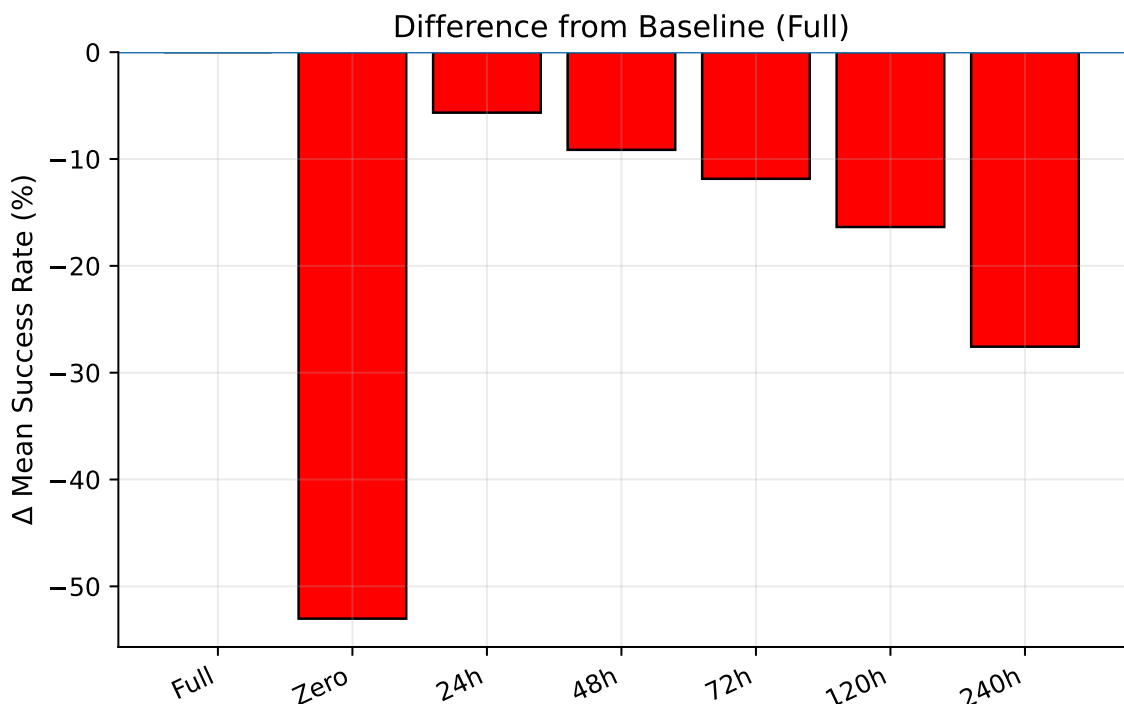


FIGURE 4.7 – Impact of Stock Allocation Levels and Resupply Delay on Mission Success Rate.

The results reveal a threshold behavior typical of supportability-limited systems. When stock levels remain above the demand-driven consumption rate, availability remains stable and mission execution probability is preserved. However, when inventory falls below critical demand thresholds, aircraft increasingly accumulate in *waitingResources* states.

This accumulation does not arise from maintenance crew limitations but from material

scarcity. The system exhibits the following dynamic:

- Inventory ↓
- Probability of stock-out ↑
- Aircraft awaiting parts ↑
- Downtime ↑
- Mission cancellations ↑

At higher inventory levels, marginal improvements in availability diminish, reflecting diminishing returns in over-provisioned systems. This behavior is consistent with multi-echelon inventory theory and reinforces the realism of the logistics representation.

These findings demonstrate that the model captures supportability degradation as a material constraint phenomenon rather than a generalized process bottleneck.

#### 4.3.4 Impact of Operational Tempo Changes

Operational tempo directly influences accumulated flight hours and failure exposure. To assess the relationship between mission demand and supportability degradation, sortie generation rates were varied while reliability and inventory parameters were held constant.

Figure 4.8 illustrates the probability of mission success as a function of operational tempo. Scenarios A and B contain an equivalent number of flights; however, Scenario A facilitates a more manageable distribution throughout the day, while Scenario B has a higher concentration of flights, requiring a greater number of available aircraft to prevent mission cancellations. The same thing occurs between situations C and D, however at a more accelerated tempo. Scenario E is the most challenging due to the high concentration of flights and the greater number of flights compared to the other scenarios.

At moderate tempo increases, the system absorbs additional operational demand while maintaining acceptable availability. However, sustained high tempo produces cumulative stress on the logistics subsystem.

The observed dynamic is:

- Operational tempo ↑
- Flight hours accumulation ↑
- Failure frequency ↑
- Spare part consumption ↑
- Inventory depletion ↑
- *waitingResources* occupancy ↑
- Availability ↓

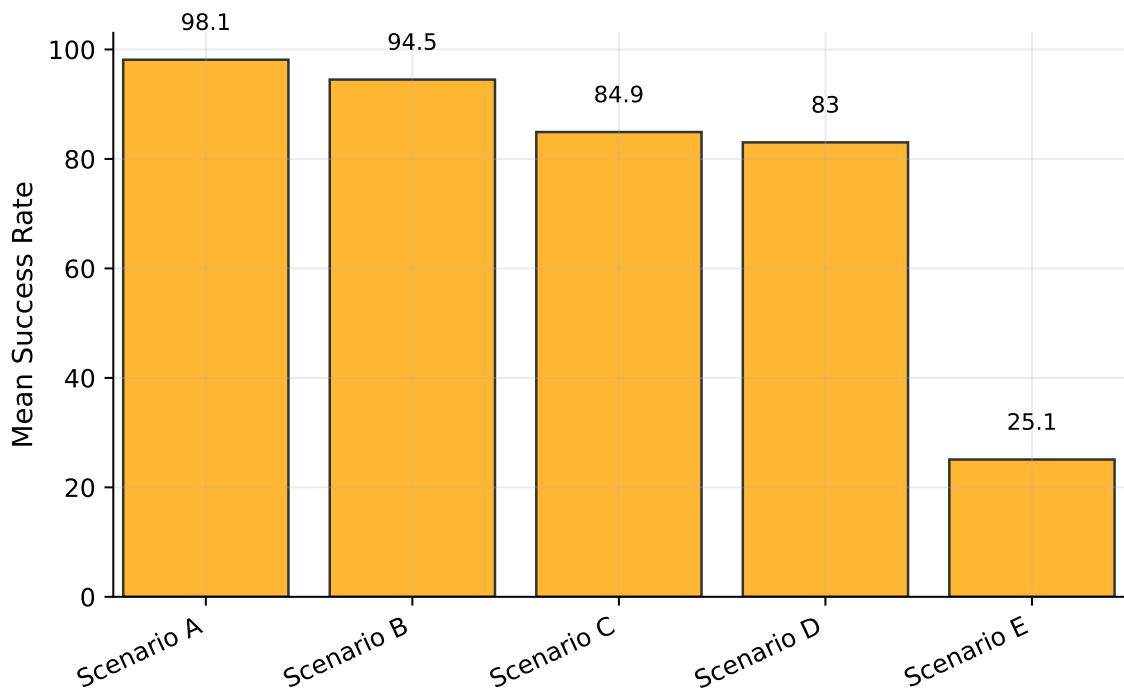


FIGURE 4.8 – Impact of Tempo Variation on Mission Success Rate.

→ Mission Success ↓

This degradation does not result from mission scheduling conflicts or workforce saturation, but from the interaction between operational stress and material support limitations.

The transition from stable to degraded performance regimes confirms that the integrated architecture captures systemic stress propagation.

### 4.3.5 Impact of Initial Fleet Configuration on Supportability

Supportability in sustained operations is not determined solely by stochastic parameters such as failure rates or repair durations. The structural configuration of the fleet at the start of the mission, including the number of aircraft allocated and their remaining flight-hour margin, plays a decisive role in determining the resilience of the system under stress.

This subsection evaluates how variations in initial fleet configuration influence availability, mission success probability, and logistics stress. Two dimensions were tested:

- Number of aircraft allocated to the mission (3 to 8 units)
- The initial remaining flight-hour balance available before mandatory maintenance

These variations directly affect the exposure to failure risk, scheduled maintenance triggering, and material demand concentration.

#### (a) Variation in the Allocated Fleet Size

The first experiment varies the number of aircraft committed to the mission while maintaining constant operational tempo and reliability parameters.

Figure 4.9 presents the probability of mission success as a function of the size of the fleet. The y-axis of the histogram is PMF, since each bar represents the probability that the result falls within a one-bar width interval, and the total sum of probabilities is equal to one.

