Advances in Production Engineering & Management
Volume 21| Number 2 | June 2026 | pp 201–220
https://doi.org/10.14743/apem2026.2.569
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

A system dynamics approach to maintenance capacity optimization under split acquisition: A military case study

Kim, T.[a], **Choi, K.**[a], **Moon, S.**[a,*]

[a]Korea National Defense University, Department of Defense Management, Nonsan, South Korea

A B S T R A C T

This study examines maintenance capacity adjustment strategies under split acquisition, a common practice in defense procurement driven by budgetary and production constraints. Using the Republic of Korea Air Force (ROKAF) F-35A as a case, the study investigates how time gaps between acquisition phases, combined with bathtub-shaped failure patterns, generate non-linear shocks in maintenance workload that threaten operational availability. A System Dynamics (SD) model is developed to simulate a 40:20 split acquisition scenario and to compare three capacity adjustment strategies: Level (fixed), Chase (reactive), and Lead (proactive). The strategies are evaluated under review intervals of 3, 5, and 10 years to reflect realistic defense planning environments. The simulation results show that the reactive Chase strategy consistently fails to achieve the availability target of 75 % due to workforce training delays. In contrast, the proactive Lead strategy successfully defends availability by anticipating future workload changes. A 3-year review interval achieves the highest cost-effectiveness, while a 5-year interval, aligned with the Mid-term Defense Plan cycle, is identified as a realistic threshold for sustaining availability. However, under a 10-year review interval, even proactive strategies lose effectiveness. The findings highlight the importance of proactive, forecast-based decision-making and suggest that synchronizing maintenance review cycles with acquisition schedules within a 5-year horizon is essential for robust maintenance policy design.

A R T I C L E I N F O

Keywords:
Simulation;
System dynamics;
Operational availability;
Maintenance capacity planning;
Bathtub curve;
Split acquisition;
Mid-term defense plan;
Fighter fleet maintenance;
F-35A

**Corresponding author:*
mseongam@hotmail.com
(Moon, S.)

Article history:
Received 1 January 2026
Revised 14 April 2026
Accepted 25 April 2026

1. Introduction

The F-35A, a core asset of modern air forces, is a fifth-generation fighter jet equipped with stealth capabilities and advanced sensor fusion technology, possessing superior operational capabilities compared to fourth-generation fighters. However, its high concentration of technology entails substantial operation and maintenance (O&M) costs. Furthermore, its complex maintenance structure, which relies on the Autonomic Logistics Information System (ALIS) — or the Operational Data Integrated Network (ODIN) — and a Global Supply Chain, makes managing its availability a highly challenging task.

In environments constrained by defense budgets and manufacturer production schedules, such as that of the Republic of Korea Air Force (ROKAF), it is common to adopt a 'Split Acquisition' approach, where required forces are introduced in phases rather than all at once. The ROKAF, for instance, initially deployed 40 F-35A aircraft and plans to acquire an additional 20 units with a time lag of approximately five years. While split acquisition provides flexibility in budget execution, it serves as a potential risk factor that causes severe 'Non-linear Shocks' in terms of maintenance workload management.

Generally, aircraft failure rates follow a 'Bathtub Curve', where rates are high during the initial infant mortality phase, stabilize, and then rise again during the wear-out phase. The problem arises when the failure rate pattern of the first batch overlaps with that of the second batch introduced after a time lag, creating unpredictable 'waves of maintenance demand'. Consequently, at certain points, a surge in demand can lead to maintenance shortages and a collapse in availability, while at other times, a sharp drop in demand results in the inefficiency of massive 'Unused Resources'.

However, existing studies on military maintenance policy have predominantly focused on calculating average maintenance requirements based on the total number of acquired units or have concentrated on reactive responses after deployment is complete. These approaches overlook the structural variability caused by 'Acquisition Patterns', leaving military organizations with rigid manpower structures unable to respond in a timely manner to rapidly changing maintenance workloads.

Therefore, this study utilizes System Dynamics (SD) modeling to simulate the '40:20 Split Acquisition' scenario of the ROKAF F-35A and aims to derive the optimal maintenance capacity adjustment strategy capable of defending availability in such a dynamic environment. Specifically, the study goes beyond merely determining the required number of personnel; it aims to demonstrate that maintenance workload shocks can only be absorbed when a proactive 'Lead' strategy, which predicts future demand, is combined with appropriate organizational flexibility. The ultimate goal is to present cost-effective and practical policy alternatives.

This study analyses the interaction between acquisition patterns and maintenance policies using SD simulation. The simulation model consists of two core modules: fighter acquisition and fighter operation, with the maintenance-capacity adjustment logic embedded within the fighter operation module. The key experimental design is as follows: First, the acquisition pattern is set to a '40:20 Split Acquisition' scenario, reflecting the reality of the ROKAF, where 20 additional units are introduced five years after the initial 40 units. Second, capacity adjustment strategies are categorized into a fixed 'Level' strategy, a reactive 'Chase' strategy that responds to shortages, and a proactive 'Lead' strategy that predicts future failure patterns. Third, to reflect the characteristics of the military organization executing these strategies, the 'Review Interval' and 'Adjustment Chunk' are set as key variables. The simulation is conducted under three realistic decision-making scenarios: 3 years, 5 years, and 10 years.

Through this approach, this study quantitatively compares and analyses the impact of each combination of strategy and decision-making interval on performance indicators such as Availability (A_o), Cumulated Shortage, and Unused Resources (UR), thereby proposing a robust maintenance policy optimized for split acquisition environments.

2. Theoretical background

2.1 Dynamic characteristics of military logistics and maintenance

In traditional reliability engineering, the failure rate of a system has been explained as following a 'Bathtub Curve', which progresses through infant mortality, constant failure, and wear-out phases over time [1]. However, the seminal work of Nowlan and Heap [2] in aircraft maintenance analysed failure data of commercial aircraft components and identified that failure patterns are not singular but can be classified into six distinct types, as shown in Fig. 1.

Such non-linear failure patterns are frequently observed in the complex operational environments of actual weapon systems. Choi and Moon [3] empirically analysed critical failure data from Republic of Korea Navy ships, demonstrating that actual operational data exhibits a complex nature combining long-term trends and short-term probabilities, rather than following a simple probability distribution. In particular, they showed that the failure rate of weapon systems changes dynamically over the operational period, as illustrated in Fig. 2, confirming that managing initial stabilization and aging is a key variable for maintenance workload at the 'System of Systems' level, unlike single components.