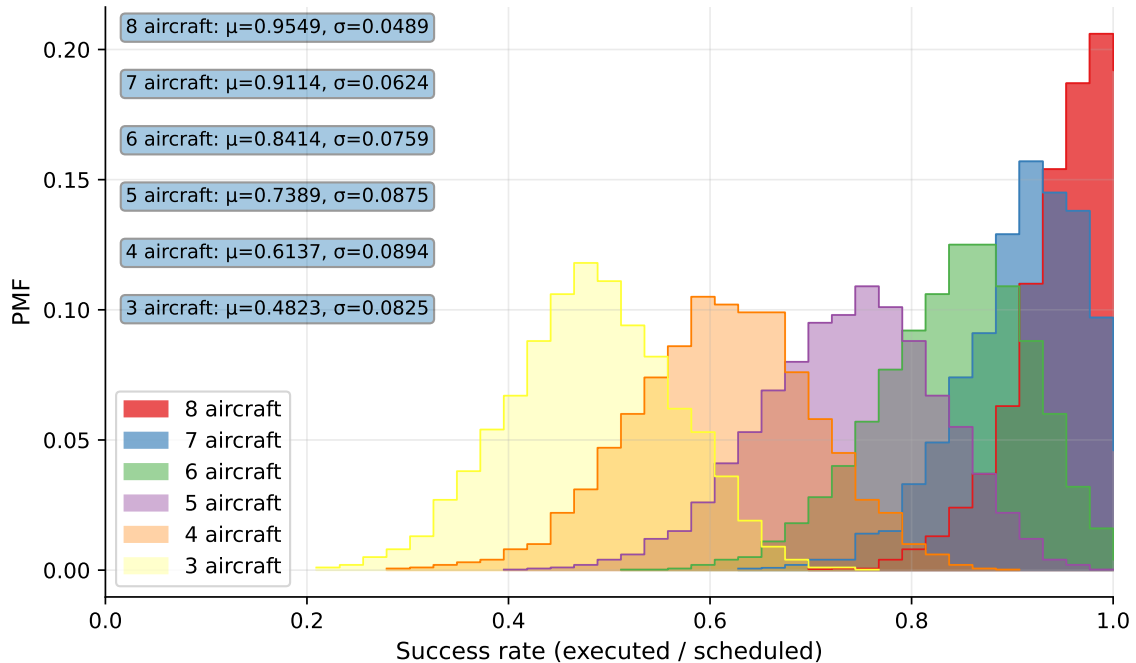


FIGURE 4.9 – Impact of Fleet Size Variation on Mission Success Rate.

The results demonstrate a clear structural relationship:

- With fewer aircraft (e.g. 3 units), the system exhibits high sensitivity to stochastic failures. A single aircraft entering the *waitingResources* state significantly reduces the mission capacity.
- As the size of the fleet increases, redundancy improves resilience against isolated failures and stock-induced downtime.

However, increasing the size of the fleet also produces a higher aggregate demand for materials, which accelerates inventory consumption. Thus, the relationship between fleet size and performance is not purely linear.

The system exhibits two competing dynamics:

Fleet size  $\uparrow$

→ Redundancy  $\uparrow$  (positive effect)

→ Aggregate consumption  $\uparrow$  (negative effect under stock constraints)

At moderate inventory levels, the redundancy effect dominates, improving mission success probability. Under tight logistics conditions, however, larger fleet allocation may accelerate stock depletion and reduce long-term supportability.

This behavior confirms that the framework captures structural trade-offs rather than assuming monotonic improvements with fleet expansion.

#### (b) Impact of Campaign Usage Limits (Limit-to-Fly Parameter)

Beyond stochastic reliability and inventory configuration, the framework incorporates a structural supportability constraint through the  $a\_limitToFly$  parameter. This parameter defines the maximum additional flight hours that an aircraft is allowed to accumulate during the campaign before being withdrawn from operational service.

Unlike failure-driven maintenance events, this transition is deterministic and policy-driven. When an aircraft reaches its predefined  $a\_limitToFly$  threshold, it transitions to the *outOfService* state. This design reflects real operational practice, in which certain maintenance levels cannot be executed during deployed operations due to:

- insufficient maintenance capability at the operational site,
- lack of required spare parts or tooling,
- excessive maintenance duration incompatible with campaign objectives,
- or risk management decisions designed to preserve cost–benefit ratio.

Therefore,  $a\_limitToFly$  represents a campaign-level sustainment boundary condition, not a stochastic degradation phenomenon.

To evaluate its impact, experiments were conducted varying the  $a\_limitToFly$  parameter across aircraft while maintaining constant failure rates, inventory levels, and operational tempo.

Figure 4.10 presents fleet availability over time under different campaign usage limits, from the most lenient Scenario A to the most strict Scenario D.

The results reveal a distinct anticipatory effect. Fleets configured with restrictive  $a\_limitToFly$  thresholds experience earlier and more abrupt reductions in operational capacity as aircraft sequentially transition to *outOfService*. This degradation is not driven by failure clustering or spare part shortages but by the exhaustion of authorized campaign usage.

On the other hand, more permissive usage limits extend aircraft participation in operations, delaying structural availability degradation. However, extended usage also increases cumulative failure exposure and spare part consumption, potentially amplifying logistics stress later in the campaign.

The dynamic observed can be summarized as:

Lower  $a\_limitToFly$

→ Earlier structural withdrawal

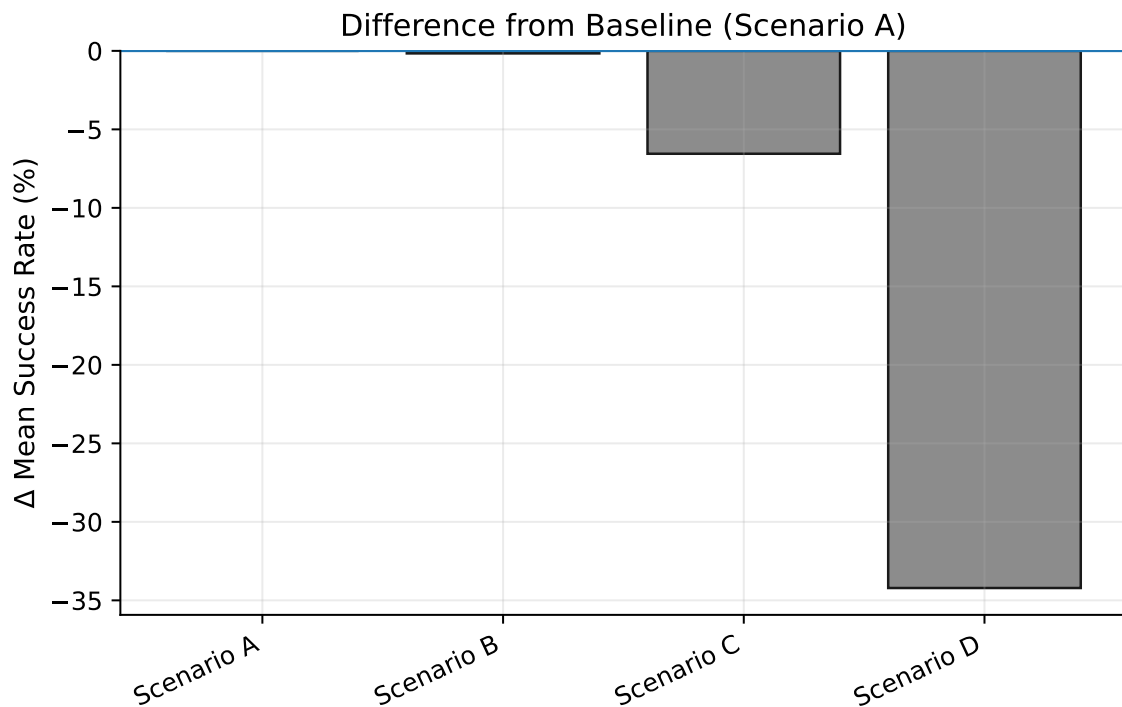


FIGURE 4.10 – Impact of Campaign Usage Limits (Flight Hour Constraints) on Mission Success Rate.

- Reduced operational redundancy
- Increased sensitivity to stochastic failures

Higher *a\_limitToFly*

- Extended operational participation
- Increased cumulative reliability exposure
- Higher material demand over time

This trade-off highlights an important supportability insight: campaign usage policy directly shapes both operational resilience and logistics stress distribution.

Importantly, the degradation observed in this experiment arises neither from maintenance workforce saturation nor from random failure clustering. It reflects a structural sustainment constraint intentionally embedded in the campaign configuration.

### (c) Structural Sensitivity and Anticipatory Implications for Support Management

The experiments conducted in this subsection demonstrate that supportability degradation during sustained operations is not driven exclusively by stochastic variability in failure behavior or spare part availability. Instead, structural decisions taken before the campaign begins, such as fleet allocation size and campaign usage limits, significantly shape the system's resilience trajectory.

Variation in fleet size revealed a structural trade-off between redundancy and aggregate logistics consumption. Allocating a larger number of aircraft increases immediate operational

resilience by reducing vulnerability to isolated failures or temporary stock shortages. However, it also increases total spare part consumption, accelerating material depletion when inventory levels are constrained. Conversely, smaller fleet allocations reduce aggregate consumption but increase sensitivity to individual aircraft withdrawal events.

The variation of the *a\_limitToFly* parameter introduces a distinct but equally important structural dimension. Unlike stochastic failures, the transition to *outOfService* under *a\_limitToFly* exhaustion reflects a deliberate campaign-level sustainment boundary. Restrictive usage limits preserve long-term asset integrity but may cause early structural reductions in operational capacity. More permissive limits extend participation in the campaign but increase cumulative reliability exposure and material demand.

The combined interpretation of these results reveals a key anticipatory insight: initial campaign configuration determines baseline vulnerability even before stochastic uncertainty unfolds. Two fleets with identical reliability characteristics and inventory levels may exhibit substantially different degradation trajectories depending solely on:

- number of aircraft allocated, and
- campaign usage limits imposed.

From a supportability perspective, this finding is critical. It indicates that cost–benefit degradation under sustained operations is influenced not only by random failures or logistics variability but also by structural policy decisions embedded in mission planning.

For the Decision Sector, this sensitivity analysis demonstrates that:

- fleet allocation decisions affect redundancy–consumption balance,
- campaign usage limits influence timing of structural availability loss,
- and both parameters interact with material constraints to shape long-term mission feasibility.

These results reinforce the anticipatory capacity of the framework. Rather than providing static availability snapshots, the model reveals how structural configuration choices propagate through operational execution, reliability exposure, and logistics stress over time.

Importantly, all observed degradation mechanisms arise from explicitly modeled supportability constraints: material availability and campaign usage limits; rather than from workforce congestion or unspecified bottlenecks. This consistency strengthens the internal validity of the framework and aligns the behavioral response analysis with the *Support and Supportability Problem* formulation presented in Chapter 1.

Having established that the model responds coherently to both stochastic and structural variations, the next section evaluates whether these analytical capabilities translate into improved S.A. and decision-support effectiveness for campaign-level supportability management.

## 4.4 Evaluation of Support Awareness Enhancement

### 4.4.1 Conceptual Framing

S.A. in the context of military air operations extends beyond the perception of isolated performance indicators. As discussed in Chapter 2, it requires the ability to:

- 1 Perceive relevant system elements and their states;
- 2 Comprehend the interactions and dependencies among those elements;
- 3 Project the likely future evolution of the system under uncertainty.

In supportability management, this translates into the ability to:

- Monitor aircraft operational status and degradation trajectories;
- Understand how reliability behavior, campaign policies, and logistics constraints interact;
- Anticipate availability degradation and mission feasibility over time.

This section evaluates whether the proposed hybrid simulation framework provides these three capabilities in a structured and transparent manner.

### 4.4.2 Perception: Visibility of Individual and System States

The first dimension of S.A. concerns the explicit visibility of relevant system elements.

The framework enhances perceptual awareness through:

- Explicit state representation of each aircraft;
- Tracking of individual *a\_limitToFly* consumption;
- Real-time inventory level monitoring;
- Identification of failure-induced versus policy-induced withdrawals.

#### Evidence Presented

The following visualizations are used to demonstrate enhanced perception:

Figure 4.11 displays the number of aircraft in each state throughout the campaign. The *outOfService* increasing level indicates a restricted scenario in which some aircraft reach the *a\_limitToFly* parameter during the campaign.

Figure 4.12 displays the number of spare items in each level and also the queue of AOG motivated for each item.

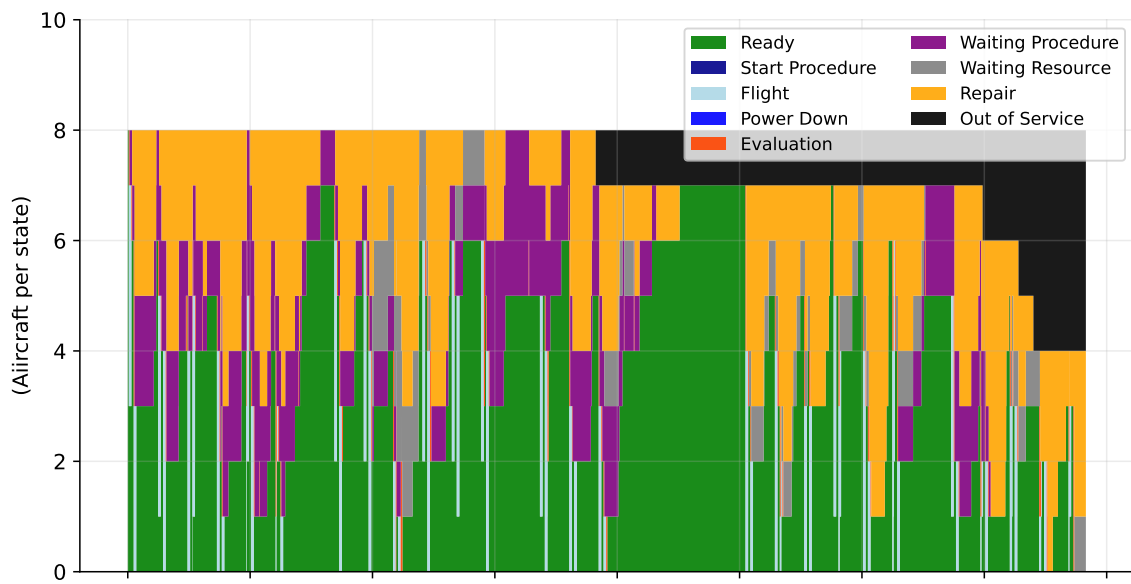


FIGURE 4.11 – Time Evolution of Aircraft State Occupancy, Showing the Distribution of Aircraft Across Operational and Maintenance States.

	Stock Level			Events	
	Local	Base	Depot	Fail	Replace
Item 01:	1	0	2	1	0
Item 02:	3	1	1	0	0
Item 03:	0	0	1	0	0
Item 04:	2	0	1	1	1
Item 05:	4	5	3	2	1
Item 06:	1	1	2	0	0
Item 07:	0	2	1	2	0
Item 08:	2	3	1	1	0

AOG List	
Item 01:	
Item 02:	
Item 03:	FAL_05
Item 04:	
Item 05:	
Item 06:	
Item 07:	FAL_03 , FAL_01
Item 08:	

FIGURE 4.12 – Logistical Dashboard Showing Stock Levels and the Queue of AOG Awaiting Resources.



FIGURE 4.13 – Detailed Operational and Maintenance Data for an Individual Aircraft, Including Status and Flight Hours Control.

Figure 4.13 illustrates the individual numbers of each aircraft, including the identification (*tailNumber*), the current flight duration (*flightTime*) and aircraft status, the cumulative balance of hours (*hrsFlown*), and the remaining balance of hours (*a\_limitToFly*).

These outputs provide decision-makers with direct and granular visibility of fleet condition and material status, something not achievable through static availability percentages alone.

#### Analytical Discussion

Unlike aggregate readiness indicators, these representations allow the Decision Sector to:

- Distinguish stochastic degradation from structural policy effects;
- Identify early warning signals of saturation;
- Observe asymmetry in individual aircraft trajectories.

This capability satisfies the perceptual component of S.A..

### 4.4.3 Comprehension: Understanding System Interdependencies

The second dimension concerns the ability to understand how elements interact.

The model explicitly represents the causal chain:

Operational demand → Reliability exposure → Failure occurrence → Maintenance demand  
 → Spare consumption → Inventory depletion → Aircraft availability reduction

This integrated structure allows the observation of how operational tempo propagates into logistics stress and availability degradation.

#### Evidence Presented

Figure 4.14 presents mission success (%), fleet operational availability (%), number of unscheduled maintenance events, number of items replacements, and number of *waitingResources*

entrances, as functions of the failure rate multiplier. All these data are the mean values obtained by Monte Carlo Process, and use relative values (compared to baseline scenario A:  $x/A$ ) for those that are not rates (%).



FIGURE 4.14 – Impact of Failure Rate Variation Across Multiple Performance Metrics, Including Mission Success, Availability, and Maintenance Workload.

These plots demonstrate that the decline in availability coincides with material constraints and results in a reduction in the mission success rate.

### Analytical Discussion

The framework makes explicit that degradation is not arbitrary. It emerges from modeled interactions between:

- Campaign configuration,
- Reliability processes,
- Inventory constraints.

This transparency enables comprehension of system-level causality rather than isolated metric monitoring.

#### 4.4.4 Projection: Anticipatory Insight Under Uncertainty

The third dimension concerns projection, the ability to anticipate future states.