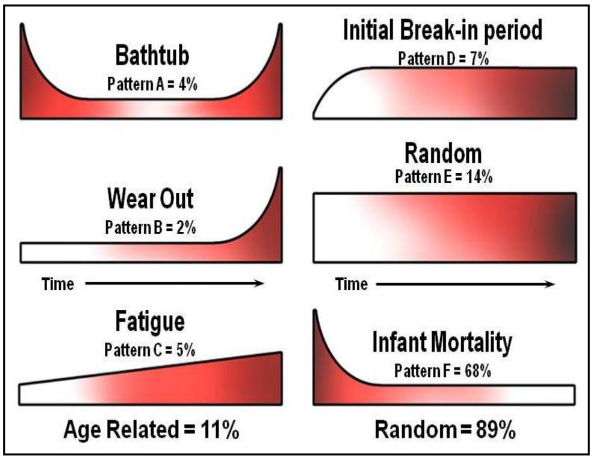

Fig. 1 Six failure patterns of aircraft components (Source: Nowlan and Heap [2])

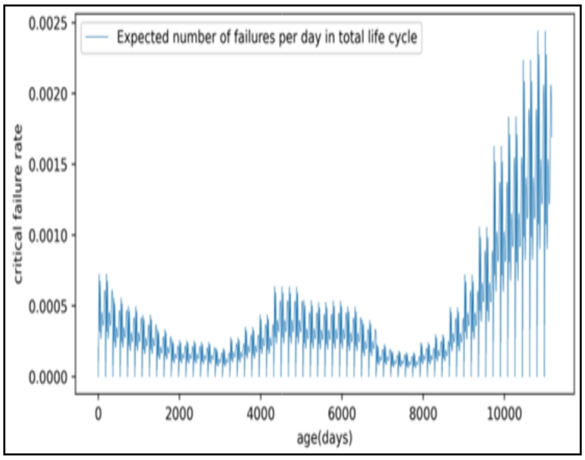

Fig. 2 Daily expected failure patterns of naval ships over the life cycle (Source: Choi and Moon [3])

From a reliability management perspective, this bathtub-shaped pattern combines a sharp decrease in initial defects with a resurgence due to late-stage wear-out. Consequently, it exhibits higher volatility over time compared to other patterns and makes maintenance workload particularly difficult to predict. This represents the most severe scenario for implementing simulation, given the uncertainty in remaining useful life prediction pointed out by De Pater *et al.* [4] and the variability in maintenance time emphasized by Jin *et al.* [5].

In particular, the 'wear-out phase' in the latter part of the bathtub curve is directly linked to aging issues in actual military aircraft operating environments. Empirical studies by Pyles [6] and Dixon [7] identified that the increase in aircraft age within a fighter fleet is a key factor causing a non-linear increase in maintenance workload by inducing airframe fatigue cracks and component obsolescence. This rise in costs and maintenance requirements due to aging has also been confirmed in domestic research. Kim *et al.* [8] analysed the impact of changes in maintenance factors on costs when calculating weapon system operation and maintenance costs through simulation, emphasizing the necessity of predicting structural changes in maintenance workload over the operational period in advance.

Furthermore, maintenance demand from the perspective of an entire military fighter fleet, rather than a single piece of equipment, becomes even more complex as individual aircraft lifecycle characteristics are combined with 'Acquisition Patterns'. Realistically, high-value weapon systems like fighter jets are typically acquired through phased split acquisition rather than a one-time purchase due to constraints on budget and production capacity. As Keating *et al.* [9] pointed out from a systems engineering perspective, this implies that the decision on acquisition patterns goes beyond simply determining the introduction timing; it becomes a critical variable determining the structure of maintenance workload for the next 30 to 40 years. In other words, the time difference in acquisition points disperses or overlaps the failure rate peaks of each introduced batch, forming macroscopic waves of maintenance workload.

However, existing maintenance policy studies have not sufficiently reflected this structural variability. Safaei *et al.* [10], and Aramon Bajestani and Beck [11] dealt with scheduling optimization under limited capacity, but they primarily focused on short-term operational efficiency premised on 'already deployed forces'. Similarly, while Mattila and Virtanen [12] and Zhang *et al.* [13] analysed maintenance availability through simulation, these studies were limited in identifying the long-term and dynamic ripple effects that changes in acquisition patterns have on the 'Capacity Requirement' itself.

Therefore, this study aims to derive an optimal maintenance capacity adjustment strategy capable of maintaining robustness amidst the uncertainty of maintenance workload through System Dynamics modeling that combines bathtub-type failure patterns with phased acquisition patterns.

2.2 Capacity adjustment strategies

The problem of optimizing manpower and facility utilization rates in response to fluctuating maintenance demand is frequently addressed in Aggregate Production Planning (APP) within the field of Operations Management [14]. APP is a macroscopic plan that adjusts production rates, employment levels, and inventory levels to cope with demand variability. In the field of military maintenance, this results in a decision-making problem of adjusting the Table of Organization (TO) and work capacity of maintenance units to achieve the Availability (A_o) target. Capacity adjustment strategies can be broadly categorized into three types: the Level Strategy, which maintains a constant workforce level; the Chase Strategy, which adjusts capacity according to demand fluctuations; and the Lead Strategy, which proactively responds by predicting future demand [14, 15].

First, the Level Strategy is a strategy that maintains maintenance capacity at a constant level regardless of demand fluctuations. This strategy has the advantage of minimizing hiring and firing costs and promoting organizational stability, making it the most commonly adopted method in military organizations where TO adjustments are rigid. As pointed out by Bunecke *et al.* [16], most weapon system operation and support (O&S) cost estimation models assume such fixed maintenance capacity, which limits their ability to immediately reflect dynamic workload fluctuations occurring during actual operations in cost or manpower requirements. Therefore, during peak periods when maintenance requirements surge, such as with the F-35A, there is a risk that fixed capacity will fail to meet demand, leading to a rapid accumulation of maintenance shortages.

Second, the Chase Strategy is a strategy that synchronizes capacity with fluctuations in maintenance demand. As studied by Safaei *et al.* [10], this refers to a reactive approach that injects manpower or assigns overtime to resolve maintenance backlogs that have already occurred under limited resources. While this strategy has the advantage of minimizing unused resources, in a military environment where there is a physical time lag in training skilled maintenance personnel, it may trigger the 'Bullwhip Effect' [14], failing to defend against availability degradation by not catching up with rapidly changing workloads in time.

Third, the Lead Strategy adopts the concept of 'Capacity Lead Strategy' from the field of facility investment planning [15]. This refers to an aggressive strategy of expanding capacity proactively before actual demand occurs when demand is expected to increase. It is a valid strategy when maintaining service levels, such as securing availability, is the top priority, even at the cost of inventory (unused resources).

In summary, the Level strategy pursues stability, the Chase strategy pursues reactive efficiency, and the Lead strategy prioritizes the effectiveness of availability defense based on known failure rate patterns.

2.3 Maintenance capacity planning and reliability metrics

Availability (A_o), a key indicator of a weapon system's combat readiness, is derived through RAM analysis, which comprehensively evaluates the system's Reliability, Availability, and Maintainability. According to Blanchard [17], operational availability (A_o) is defined as a function of Mean Time Between Failure (MTBF), Mean Time To Repair (MTTR), and Mean Logistics Delay Time (MLDT), as shown in Eq. 1.

$$A_o = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR} + \mathrm{MLDT}} \tag{1}$$

Here, MTBF is an inherent reliability characteristic determined during the acquisition phase, whereas MLDT is a variable factor determined by the capacity of maintenance personnel and facilities. Kullstam [18] mathematically demonstrated the sensitivity of availability to the number of maintenance channels in an M-out-of-N system where M out of N repairable systems must be operational. Similarly, Sharma and Kumar [19] emphasized that integrated management of RAM indicators is essential in performance modeling of critical systems.