The framework supports projection through Monte Carlo experimentation, generating probabilistic distributions rather than single deterministic outcomes.

#### Evidence Presented

Figure 4.15 displays the probability distribution of mission success. The histogram is the PMF, while the curve is the Cumulative Distribution Function (CDF). The numbers shown in this figure illustrate how the results may be used to understand the probabilities for decisions. In Black, the mean value (149 flights) was obtained using the Monte Carlo process. In dark blue, the minimum number of flights that occurred in 80% of the iterations is represented. And finally, the probability of being able to accomplish at least 70% (or 146) of the flights (62.08%).

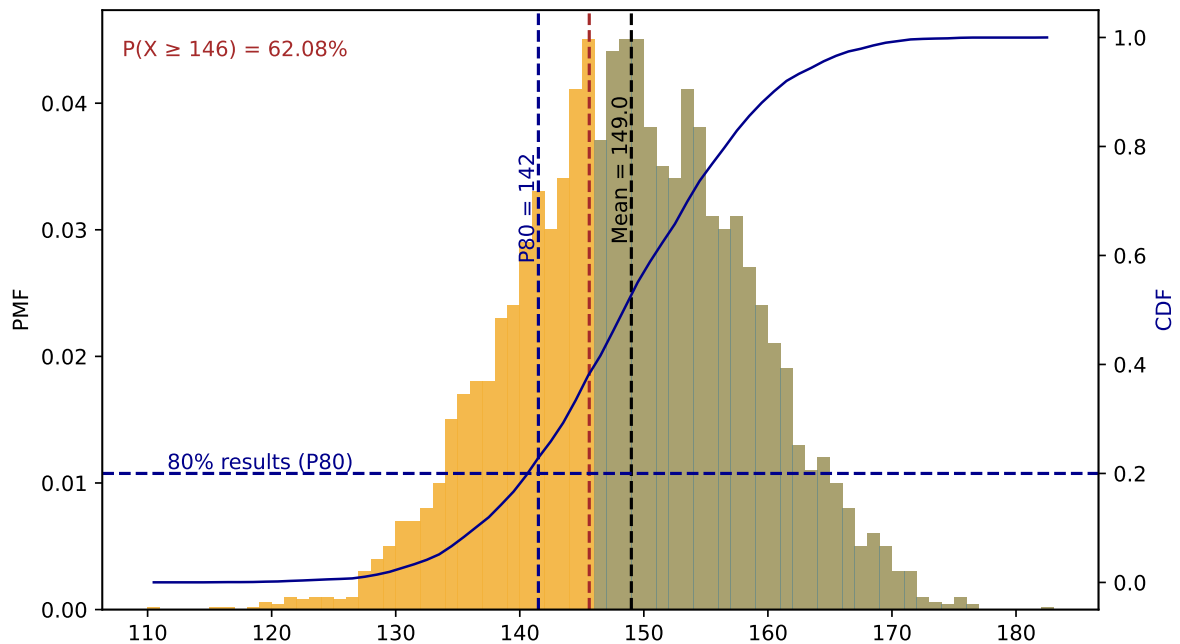


FIGURE 4.15 – Probability Distribution (Histogram) of Mission Success Used for Risk Analysis Based on Monte Carlo Simulation Results.

Figure 4.16 illustrates the probability of the campaign falling below an availability threshold. The histogram is the PMF, while the curve is the CDF. The analysis, in this case, is over the possibility of the operational availability being less than 50%. This analysis examines the probability of operational availability declining below 50%. The results indicate that this occurs in the majority of rounds, since only 38.45% of the outcomes exceeded the threshold.

These outputs allow decision-makers to quantify:

- Risk of availability collapse;
- Probability of sustaining mission tempo;
- Sensitivity to campaign configuration choices.

### Analytical Discussion

Projection capability enables:

- Risk-informed mission authorization;

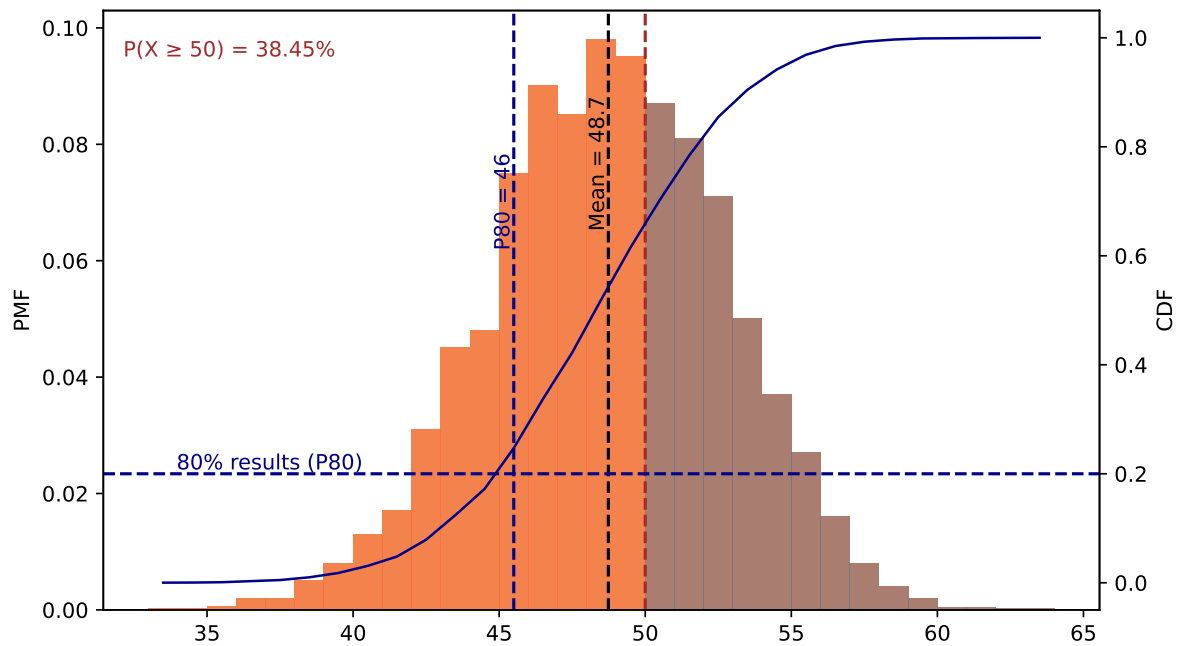


FIGURE 4.16 – Probability Distribution (Histogram) of Fleet Availability Used for Risk Analysis Based on Monte Carlo Simulation Results.

- Evaluation of alternative configurations before execution;
- Early detection of supportability vulnerability.

Instead of reacting to degradation, the Decision Sector can anticipate it.

#### 4.4.5 Comparison With Fragmented or Static Approaches

To strengthen the argument, a comparative demonstration is included.

A simplified deterministic assessment is contrasted with simulation-based outputs.

- Deterministic approach: average availability  $\times$  mission duration
- Simulation approach: stochastic degradation trajectory

The deterministic method fails to reveal:

- Timing of collapse,
- Distribution of outcomes,
- Structural sensitivity to *a\_limitToFly* policy.

This comparison reinforces the added S.A. capability of the proposed framework.

### 4.4.6 Synthesis

The results presented in this section demonstrate that the proposed simulation framework enhances S.A. in three dimensions:

- It improves perception by making aircraft and inventory states explicitly observable;
- It improves comprehension by revealing the causal interactions between operations, reliability, and logistics;
- It improves projection by quantifying future states probabilistically under uncertainty.

These capabilities directly address the derivative dissertation problem identified in Chapter 1: the need for improved precision, S.A., and anticipatory capability in supportability-related decision-making.

The next section evaluates whether these enhanced awareness capabilities translate into measurable anticipatory and decision-support advantages.

## 4.5 Evaluation of Anticipatory Capability and the Effectiveness of Decision-Support

### 4.5.1 Conceptual Framing

While S.A. provides visibility and understanding of system behavior, the effectiveness of decision-support requires the ability to use that awareness to evaluate alternatives and anticipate consequences before execution.

In the context of this research, anticipatory capability refers to the ability of the framework to:

- Quantify the probability of mission success under uncertainty;
- Identify configuration-dependent degradation risks;
- Reveal structural vulnerabilities prior to operational commitment;
- Compare alternative campaign configurations in terms of support resilience.

This section evaluates whether the proposed hybrid simulation framework provides these capabilities in a structured, transparent, and decision-relevant manner.

## 4.5.2 Anticipatory Evaluation of Fleet Configuration Decisions

Fleet configuration constitutes a structural decision class that directly influences the logistics support at the campaign level. In the context of sustained air operations, the configuration is not defined solely by the number of aircraft allocated to the mission, nor exclusively by campaign usage limits. Rather, it emerges from the interaction between fleet size and the remaining usage margin embedded in each aircraft through the campaign-level *a\_limitToFly* parameter.

Fleet size determines operational redundancy and aggregate exposure to consumption. A larger allocation increases resilience against individual failures but simultaneously amplifies spare consumption and cumulative reliability exposure. In contrast, a smaller allocation reduces consumption pressure but increases vulnerability to localized degradation and structural collapse. The trade-off is therefore inherently non-linear and configuration-dependent.

Figure 4.9 presents the probability of mission success as a function of fleet size under baseline logistics conditions. The results demonstrate that reductions in allocated aircraft significantly increase the probability of early availability collapse. However, beyond a certain allocation threshold, marginal gains diminish due to accelerated spare consumption and reliability exposure across a larger active fleet. This confirms that fleet size alone does not linearly translate into increased sustainability.

Fleet configuration must therefore be analyzed in conjunction with campaign usage limits. The *a\_limitToFly* parameter operationalizes a sustainment policy decision: it defines the allowable exposure of each aircraft during the campaign before structural withdrawal occurs. Restrictive limits preserve post-campaign structural health but may induce early operational attrition within the campaign. Permissive limits delay structural withdrawal but increase exposure to failure-induced material stress.

Figure 4.10 integrates these effects by showing the probability of availability collapse under different combinations of fleet allocation and campaign usage restriction. The results indicate that identical fleet sizes can produce significantly different sustainability profiles depending on usage policy. Similarly, the same usage policy may perform adequately under larger allocations but induce unacceptable collapse risk under smaller ones.

This interaction confirms that effective support evaluation requires simultaneous consideration of both dimensions. A fleet of five aircraft with permissive usage limits may sustain the campaign with acceptable risk, whereas the same fleet with restrictive limits may experience structural withdrawal before campaign completion. Conversely, increasing allocation without adjusting usage policy may accelerate spare depletion without proportionally increasing mission sustainability.

The framework enables the Decision Sector to evaluate this joint configuration probabilistically rather than heuristically. Instead of asking “Is five aircraft sufficient?” or “Is this usage limit conservative enough?”, the model allows the formulation of risk-based questions such as: “What is the probability that this specific fleet configuration, defined by allocation and usage policy, will sustain the campaign under current logistics constraints?”

This represents a substantive shift from deterministic planning toward probabilistic anticipatory evaluation. Fleet configuration is no longer treated as a static input but as a controllable policy variable whose structural implications can be quantified *ex ante*. By revealing the non-linear interaction between redundancy and structural exposure, the framework enhances S.A. and strengthens supportability-oriented decision-making before operational execution.

### 4.5.3 Quantification of Cost–Benefit Risk

The overarching *support and supportability problem* addressed in this research concerns the risk of degradation in cost-benefit during sustained operations. Such degradation does not arise solely from insufficient sortie generation or isolated failures, but from imbalances between operational ambition and logistics capability. Consequently, anticipatory decision-support must move beyond point estimates and incorporate explicit quantification of risk associated with alternative configurations.

The distributional outputs previously presented, specifically the mission success histograms (Figures 4.15 and 4.9) and the availability threshold analysis (Figure 4.16), provide the analytical basis for this quantification. Their value lies not in the descriptive statistics themselves, but in the ability to translate operational configurations into probabilistic risk profiles.

The mission success distribution allows decision-makers to associate any desired performance target with an explicit probability of attainment. Rather than assuming that the expected number of flights will be achieved, the Decision Sector can evaluate the likelihood of achieving minimum acceptable sortie levels. In cost–benefit terms, operational benefit is therefore expressed probabilistically, enabling risk-aware planning rather than reliance on deterministic expectations.

Similarly, the availability threshold distribution enables the quantification of structural risk. By defining critical availability levels, such as the point at which mission feasibility becomes compromised, the Decision Sector can evaluate the probability of structural degradation under each configuration. This reframes availability from a static indicator into a stochastic vulnerability measure.

When considered jointly, these distributions reveal that cost–benefit trade-offs are inherently configuration-dependent. Increasing fleet allocation or relaxing campaign usage limits may raise expected mission output, but also alter the probability of structural stress or spare depletion. Conversely, restrictive configurations may preserve resources while increasing the likelihood of mission shortfall. The relationship is not linear and cannot be inferred from average indicators alone.

Figure 4.9 strengthens this interpretation by demonstrating how fleet size alters the dispersion and stability of mission outcomes. The widening or narrowing of distributions across configurations reflects changes in systemic resilience, making variability itself a decision-relevant metric. Variance and tail risk become as important as mean performance.

In this context, cost–benefit is no longer treated as a deterministic ratio between sorties and resource consumption. Instead, it becomes a probabilistic surface defined by the joint distribution of mission success and structural availability. The framework enables the Decision Sector to identify configurations that balance acceptable mission achievement probability with tolerable structural risk exposure.

This capacity to quantify trade-offs before execution represents a direct enhancement of anticipatory capability. It allows operational ambition to be evaluated against logistics sustainability under uncertainty, thereby addressing the core supportability problem that motivated this research.

#### 4.5.4 Synthesis

The results presented in this section demonstrate that the proposed framework provides anticipatory capability by:

- Quantifying risk before execution;
- Revealing structural sensitivity to configuration choices;
- Allowing probabilistic comparison of alternatives;
- Making explicit the trade-offs between redundancy, reliability exposure, and logistics sustainability.

Unlike static or fragmented planning tools, the framework does not merely report expected availability, it reveals the distribution of possible futures and their dependency on decision variables.

This anticipatory dimension directly supports improved supportability-related decision-making, thereby advancing the hypothesis stated in Chapter 1.

The following section integrates these findings within a realistic operational case study.

## 4.6 Case Study: Supportability Assessment During Sustained Military Air Operation

### 4.6.1 Operational Context

The proposed simulation framework was applied during the planning and execution of a real operational campaign involving a fighter fleet participating in COMAO – Composite Air Operations 2024 – Training Phase (PHASE\_1), followed by CRUZEX – Cruzeiro do Sul Exercise 2024 – Large-Scale Multinational Air Exercise (PHASE\_2).

The entire campaign extended over 30 calendar days and comprised:

- A PHASE\_1 - training phase;
- An operational pause of approximately one week;
- A PHASE\_2 - execution phase;
- No flight operations on Sundays.

At the planning stage, the fleet was undergoing progressive delivery from the industry, and the final number of aircraft available during the campaign was uncertain. In addition, aircraft presented heterogeneous initial flight-hour balances and individual *a\_limitToFly* constraints. Spare part stock levels were limited and partially uncertain.

The central decision variable under the control of the Decision Sector was the flight tempo, defined by the daily flight schedule. Unlike fleet size or stock levels, which were partially constrained by industrial and logistical factors, flight tempo represented a deliberate operational choice largely based on experience and subjective judgment.

The supportability question was therefore formulated as:

*Would a given flight tempo configuration remain sustainable over the campaign without inducing unacceptable degradation of availability due to reliability exposure and logistics constraints?*

## 4.6.2 Planning-Phase Scenario Exploration

During the planning phase, several alternative flight schedule configurations were evaluated:

- *flights\_full*: 4 departures at 10h00 and 4 at 14h00 daily;
- *flights\_half*: 2 departures at 10h00 and 2 at 14h00 daily;
- *flights\_morning*: 4 departures at 10h00 daily;
- *comao\_half\_cruzex\_full*: PHASE\_1 as *flights\_half* and PHASE\_2 as *flights\_full*;
- *comao\_morning\_cruzex\_full*: PHASE\_1 as *flights\_morning* and PHASE\_2 as *flights\_full*;

Each configuration was simulated under uncertainty in:

- Fleet size (due to progressive industrial delivery),
- Initial flight-hour balance per aircraft,
- Individual *a\_limitToFly* values,

- Spare stock levels,
- Stochastic failure behavior.

The objective was not to identify an “optimal” schedule in isolation, but to assess structural vulnerability and the risk of supportability degradation under different tempo intensities.

### **Key Insight**

Simulations indicated that overly ambitious flight tempos could:

- Accelerate spare part consumption;
- Increase frequency of *waitingResources* states (aircraft grounded due to spare shortage);
- Induce structural fleet disruption before PHASE\_2.

This analysis provided quantitative evidence that flight schedule dimensioning directly affects campaign sustainability.

### **4.6.3 Bottleneck Identification and Anticipatory Intervention**

Two dominant supportability constraints emerged during scenario exploration:

- *waitingResources*: grounded aircraft due to insufficient spare stock;
- *waitingProcedure*: delay associated with industrial case resolution when technical support was required.