In other words, for an F-35A fleet in which the age structure changes according to the acquisition pattern, causing MTBF to fluctuate along the bathtub curve, dynamic adjustment of maintenance capacity is required to control MLDT in order to maintain the target availability.

Maintenance policies to respond to fluctuating failure rates are evolving beyond simple corrective maintenance into Condition-Based Maintenance (CBM) and Predictive Maintenance. Recent studies emphasize the importance of strategic agility; for instance, Bányai [20] demonstrated how agile, condition-based maintenance strategies significantly improve the cost efficiency of complex production systems. Furthermore, addressing the non-linear deterioration of assets requires advanced modeling techniques. Peng *et al.* [21] addressed the optimization of CBM policies in systems with non-homogeneous degradation processes, while Chen *et al.* [22] proposed an imperfect maintenance model considering the impact of changing operational conditions on system deterioration. Advancing this field further, Alrabghi [23] recently proposed a robust modeling approach for tracking such complex asset degradation using digital twins. Jeang *et al.* [24] studied replacement and repair policies to determine the optimal availability of system components, and Fadaeefath Abadi *et al.* [25] proposed an approach to dynamically optimize maintenance costs based on availability in K-out-of-N systems.

These studies suggest that maintenance policies should not be fixed but flexibly adjusted according to the system's condition and operational goals. However, scaling these strategies from individual components to an entire fleet introduces significant complexity. Most preceding studies still focus on single systems or small groups, limiting their ability to address macroscopic maintenance workload issues in interdependent large-scale fleets, such as the production lines examined by Albino *et al.* [26]. Building on this limitation, Selech *et al.* [27] recently highlighted through their reliability analysis and cost evaluation of corrective maintenance for a fleet of vehicles that managing fleet-level availability requires a macroscopic perspective that accounts for interdependent maintenance workloads.

Consequently, the management of assets with long life cycles, such as military aircraft, requires a strategic planning framework that goes beyond the tactical level. Al-Turki [28] emphasized that maintenance management is not merely operational support but a core function for achieving the organization's strategic goals, presenting a strategic framework that includes the setting of appropriate planning horizons and review cycles. In particular, Turan *et al.* [29] approached the problem of long-term fleet renewal under uncertainty using simulation-based optimization, analyzing the ripple effects of changes in acquisition schedules on the operation and maintenance phase.

Adamides *et al.* [30] modeled a military aircraft engine maintenance system to evaluate the dynamic impact of policy changes on performance. These preceding studies support the need for strategic decision-making that predicts future demand and adjusts capacity in 'chunks', rather than relying on immediate responses, given the rigidity of resources like maintenance personnel, which require time for recruitment and training. Specifically, Park *et al.* [31] analysed the maintenance backlog phenomenon caused by the interaction of fixed maintenance intervals and capacity constraints through a simulation of naval ship maintenance queues. They quantitatively proved that the mismatch between maintenance interval and processing capacity is a primary cause of availability degradation, emphasizing that dynamic queue analysis beyond static requirement calculation is essential when establishing maintenance policies.

3. Research model and simulation design

3.1 Model structure

The first step in System Dynamics modeling is to establish the boundaries of the model consistent with the research purpose and to structure the interactions among internal system components [32]. To analyse the dynamic performance of maintenance capacity according to fighter acquisition patterns, this study defines the entire system as a closed loop and constructs the model by focusing on core operational elements, excluding external environmental variables such as international affairs or rapid technological changes.

As shown in Fig. 3, the simulation model consists of two core subsystems: (1) the Fighter Acquisition Module and (2) the Fighter Operation Module. Each module is organically connected through material flows and information feedback.

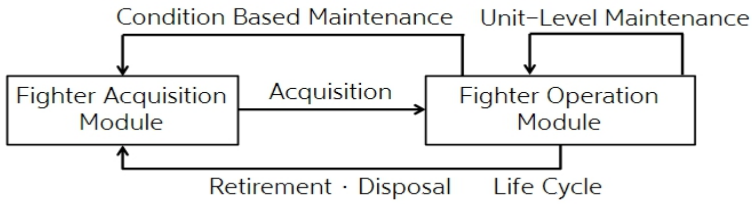

Fig. 3 Overview of the simulation model structure

Fighter acquisition module

The acquisition module is the starting point of the simulation and determines the physical scale of the entire system (see Fig. 4). This module consists of three main flows: Adoption, Condition-Based Maintenance (CBM), and Abandonment.

Depending on the acquisition pattern, new fighters flow into the "Adopted Equipment" stock. The variables were separated to allow the number of aircraft introduced at each time point to be specified. Aircraft that have exceeded a certain operational time after introduction transition to the "CBM Equipment" state through the "Start of CBM" flow to undergo intensive maintenance. Upon completion, they return to operational status via "Return from CBM."

"Natural Retirement" of aircraft that have reached the end of their service life and "Loss due to Accident" are integrated into the "Abandon Rate," which flows into "Abandoned Equipment." The operational fleet size and age distribution, which are the output values of this module, become key input variables determining the Failure Function in the Operation Module.

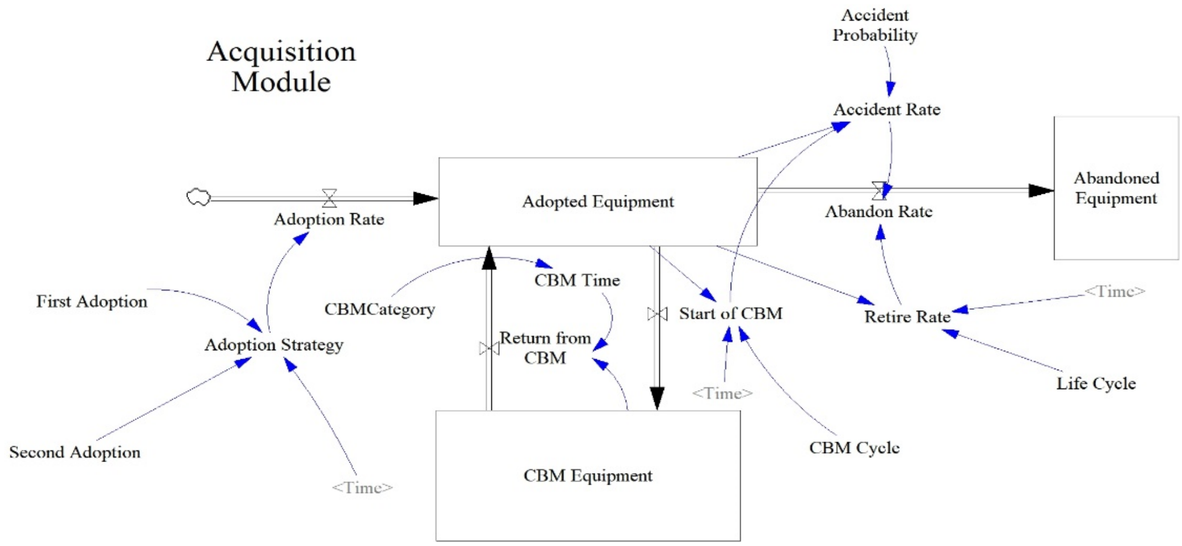

Fig. 4 Structure of the fighter acquisition module

Fighter operation module

The Operation Module is the core part of the model where actual fighter operation and maintenance activities take place and Availability (A_o) and Queue are determined (see Fig. 5).