The *waitingProcedure* parameter has been determined as being very important through sensitivity analysis. Lowering the mean industrial response time made projected availability during peak operational demand much better. Figure 4.17 illustrates the effect, showing the best case scenario A as the minimum delay for industry responses, compared to incremental delay scenarios B, C and D. Scenario D was the expected delay before the campaign, seriously impacting the mission success rate, due to the operational availability fall.

Based on these results, decision-makers negotiated a reduction in response time with the industrial stakeholder prior to PHASE\_1. The industrial partner, recognizing the strategic relevance of the exercise, agreed to shorten the average case resolution delay.

This constitutes a clear example of model-driven anticipatory action, where potential constraints were identified and mitigated before they manifested during execution.

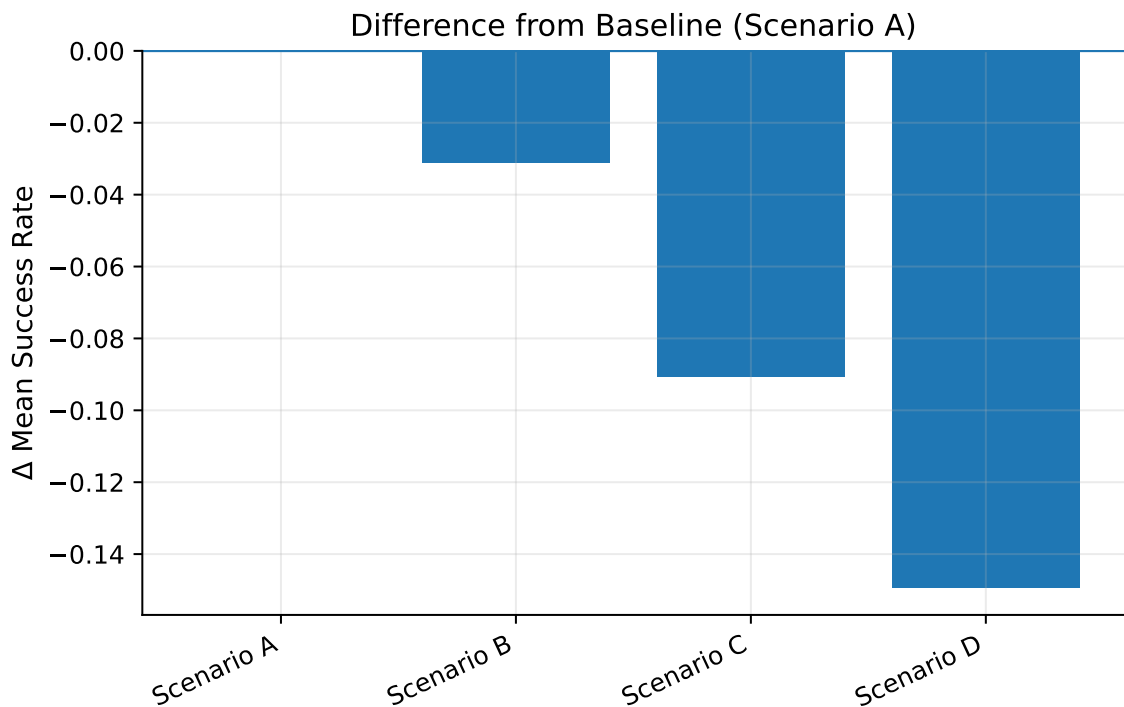


FIGURE 4.17 – Impact of *waitingProcedure* Delay on the Mean Mission Success Rate.

#### 4.6.4 Calibration During PHASE\_1

During PHASE\_1 operations, the model was iteratively updated using field observations, including:

- Adjustments in movement delays;
- Observed failure behavior;
- Logical checks.

Availability degradation during PHASE\_1 occurred in line with simulation trends. Instances of *waitingResources* were observed due to low stock levels, confirming the relevance of logistics constraints identified in planning simulations.

At the conclusion of PHASE\_1:

- The model was frozen;
- Final fleet configuration was established;
- Final spare stock levels were inserted;
- The official final flight schedule was adopted.

This frozen configuration became the basis for the PHASE\_2 forecast.

### 4.6.5 Monte Carlo Forecast for PHASE\_2

Following calibration with observed parameters from the preceding PHASE\_1, the framework was used to generate a probabilistic forecast for the PHASE\_2 segment of the campaign. A total of 10,000 Monte Carlo replications were executed under the finalized operational configuration. This replication level was selected to ensure stabilization of the outcome distribution and statistical robustness of the estimated probabilities.

Within the overall campaign schedule, 42.6% of the planned sorties corresponded specifically to PHASE\_2 activities. Mission success was defined strictly in logistical terms as the successful take-off of an aircraft. Events external to logistics constraints, such as weather-induced cancellations, were excluded from the failure definition in order to isolate the supportability dimension of performance. This definition ensured that the forecast evaluated the system's ability to sustain operational ambition under reliability and logistics uncertainty, rather than external operational disturbances.

The Monte Carlo process produced a full probability distribution of expected successful take-offs during PHASE\_2. Rather than generating a single deterministic estimate, the model provided a range of possible outcomes, each associated with an explicit probability. This distribution allowed decision-makers to evaluate not only the expected performance level but also the dispersion, tail behavior, and likelihood of underperformance relative to predefined thresholds. In doing so, the forecast operationalized probabilistic anticipatory capability, transforming the campaign plan into a risk-informed projection of support performance.

### 4.6.6 Ex-Post Validation

Upon completion of PHASE\_2, the realized number of successful take-offs was compared with the forecast distribution generated prior to execution. The observed outcome fell within the modal region (most frequently repeated value during iterations) of the Monte Carlo distribution and remained inside the 95% probability interval predicted by the model.

This convergence between forecast and realization provides empirical evidence of structural adequacy. It indicates that the integrated representation of aircraft reliability, maintenance processes, spare constraints, and campaign policies was sufficient to reproduce the system's probabilistic behavior under real operational conditions. The model neither overestimated nor underestimated mission sustainability in a manner inconsistent with observed outcomes.

While a single campaign does not constitute universal statistical validation, the alignment between predicted and realized results demonstrates that the framework can produce operationally meaningful probabilistic forecasts when calibrated with real data. More importantly, it confirms that the model is capable of translating configuration choices and logistics constraints into realistic risk profiles. This ex-post consistency strengthens confidence in the framework's anticipatory capability and supports its use as a structured decision-support instrument in future sustained operations.

### 4.6.7 Interpretation in Terms of Supportability

The case study demonstrates three fundamental contributions:

#### 1. Structural Awareness of Flight Tempo Risk

The framework revealed how schedule intensity directly influences spare consumption and availability degradation. This transformed flight tempo selection from experience-based estimation to probabilistic risk assessment.

#### 2. Anticipatory Bottleneck Identification

The *waitingProcedure* delay was identified as a critical vulnerability before peak operational stress. Proactive negotiation reduced this constraint prior to PHASE\_2.

#### 3. Probabilistic Mission Forecasting

Instead of relying on deterministic availability assumptions, the Decision Sector received a distribution of possible outcomes, allowing explicit evaluation of risk tolerance.

The framework thus enabled the transition from reactive support management to structured, anticipatory decision-support.

### 4.6.8 Limitations

This case study represents a single empirical application.

Although predictive alignment was strong and calibration consistent with field observations, broader validation across additional campaigns or fleet configurations would strengthen generalizability.

The present case should therefore be interpreted as:

- Empirical demonstration of model capability;
- Evidence of operational utility;
- Indication of structural adequacy;
- Rather than definitive proof of universal predictive validity.

## 4.7 Hypothesis Evaluation and Discussion

### 4.7.1 Restatement of the Research Hypothesis

This research was guided by the hypothesis that:

- *An integrated simulation-based decision-support framework, combining agent-based modeling of individual aircraft behavior with discrete-event modeling of operational, maintenance, and logistics processes, may enhance decision-making capability by improving precision, S.A., and anticipatory capability, thereby supporting more effective management of logistics support and the cost-benefit ratio of military air operations within the defined scope of the study.*

This section evaluates the extent to which the results presented in Sections 4.2 to 4.6 support this hypothesis.

### 4.7.2 Evaluation of Precision

Precision was defined in this research as the ability of the framework to produce stable, coherent, and probabilistically meaningful outputs that realistically represent logistics support dynamics under uncertainty.

The robustness analyses (Section 4.2) demonstrated:

- Stability of results under Monte Carlo experimentation;
- Coherent sensitivity to parameter variation;
- Absence of non-physical or structurally inconsistent behavior.

The precision analyses (Section 4.3) showed that:

- Availability degradation patterns were logically consistent with modeled constraints;
- Variation in fleet size and campaign usage limits produced predictable structural effects;
- Spare-induced degradation mechanisms were transparently represented.

Most importantly, the PHASE\_2 case study (Section 4.6) provided empirical alignment between forecasted and realized mission outcomes. The realized number of successful take-offs fell within the modal interval of the simulated distribution generated from 10,000 replications.

While a single case does not establish universal predictive validity, it provides empirical indication that the framework can generate operationally meaningful forecasts when calibrated with real data.

Taken together, these results support the claim that the framework enhances precision in supportability-related forecasting.

### 4.7.3 Evaluation of Support Awareness Enhancement

S.A. was conceptualized according to three dimensions: perception, comprehension, and projection.

*Perception* was enhanced through explicit representation of:

- Individual aircraft states;
- *a\_limitToFly* consumption trajectories;
- Spare inventory levels;
- *waitingResources* and *waitingProcedure* states.

*Comprehension* was supported by explicit modeling of causal interactions between:

- Operational tempo,
- Reliability exposure,
- Maintenance demand,
- Inventory constraints.

The framework made visible how schedule intensity propagates into spare depletion and availability degradation.

*Projection* was enabled through Monte Carlo experimentation, providing probability distributions rather than deterministic estimates. Decision-makers were able to evaluate the likelihood of availability collapse, mission sustainability, and structural withdrawal timing.

In the PHASE\_1 and PHASE\_2 planning phase, this enhanced awareness allowed identification of critical schedule sensitivities and industrial response bottlenecks prior to peak operational stress.

The results therefore indicate that the framework contributes to improved S.A. by revealing system states, interdependencies, and future trajectories under uncertainty.

### 4.7.4 Evaluation of Anticipatory Capability and Decision-Support Effectiveness

Anticipatory capability was defined as the ability to evaluate alternative configurations before execution and to identify structural vulnerabilities in advance.

The framework supported anticipatory decision-making by:

- Comparing alternative flight tempo configurations;

- Quantifying risk of availability degradation;
- Identifying sensitivity to industrial response delay;
- Revealing the impact of *a\_limitToFly* policies on campaign sustainability.

A concrete example of anticipatory impact occurred when sensitivity analysis revealed the critical role of *waitingProcedure* delays. This led to negotiation with the industrial stakeholder, reducing response time prior to PHASE\_2 execution.

This intervention illustrates that the framework did not merely describe system behavior but influenced decision-making in a manner aligned with improved supportability management.

#### 4.7.5 Relation to the *Support and Supportability Problem*

The broader problem identified in Chapter 1 concerned the degradation of cost-benefit ratio in sustained military air operations due to insufficient supportability management under uncertainty.

The results of this chapter demonstrate that the framework:

- Quantifies the relationship between flight tempo and logistics stress;
- Reveals structural trade-offs between operational ambition and sustainment capacity;
- Provides probabilistic indicators of supportability risk.

By enabling decision-makers to align flight schedule ambition with logistics capability, the framework contributes to preventing undesirable degradation of cost-benefit during sustained operations.

#### 4.7.6 Limitations and Scope of Hypothesis Confirmation

It is important to acknowledge the scope and limitations of the present evaluation.

- The empirical validation is based on a single real campaign.
- Generalization to other fleet types or operational contexts requires further application.
- The model assumes accurate parameterization of reliability and logistics inputs.

Therefore, the hypothesis is supported within the operational scope and context evaluated in this research. Broader generalization should be pursued through future studies and additional applications.

### 4.7.7 Final Assessment

Within the defined scope of this dissertation, the evidence presented throughout Chapter 4 supports the research hypothesis and confirms the fulfillment of the stated objectives.

The general objective of developing and evaluating a simulation-based decision-support framework capable of enhancing precision, S.A., and anticipatory capability in support-related decisions was achieved. The Monte Carlo analyses demonstrated stable probabilistic convergence and realistic forecasting behavior, confirming improved precision relative to deterministic planning approaches. The integrated architecture, combining operational execution, maintenance workflows, and logistics constraints within a unified environment, enhanced S.A. by explicitly representing the interdependencies that govern availability degradation. The anticipatory evaluation of fleet configurations and campaign usage policies demonstrated that the framework enables ex-ante assessment of sustainability risks, influencing decision-making before operational execution.

The specific objectives were likewise satisfied. The agent-based representation of aircraft at the tail-number level allowed explicit modeling of heterogeneous state evolution, in contrast to uniform fleet abstractions. Discrete-event simulation provided structured representation of operational scheduling, maintenance processes, and logistics interactions with temporal coherence. Stochastic representations of failures, repair durations, and supply delays replaced fixed-value assumptions, allowing uncertainty to propagate realistically through the system. Monte Carlo experimentation generated full probability distributions of mission outcomes rather than single-point estimates, operationalizing probabilistic analysis. Finally, the comparative evaluations demonstrated that the integrated framework provides greater visibility of structural risk and configuration-dependent degradation than fragmented or static planning approaches.

Beyond methodological fulfillment, this research also produced a deeper systemic understanding of sustained military air operations. Through the process of modeling, calibration, validation, and application, the dynamic interplay between operational ambition, reliability exposure, spare constraints, and campaign-level policy decisions became structurally explicit. The framework made visible mechanisms that, in practice, are often perceived only indirectly through experience. In this sense, the research not only generated a computational tool but also clarified the underlying logic governing logistics support during sustained operations.

Taken together, these results indicate that the proposed hybrid framework constitutes a meaningful methodological and analytical contribution to supportability-oriented decision-support in sustained military air operations. By enhancing precision, S.A., and anticipatory capability, the framework improves the ability to manage the degradation of the cost–benefit relationship under uncertainty. Within the established assumptions and limitations, the research hypothesis is therefore supported.

## 5 Conclusion

This research addressed the broader *Support and Supportability Problem* inherent to sustained military air operations: the risk of degradation in cost–benefit resulting from insufficient integration between operational ambition and logistics capability under uncertainty. Rather than assuming the absence of simulation tools in the domain, this work began from the recognition that existing planning approaches frequently lack an integrated representation of operational and logistics dynamics, probabilistic visibility of future system states, and structured support for anticipatory decision-making. In such contexts, decisions concerning flight tempo, sustainment policy, and campaign configuration are often grounded primarily in experience and deterministic indicators, with limited insight into how stochastic effects propagate across time and organizational boundaries.

The central proposition of this dissertation was that enhancing precision, support awareness, and anticipatory capability would directly improve decision-making related to supportability in sustained air operations. The hybrid framework developed in this work was therefore conceived not merely as a computational instrument, but as a structured analytical environment capable of representing the coupled dynamics between aircraft behavior, maintenance processes, and logistics constraints under uncertainty. By integrating agent-based modeling of individual aircraft with discrete-event representation of maintenance workflows and explicit modeling of spare availability and campaign-level policy parameters, the framework consolidates operational execution, reliability exposure, and logistics support within a unified and transparent architecture. Monte Carlo experimentation was incorporated to ensure that outputs were expressed probabilistically rather than deterministically, enabling decision-makers to interpret not only expected outcomes but also associated variability and risk.

From a methodological standpoint, the framework contributes by bridging paradigms that are frequently applied in isolation. Aircraft are modeled as autonomous entities with state-dependent behavior, while maintenance and logistics interactions are governed by structured process logic. Campaign-level constraints, such as the *a\_limitToFly* parameter, are embedded directly into aircraft state transitions, allowing policy decisions to influence availability trajectories explicitly. This integration ensures coherence between operational planning and sustainment capability, avoiding the fragmentation that characterizes many existing models.

Analytically, the results demonstrate that availability degradation in sustained operations is not solely a consequence of stochastic failure behavior, but emerges from configuration-dependent

interactions among fleet allocation, flight tempo, spare stock levels, industrial response delays, and usage policies. The framework revealed how spare shortages and procedural delays propagate into mission-level effects, how campaign parameters can induce structural availability loss, and how alternative configurations can produce significantly different probabilistic sustainability profiles. These findings reinforce the view that supportability is a dynamic systems property shaped by interactions rather than isolated variables.

The practical application to the PHASE\_1 training phase and the subsequent PHASE\_2 provided empirical evidence of relevance. During planning, the framework informed flight schedule dimensioning and exposed the potential risks associated with aggressive tempo configurations. It identified the *waitingProcedure* delay as a critical bottleneck and supported negotiation with the industrial stakeholder, resulting in reduced procedural response times. At the conclusion of the campaign, the probabilistic forecast generated by the model aligned with realized mission outcomes, demonstrating structural adequacy under real operational conditions. While this validation is limited to a single campaign, it illustrates that the framework can influence real decision-making processes and not merely serve as an academic demonstration.