The aircraft transferred from the Acquisition Module are combined with the Bathtub-type Failure Rate Lookup Function to calculate the "Failure Rate." Aircraft that fail accumulate in the "Queue for Repair." Accumulated failed aircraft move to the "Equipment in Repair" stage to undergo repairs under the constraints of the currently secured "Repair Capacity."

At this point, "New Repair Capacity" fluctuates dynamically according to the maintenance capacity adjustment strategy (Level, Chase, etc.), regulating the "Repair Rate." Finally, the "Equipment in Field" is compared in real-time with the "Target Availability," and this gap acts as a trigger for adjusting maintenance capacity.

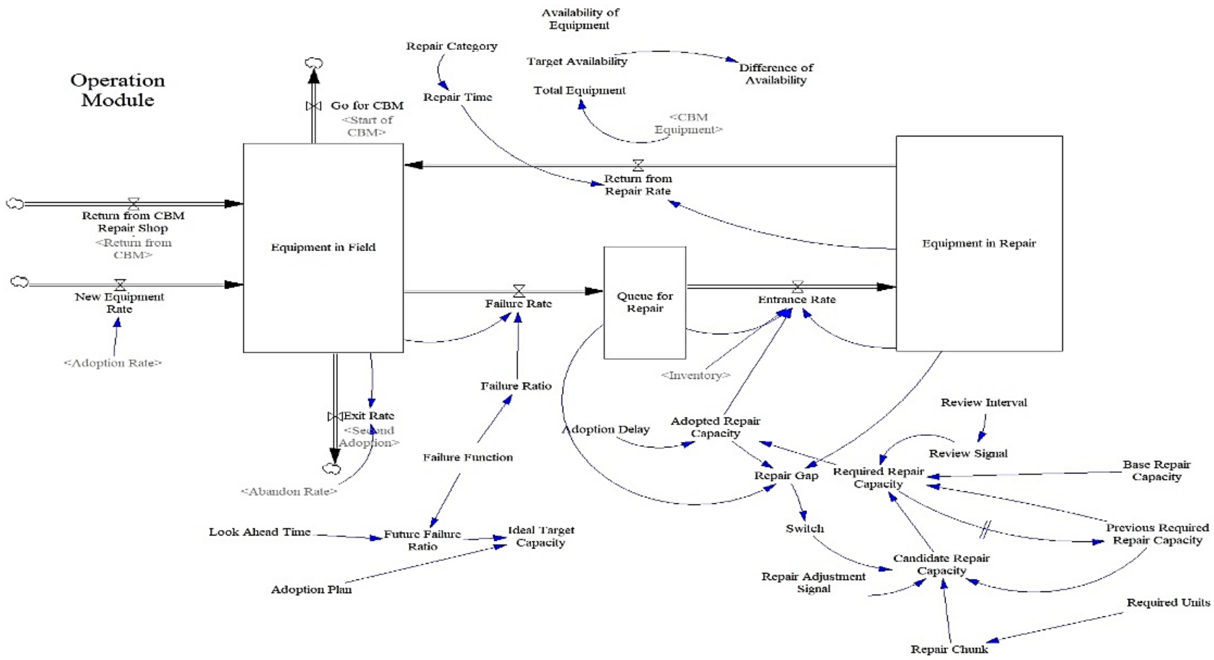

Fig. 5 Structure of the fighter operation module

3.2 Definition of acquisition scenarios and capacity adjustment strategies

Acquisition scenario

Reflecting the acquisition reality of the ROKAF F-35A, a '40:20 Split Acquisition' model was established. In this model, 40 aircraft are introduced at the start of the simulation (Time = 0), and an additional 20 aircraft are introduced in the fifth year (Time = 1,825 days), resulting in a total fleet of 60 units.

The failure rate function follows the Bathtub Curve and is designed so that the failure rate waves of the first and second batches overlap with a time lag. The failure patterns resulting from the acquisition scenario are shown in Fig. 6.

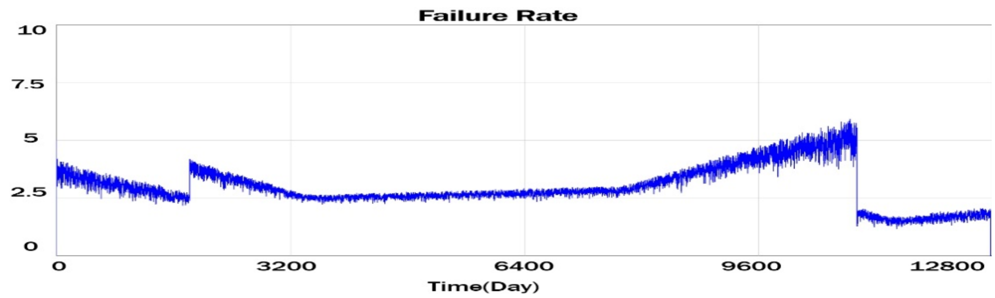

Fig. 6 Failure patterns according to the 40:20 split acquisition scenario

Maintenance capacity adjustment strategies

The decision-making logic of the maintenance manager was modeled using the following three strategies.

First, the Level Strategy maintains maintenance capacity at a constant level throughout the life cycle. In this study, three baselines were established: (1) Level 10 (Efficiency Type), which meets only the requirements of the stable period at minimum cost; (2) Level 12 (Target Type), which achieves the target availability (75 %) on average; and (3) Level 20 (Upper Bound), which can handle the maximum load.

Second, the Chase Strategy is a reactive strategy that expands maintenance capacity when a maintenance backlog occurs~~,~~ and availability falls below the target. The adjustment target is calculated based on the 'average maintenance demand during the *past* review interval.'

Third, the Lead Strategy is a proactive strategy that recognizes future acquisition schedules and failure rate curves in advance. It expands maintenance capacity before actual demand occurs, taking into account the delay in personnel training. The adjustment target is calculated based on the 'average expected demand during the *future* review interval'.

3.3 Data collection and parameter settings

To ensure the validity and realism of the simulation, key parameters were established based on ROKAF and F-35A-related literature, as well as defense planning systems. In cases where access to operational data of certain military aircraft was restricted due to security reasons, simulation parameters were set based on empirical data from public reports published by the US Department of Defense (DoD) and the Congressional Research Service (CRS). In particular, reliability and maintainability indicators for the F-35 were obtained by referencing the Director, Operational Test and Evaluation (DOT&E) Annual Reports (FY14–FY24) and CRS F-35 Program Reports. For variables lacking specific data, values were set at levels suitable for explaining the dynamic behaviour of the system based on logical assumptions derived from the existing literature and expert consultation.