Before the adoption of this framework, supportability-related decisions during sustained operations were primarily based on deterministic availability indicators, aggregated metrics, and experience-based judgment. Although such approaches provided operational intuition, they offered limited visibility of how uncertainty and structural interactions might shape future outcomes. The framework developed in this dissertation introduces probabilistic forecasting of mission sustainability, explicit visualization of reliability–logistics interactions, and structured comparison of alternative operational configurations. In doing so, it shifts decision-making from reactive management of support constraints toward anticipatory governance of supportability. The contribution is therefore not merely computational but cognitive and organizational: it changes how uncertainty is perceived, interpreted, and incorporated into operational planning.

The general objective of this research was to develop and evaluate a simulation-based decision-support framework capable of improving precision, support awareness, and anticipatory capability in the context of military air operations supportability. Based on the results obtained, this objective can be considered achieved within the defined scope of the study.

The adoption of simulation-based decision-support frameworks introduces important ethical considerations, particularly regarding the interpretation and use of model outputs. While such models can significantly enhance decision-making capability, there is a risk of overconfidence in model predictions, especially when probabilistic results are perceived as deterministic forecasts.

Decision-makers may attribute excessive reliability to model outputs, potentially overlooking underlying assumptions, data limitations, and structural simplifications. This may lead to decisions that are insufficiently critical or inadequately contextualized.

Therefore, the use of the proposed framework must be accompanied by a clear understanding that it does not replace expert judgment but rather supports it. The model should be interpreted as an analytical aid that enhances understanding of system behavior under uncertainty, rather

than as a prescriptive or definitive solution.

Ensuring transparency in assumptions, maintaining traceability of inputs, and fostering critical interpretation of outputs are essential practices to mitigate risks associated with overreliance on decision-support tools.

Regarding the specific objectives:

- The representation of individual aircraft behavior using an agent-based approach was successfully implemented, enabling the modeling of heterogeneous fleet dynamics through a tail-number approach.
- The integration of operational execution, maintenance processes, and logistics support through discrete-event simulation was achieved, allowing the consistent representation of process flows and resource constraints.
- Stochastic representations of failures, repair times, and logistics delays were incorporated, enabling the model to capture uncertainty inherent to real-world operations.
- Monte Carlo experimentation allowed the generation of probabilistic outputs, supporting the analysis of mission success, availability, and logistics risk under different scenarios.
- The framework demonstrated its ability to improve decision-support quality by providing structured, probabilistic insights, enhancing precision, support awareness, and anticipatory capability when compared to static or fragmented approaches.

Therefore, both the general and specific objectives were fulfilled, supporting the validity of the proposed approach as a decision-support tool.

Despite these contributions, the demonstrated scope of applicability remains bounded. Empirical validation is based on a single campaign, and broader institutional confidence would require repeated application under diverse operational contexts. Generalization to other fleet types or logistics architectures would necessitate parameter adaptation and possibly structural adjustments. The model assumes accurate estimation of reliability and inventory parameters, and human maintenance workforce constraints were not explicitly represented. These limitations do not undermine the structural logic of the framework but define the boundaries within which its current validation holds.

In addition to the structural limitations previously discussed, it is important to consider the degree of uncertainty associated with the results produced by the framework. Although Monte Carlo simulation enables the explicit representation of variability and risk, the accuracy of the outputs remains dependent on the quality and representativeness of input data, including failure rates, repair times, and logistics parameters.

Uncertainty in model inputs propagates through the simulation, affecting the resulting probability distributions. Therefore, the outputs should not be interpreted as precise predictions, but as probabilistic estimations conditioned on the assumptions and data available.

Furthermore, the model does not capture all sources of uncertainty present in real operations, such as human factors, organizational variability, or unexpected external disruptions. As such, the framework provides a structured approximation of system behavior rather than a complete representation of reality.

These considerations reinforce the importance of interpreting results within their proper context and using them as part of a broader decision-making process.

Although the framework demonstrated methodological robustness and practical utility, it currently operates as a validated decision-support prototype rather than a fully institutionalized operational tool. Transitioning to institutional deployment would require automated integration with maintenance and logistics information systems, standardized parameter update routines, automated generation of decision-oriented reports, and development of a user interface tailored to decision-makers. Expanded empirical validation across multiple campaigns would strengthen statistical confidence in predictive performance. Organizational embedding would require clear assignment of model ownership, formal governance procedures for parameter maintenance, and traceability mechanisms linking simulation outputs to operational decisions.

Institutional adoption of this framework also demands cultural transformation. In practice, sustainment-related decisions are frequently driven by experiential judgment and organizational habit, often without formal probabilistic assessment of risk or explicit modeling of systemic interactions. Such practices, while grounded in operational expertise, are inherently vulnerable to cognitive bias, fragmented support awareness, and reactive adaptation to emerging constraints. The introduction of an integrated probabilistic framework challenges this paradigm by replacing implicit reasoning with explicit risk quantification. This shift represents not only a methodological advancement but a necessary correction in the epistemic foundations of supportability decision-making.

The framework developed in this research presents several characteristics that align with the foundational principles of digital twin systems, including the integration of multiple subsystems, representation of individual asset behavior, and the ability to simulate future operational scenarios. However, in its current form, the model does not fully meet the requirements of a digital twin, primarily due to the absence of automated, real-time data integration and continuous synchronization with the physical system. The current implementation relies on manually updated inputs and predefined scenarios. Nevertheless, the structure and logic of the proposed framework provide a suitable basis for future development toward a digital twin of military aircraft fleet operations. Such evolution would require integration with operational databases, maintenance management systems, and logistics information systems, enabling real-time updating and continuous calibration of model parameters. In this context, the framework can be understood as a digital twin precursor, capable of supporting future advancements in real-time decision-support and predictive analytics in military aviation logistics.

Future developments may include:

1. explicit modeling of maintenance workforce constraints;

2. coupling with cost modeling to directly quantify cost–benefit trade-offs.
3. integration with optimization modules for schedule design;
4. expansion to multi-base or multi-echelon logistics structures; and
5. real-time updating and continuous calibration of model parameters.

Longitudinal validation across successive campaigns would further reinforce confidence in predictive robustness and institutional relevance.

Ultimately, this dissertation addressed a fundamental challenge in sustained military air operations: aligning operational ambition with logistics capability under uncertainty. By integrating aircraft-level dynamics, maintenance processes, and spare constraints within a probabilistic hybrid simulation framework, it demonstrated that precision, support awareness, and anticipatory capability in support-related decision-making can be meaningfully enhanced. The work does not eliminate uncertainty; rather, it renders uncertainty visible, quantifiable, and actionable. This transformation, from implicit risk to explicit probabilistic insight, constitutes the central contribution of the research and its enduring value for logistics support management.

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## FOLHA DE REGISTRO DO DOCUMENTO

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6. AUTOR(ES): <b>Gustavo Henrique Munhoz</b>			
7. INSTITUIÇÃO(ÕES)/ÓRGÃO(S) INTERNO(S)/DIVISÃO(ÕES): Instituto Tecnológico de Aeronáutica – ITA			
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10. APRESENTAÇÃO: <span style="float: right;"><input checked="" type="checkbox"/> Nacional    <input type="checkbox"/> Internacional</span> ITA, São José dos Campos. Curso de Mestrado. Programa de Pós-Graduação em Ciências e Tecnologias Aeroespaciais (PG/CTE). Área de Gestão Tecnológica. Orientador: Prof. Dr. Fernando Teixeira Abrahão. Defesa em 30/03/2026. Publicada em 2026.			
11. RESUMO: <p>This dissertation addresses the challenge of decision-making in military air operations under conditions of uncertainty, where limited foresight of system behavior and resource constraints can degrade operational effectiveness and cost-benefit performance. To support decision-making in this context, a simulation-based decision-support framework is developed, integrating agent-based modeling of individual aircraft behavior with discrete-event simulation of operational, maintenance, and logistics processes. The framework incorporates stochastic representations of failures, repair durations, and supply delays, and employs Monte Carlo experimentation to generate probabilistic indicators related to mission success, aircraft availability, maintenance workload, and logistics constraints. The proposed approach is applied to a case study based on sustained military air operations, including calibration with data from COMAO 2024 (Composite Air Operations – Training Phase) and forecasting analysis for CRUZEX 2024 (Cruzeiro do Sul Exercise – Large-Scale Multinational Air Exercise). These scenarios provide a realistic operational environment to evaluate the framework’s capability to represent system dynamics and support planning under uncertainty. Results demonstrate that the framework enhances decision-support by improving precision, support awareness, and anticipatory capability, enabling more informed assessment of future system states and risks. Rather than predicting exact outcomes, the framework provides probabilistic insight into system behavior, supporting more robust and informed decision-making in complex operational environments.</p>			
12. GRAU DE SIGILO: <p style="text-align: center;"> <input checked="" type="checkbox"/> <b>OSTENSIVO</b>                                          <input type="checkbox"/> <b>RESERVADO</b>                                          <input type="checkbox"/> <b>SECRETO</b> </p>			