To further clarify the operational basis of the model, the Base Repair Capacity (BRC) levels were established to represent three distinct organizational postures along the capacity-cost spectrum. Specifically, Level 12 (Target Capacity) was mathematically derived as the 'life-cycle average capacity' required to maintain the target availability (75 %) across the entire operational period. In contrast, Level 10 (Minimum Capacity) represents a cost-centric, extreme-efficiency posture calibrated to cover only the lowest steady-state demand during the mid-lifecycle stable period, inherently lacking the buffer to handle demand surges. Conversely, Level 20 (Maximum Capacity) represents a zero-risk, maximum-readiness posture calculated to fully cover the absolute peak demand expected during the simultaneous convergence of the wear-out phase and the second acquisition shock.

In this study, the 'Chunk', which is the unit of maintenance capacity adjustment significantly affecting performance, is defined not simply as a headcount but as a 'Minimum Integrated Maintenance Cell' capable of performing the F-35A's 'Nose-to-Tail' maintenance concept. Considering the operational characteristics of the F-35A, which requires a high level of specialized teamwork, maintenance is performed by organizational units such as a 'Flight' or 'Shift' rather than by individuals. Therefore, meaningful capacity adjustments occur at the unit level. Consequently, a unit corresponding to approximately 8–10 % of the Base Repair Capacity (BRC 12) was defined as Chunk = 1. This represents an agile organizational adjustment. Chunk = 2 and 3 represent medium- to large-scale organizational restructuring, such as expanding multiple maintenance lines. Due to their scale, these larger chunks are realistically feasible only under longer strategic review intervals.

The 'Review Interval', the decision-making cycle for capacity adjustment, was set in three stages—3 years, 5 years, and 10 years—reflecting defense planning and budgeting cycles. The 3-year interval represents the characteristics of a flexible organization where personnel adjustments are possible relatively frequently through urgent requirement requests. The 5-year interval represents the characteristics of a general military organization that reviews unit structure and personnel every five years in alignment with the Mid-term Defense Plan cycle. The 10-year interval implies a rigid organization that performs adjustments only during long-term military structural reforms or weapon system lifecycle phase transitions. The maximum adjustable Chunk for each review interval was set to 1, 2, and 3, respectively.

Since the purpose of this study is to calculate the optimal 'Maintenance Capacity' according to acquisition patterns, it is assumed that repair parts required for maintenance are sufficiently secured and do not cause a maintenance backlog.

The definitions, initial values, and equations of the key variables applied in this simulation are detailed in Table A1 in Appendix A.

3.4 Experimental design

This study established a total of 9 experimental conditions by combining the maintenance capacity adjustment strategy (Level, Chase, Lead) with the institutional flexibility of the organization (Review Interval and Adjustment Chunk) under a fixed '40:20 split acquisition' pattern. The specific experimental conditions are detailed in Table 1.

These 9 conditions can be categorized into four groups based on the decision-making cycle for adjusting maintenance capacity:

The Baseline Group (S1–S3) represents scenarios where maintenance capacity remains fixed (Level Strategy) without adjustment. This reflects situations in which the manpower structure is rigid due to realistic constraints or the absence of a strategic plan, serving as a reference point for evaluating the performance of variable strategies.

The 3-Year Interval Group (S4, S5) assumes a highly flexible organizational environment characterized by a relatively short review cycle and small-scale adjustments (Chunk = 1). This reflects ideal conditions in which personnel adjustments can be made frequently, such as through urgent requirement requests.

The 5-Year Interval Group (S6, S7) assumes a 5-year review cycle, aligned with the ROK military's Mid-term Defense Plan, and medium-scale adjustments (Chunk = 2). This represents the level of organizational flexibility achievable under the current realistic institutional framework.

The 10-Year Interval Group (S8, S9) assumes a long-term unit restructuring cycle and large-scale adjustments (Chunk = 3). This reflects the characteristics of a rigid bureaucratic organization where decision-making is slow and changes occur only in large increments.

Table 1 Experimental conditions for simulation

Condition	Strategy	Description
S1	Level (10)	Fixed at BRC 10 (Minimum Cost)
S2	Level (12)	Fixed at BRC 12 (Average Demand)
S3	Level (20)	Fixed at BRC 20 (Maximum Load, Upper Bound)
S4	Chase (1)	Comparison of adjustment effects up to 1 unit under a 3-year review cycle
S5	Lead (1)	
S6	Chase (2)	Comparison of adjustment effects up to 2 units under a 5-year review cycle (Mid-term Defense Plan environment)
S7	Lead (2)	
S8	Chase (3)	Comparison of adjustment effects up to 3 units under a 10-year review cycle
S9	Lead (3)	

3.5 Model validity assessment

Validation of a System Dynamics model is the process of verifying whether the model reflects the structural characteristics of the actual system and whether the simulation results reproduce realistic behaviour. In this study, a three-step verification process was performed—(1) structural validity, (2) dimensional consistency, and (3) behavioural reproduction—based on the validation procedures proposed by Sterman [33].

First, to ensure structural validity, the causal relationships regarding the F-35 operation and maintenance process reviewed in Section 2 and the bathtub-type failure patterns presented by Nowlan and Heap [2] were reflected in the model. In addition, the 'Check Model' and 'Units Check' functions of the Vensim DSS software were utilized to confirm that there were no errors in variable settings and that the units of all variables were mathematically consistent without contradiction.

To evaluate the model's robustness, 'Extreme Condition Tests' were conducted to verify whether the model responds logically when extreme values are assigned to input variables. For example, when the acquisition quantity was set to '0', it was confirmed that the number of operating aircraft and failures converged to '0' over time, demonstrating that the model exhibits logical behaviour consistent with physical reality.

Furthermore, it was verified that the failure rate function, a key input variable of this study, operates as intended in the simulation. As shown previously in Fig. 6, the failure rate curve set over the simulation period is accurately reproduced within the model. In particular, it was confirmed that the model accurately simulates the dynamic pattern where the failure rate stabilizes after the initial peak and rises again during the wear-out phase as the life cycle of the introduced aircraft increases according to the acquisition pattern.

Consequently, it was confirmed that the simulation model of this study has sufficient validity to analyse the dynamic changes in maintenance workload resulting from changes in acquisition patterns.

4. Simulation results and discussion

This section presents a quantitative analysis of the impact of Level, Chase, and Lead strategies on Operational Availability (A_o), Cumulated Shortage (CS), and Unused Resources (UR) under the split acquisition scenario. Specifically, the performance variations of each strategy according to organizational flexibility—defined by the review interval and adjustment chunk—are compared using time-series graphs and performance metrics.

4.1 Limitations of level strategy and maintenance workload shocks

We analysed the patterns of maintenance workload shocks resulting from the split acquisition pattern when maintenance capacity was fixed. The simulation results confirmed that split acquisition generates massive peaks in maintenance demand immediately after the initial introduction, at the time of the additional introduction in the 5th year, and during the latter half of the life cycle (wear-out period). The results show clear limitations in coping flexibly with these fluctuations using a fixed maintenance capacity, as shown in Fig. 7.

Under the Minimum Capacity Strategy (BRC 10), which prioritizes cost-efficiency, the maintenance queue surged to uncontrollable levels from the initial introduction phase. In particular, as illustrated in Fig. 8, when the second acquisition shock hit in the 5th year, the queue reached a peak and continued to accumulate without being resolved. Although it decreased slightly upon entering the stable period, the queue surged again rapidly as the fleet entered the wear-out period, leading to a complete collapse of availability.

The Average Capacity Strategy (BRC 12), based on the average demand over the life cycle, successfully defended against the initial shock. However, it failed to completely absorb the shock in the 5th year, only recovering to normal levels after entering the stable period. Furthermore, during the wear-out period, the workload surged due to insufficient capacity, demonstrating limitations in sustaining combat power.

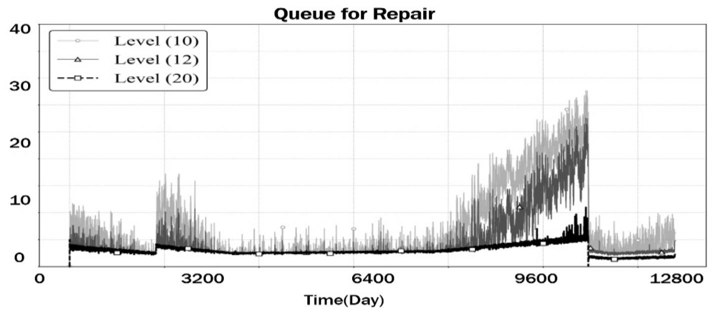

Fig. 7 Comparison of maintenance workload response patterns of the Level strategy

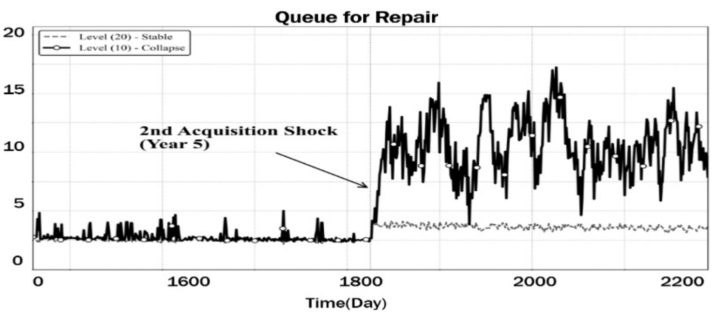

Fig. 8 Maintenance workload shock caused by the 2nd acquisition in the 5th year

The Maximum Capacity Strategy (BRC 20), which considers the maximum load, demonstrated effective defense capabilities by maintaining the queue at a constant level without significant surges throughout the life cycle. However, as shown in Fig. 9, this strategy generates substantial unused resources during the stable period, causing serious budgetary inefficiency.

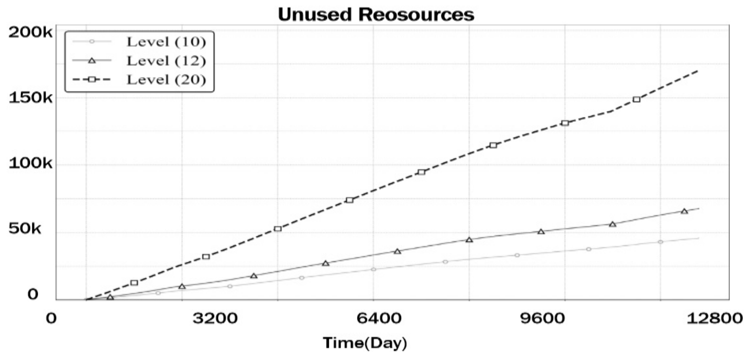

Fig. 9 Comparison of unused resource variation patterns of the Level strategy

4.2 Performance analysis of dynamic adjustment strategies

To overcome the rigidity and inefficiency of resource operation inherent in the Level strategy, this section analyses the performance of the Chase and Lead strategies, which dynamically adjust maintenance capacity according to changing conditions.

In particular, this study focuses on the fact that the success or failure of a strategy is closely linked not merely to 'which strategy is chosen' but to the 'decision-making cycle' of the organization executing it. Therefore, the analysis is structured into three environments based on the maintenance capacity review interval: 3 years, 5 years, and 10 years.

The focus of the performance analysis is to identify whether the Chase and Lead strategies can consistently maintain the target availability (75 %) under each interval environment and how effectively they can control the 'Queue for Repair', a potential risk indicator.

Performance comparison under 3-year review interval

A 3-year review interval, which allows for the most frequent decision-making, combined with small-scale adjustments (Chunk = 1), represents the most flexible condition available to a maintenance organization. Under these conditions, a stark contrast was observed between the performance of the reactive Chase 1 strategy and the proactive Lead 1 strategy.

First, the Chase 1 strategy recorded an availability of 74.33 %, failing to meet the target (75 %) despite the frequent reviews conducted every three years. This failure was the result of the structural limitations of a reactive approach, which only responds after a maintenance queue has formed, combined with the physical constraint of being able to increase capacity by only one unit at a time. Specifically, during the steep ascent phase of the bathtub curve, the rate of increase in maintenance demand outpaces the rate of capacity expansion. The Chase strategy failed to overcome this time lag, resulting in a prolonged accumulation of the maintenance queue.

In contrast, the Lead 1 strategy recorded an availability of 76.46 % under the same physical constraints, consistently achieving the target. The Lead strategy is designed to ensure maintenance capacity stays ahead of demand by predicting future workload and proactively expanding capacity by one unit before the peak arrives. Although the magnitude of a single adjustment was small, this proactive response succeeded in mitigating the impact of the rapid workload shock by fundamentally preventing the initial formation of the maintenance queue.

Consequently, the key factor distinguishing between the success and failure of the two strategies in the 3-year review environment was 'Timing'. The results confirm that the more limited the adjustment capacity (Chunk = 1), the more pronounced the limitations of reactive responses become, making proactive action the only viable solution (see Fig. 10).

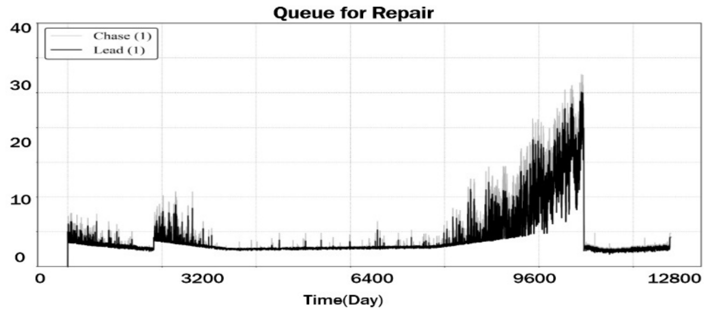

Fig. 10 Comparison of maintenance workload response patterns under 3-year review interval

Performance comparison under 5-year review interval

In the 5-year review environment, which is similar to the ROK military's Mid-term Defense Plan cycle, the contrast between success and failure depending on strategy selection became even more pronounced. This interval represents the threshold of realistically achievable flexibility, where the structural vulnerability of the Chase strategy is clearly exposed.

The Chase 2 strategy failed to cope with the second acquisition shock caused by the split acquisition pattern. This failure occurred because an immediate response was impossible at the moment the maintenance workload surged due to the introduction of the second batch, given the 5-year review interval. Consequently, the maintenance shortage persisted until the next decision point, causing the queue to increase explosively, which led to an irreversible degradation of availability.

In contrast, the Lead 2 strategy detected the impending second acquisition shock around the 5th year in advance and made the decision to proactively expand maintenance capacity by 2 units, the maximum allowable adjustment at that time. Notably, this proactive injection of maintenance capacity was synchronized in a timely manner with the workload increase resulting from the additional acquisition pattern. As a result, the Lead 2 strategy succeeded in effectively controlling the formation of queues and defending the target availability even under the 5-year interval.

This implies the critical importance of synchronizing the acquisition cycle with the maintenance review cycle when establishing maintenance policies. In other words, even if the review cycle is relatively long, accurately predicting the timing of acquisition shocks and responding proactively can secure a 'Realistic Threshold' for achieving availability targets (see Fig. 11).

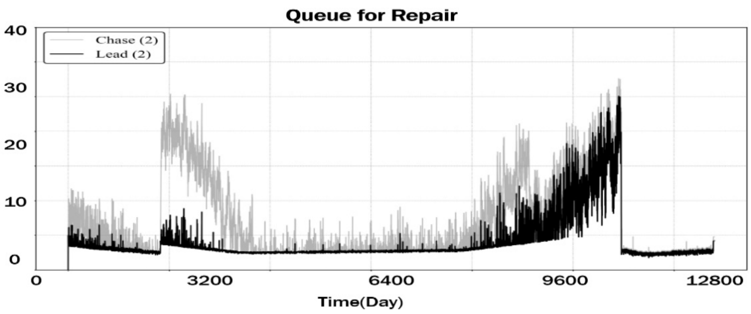

Fig. 11 Comparison of maintenance workload response patterns under 5-year review interval

Performance comparison under 10-year review interval

In the review environment where decision-making occurs on a 10-year cycle, a phenomenon of 'Strategic Neutralization' was observed, rendering the comparison of the relative performance of the Chase and Lead strategies meaningless. Under this condition, although the maximum adjustment scale was significantly expanded to 3 units (Chunk = 3), providing a powerful means of response, the lack of a timely response negated all the effects of resource injection.

Specifically, at the first and second peak points caused by split acquisition, both strategies missed the appropriate response timing, failing to prevent the surge in the maintenance queue. The Chase 3 strategy demonstrated inefficiency by injecting large-scale maintenance capacity belatedly when the workload had already peaked and was declining. This resulted in the generation of massive unused resources, with availability remaining at 72.39 %.

The Lead 3 strategy also showed clear limitations. Although it attempted to respond proactively, its proactive response was insufficient to precisely track the fluctuations of the bathtub curve during the long 10-year gap. The final availability was 72.85 %, failing to achieve the target (75 %).

This suggests that "even with accurate predictive information and powerful adjustment means, they are futile if the execution cycle does not support them." In other words, it was quantitatively confirmed that if the decision-making cycle becomes longer than the cycle of the waves created by the acquisition pattern, no maintenance strategy can maintain effectiveness (see Fig. 12).

Overall, the Lead Strategy demonstrated superior capability in suppressing maintenance queues compared to the Chase Strategy across all comparative conditions. However, the effectiveness of this Lead Strategy is decisively influenced by the organization's review interval.

In the 3-year review environment, the Lead Strategy proved to be the optimal solution, perfectly absorbing the shocks of split acquisition. Even in the 5-year review environment, it successfully maintained the availability threshold. However, in the 10-year review environment, the effectiveness of the strategy vanished.

This implies that to achieve availability targets in a split acquisition environment, securing a 'decision-making cycle within 5 years' is an essential prerequisite, along with the adoption of a Lead Strategy.

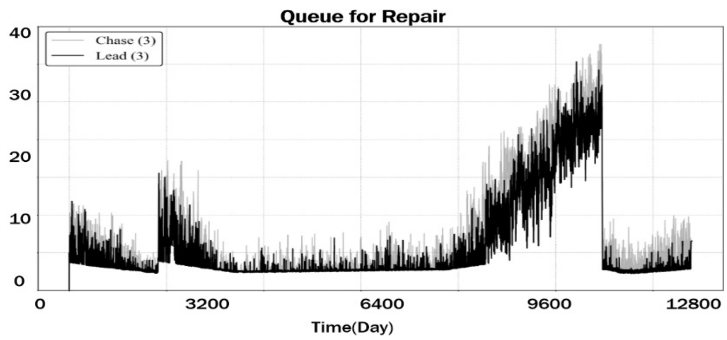

Fig. 12 Comparison of maintenance workload response patterns under 10-year review interval

4.3 Comprehensive discussion and implications

According to the simulation results, among the 9 experimental conditions, the strategies that stably defended the target availability (75 %) were narrowed down to four: Level (20), Level (12), Lead (1), and Lead (2). These are highlighted by shading in Table 2. However, optimal decisions cannot be made solely based on whether the availability target is met; the risk associated with maintenance shortages and the costs arising from unused resources must be comprehensively considered.

Table 2 Average performance metrics by scenario (values in parentheses indicate standard deviation)

Strategy	Availability (%)	Cumulated shortages	Unused resources
Level (20)	78.44 (7.13)	384 (222)	84,265 (48,456)
Lead (1)	76.46 (10.2)	1,197 (1,119)	31,867 (17,852)
Level (12)	76.19 (9.93)	1,316 (930)	34,144 (19,601)
Lead (2)	75.38 (10.66)	1,438 (1,251)	32,148 (15,856)
Chase (1)	74.33 (10.63)	1,792 (1,331)	28,074 (15,376)
Chase (2)	73.70 (10.20)	1,799 (1,504)	25,650 (14,125)
Lead (3)	72.85 (12.60)	2,222 (1,341)	27,814 (14,556)
Level (10)	72.66 (12.66)	2,344 (1,381)	45,559 (13,998)
Chase (3)	72.39 (12.32)	1,843 (1,381)	27,559 (14,368)

Accordingly, the comparative analysis of the Cost-Effectiveness of these four effective strategies is as follows.

First, the Level Strategy has several limitations and inefficiencies. The Level (20) strategy maintains a maintenance capacity of 20 units throughout the 30-year life cycle to match the maximum load. While this appears to be a safe option for ensuring availability, it generates massive unused resources during stable periods when maintenance demand is low, causing substantial waste of the defense budget. The Level (12) strategy maintains capacity at the life-cycle average, making it more cost-efficient than Level (20). However, it lacks the buffering capability to handle unexpected variables or minor fluctuations in demand, harboring inherent instability where availability hovers on the borderline of the target.

Second, the Lead Strategy demonstrates both efficiency and optimality. The Lead (1) strategy demonstrated the best cost-effectiveness. Notably, Lead (1) achieved an availability of 76.46 % while incurring fewer unused resources than the Level (12) strategy. This proves that even without maintaining a massive standing force, the same goal can be achieved at a much lower total cost by expanding capacity only when necessary and flexibly reducing it during low-load periods through precise 3-year forecasting. In other words, from the perspective of Life Cycle Cost (LCC), Lead (1) is judged to be the 'Optimal Solution' that minimizes the waste of unused resources.

Third, the Lead (2) strategy represents a realistic alternative. If adjustments on a 3-year basis are restricted due to institutional limitations, the Lead (2) strategy becomes the only viable alternative. Lead (2) recorded an availability of 75.38 %, defending the threshold even under the Mid-term Defense Plan cycle. Although the precision of unused resource management is somewhat lower than that of Lead (1), it can be considered a 'Realistic Second-Best Solution' that achieves the target within institutional constraints without the excessive resource injection of Level (20).

It should not be overlooked that the performance of this Lead Strategy presupposes 'Perfect Information', meaning the acquisition schedule and bathtub-type failure patterns are known in advance. The Lead Strategy in this model is an ideal model that fundamentally blocks maintenance shortages by predicting the timing of future shocks and securing capacity in advance, considering personnel training delays. Therefore, to succeed with the Lead Strategy in reality, securing not only policy commitment but also 'Forecasting Accuracy' and the supporting data analytics capabilities is a prerequisite.

In conclusion, the optimal maintenance policy that satisfies both availability targets and budget efficiency in the ROKAF's 40:20 split acquisition environment can be summarized as a 'Lead (1)-based 3-year response'. However, considering institutional rigidity, a 'Lead (2)-based 5-year response' is a realistic, applicable solution, while inefficient Level (20) or Chase strategies that fail to meet targets should be avoided.

4.4 Sensitivity analysis on failure patterns

To ensure the generalizability and structural robustness of the simulation findings, a sensitivity analysis was conducted on the shape of the bathtub failure curve, a central driver of the model. While the baseline simulation utilized empirical failure rates, actual operating environments may exhibit varying degrees of initial defects and rates of aging due to differences in operational intensity or environmental factors. Accordingly, two alternative failure functions were modeled and tested: (1) Steep Infant Mortality, which assumes a 20 % higher initial defect rate that stabilizes more rapidly, and (2) Early Wear-out, where the aging-induced failure surge commences two years earlier than the baseline.

Performance under steep infant mortality

Table 3 summarizes the system performance under the Steep Infant Mortality assumption. Despite the amplified initial maintenance workload shock, the proactive Lead strategies (Lead 1 and Lead 2) successfully defended the target availability of 75 %, achieving 76.44 % and 76.18 %, respectively. Conversely, all reactive Chase strategies failed to reach the threshold. This finding quantitatively reaffirms that reactive capacity adjustments are structurally limited by physical time delays during periods of rapid failure influx. It highlights that proactive capacity expansion remains effective even when the initial defect rate is more severe than anticipated.

Impact of early wear-out and the scale of adjustment

Table 4 presents the results under the Early Wear-out scenario, which represents a demanding operational condition characterized by a premature surge in late-stage maintenance demands. Under this accelerated degradation, a notable structural shift occurred: the performance ranking between Lead (1) and Lead (2) inverted. While Lead (1) was the optimal solution under baseline conditions, Lead (2) (Availability: 74.94 %, CS: 1,420) demonstrated superior performance over Lead (1) (Availability: 73.92 %, CS: 1,700) in this scenario.

This result implies that confronting an exponentially accelerating wear-out curve requires not only accurate forecasting (Lead strategy) but also a sufficiently large organizational 'Adjustment Chunk' (Chunk = 2) to match the steepness of the demand curve. The Lead (2) strategy, aligned with a 5-year review cycle, proved capable of buffering this massive wave more effectively than the more frequent but smaller capacity adjustments of Lead (1).

In summary, the sensitivity analysis corroborates the study's core proposition. Regardless of variations in the failure curve profile, reactive capacity planning (Chase) remains structurally vulnerable in split acquisition environments. Proactive decision-making (Lead), when synchronized with an appropriate review interval and adjustment scale, has proven to be a structurally sound mechanism for safeguarding operational availability across diverse operational conditions.

Table 3 Sensitivity analysis for steep infant mortality (values in parentheses indicate standard deviation)

Strategy	Availability (%)	Cumulated shortages	Unused resources
Level (20)	78.74 (13.32)	367 (214)	86,207 (49,094)
Lead (1)	76.44 (10.4)	1,139 (874)	31,928 (18,013)
Lead (2)	76.18 (11.02)	1,527 (1,085)	30,058 (16,486)
Level (12)	75.28 (10.74)	1,552 (1,192)	35,812 (20,209)
Chase (1)	74.08 (11.16)	1,878 (1,389)	26,281 (14,349)
Chase (3)	73.48 (12.81)	1,830 (1,317)	28,218 (15,011)
Lead (3)	73.48 (13.07)	1,830 (1,279)	28,218 (15,203)
Level (10)	73.24 (13.32)	1,867 (1,249)	24,728 (13,831)
Chase (2)	71.45 (10.64)	2,082 (1,396)	24,714 (14,440)

Table 4 Sensitivity analysis for early wear-out (values in parentheses indicate standard deviation)

Strategy	Availability (%)	Cumulated shortages	Unused resources
Level (20)	77.36 (7.51)	429 (285)	83,309 (46,977)
Lead (2)	74.94 (11.28)	1,420 (1,169)	29,985 (16,209)
Lead (1)	73.92 (11.55)	1,700 (1,318)	30,707 (18,027)
Level (12)	73.68 (11.03)	1,721 (1,426)	33,442 (18,880)
Chase (1)	73.39 (11.39)	1,977 (1,505)	28,020 (15,711)
Chase (3)	73.27 (10.95)	2,034 (1,551)	27,509 (14,735)
Lead (3)	72.03 (12.79)	2,073 (1,502)	26,822 (14,899)
Chase (2)	71.26 (10.95)	2,573 (1,670)	24,387 (14,472)
Level (10)	69.81 (14.32)	2,556 (1,551)	22,906 (13,075)

4.5 Robustness across alternative split-acquisition structures

While the baseline simulation was modeled on the ROKAF's specific '40:20 split with a five-year gap', it is necessary to examine how the study's conclusions hold under different acquisition structures, as batch sizes and time lags may vary in other military contexts. To verify this, supplementary simulation tests were conducted under alternative configurations, such as a balanced 30:30 ratio and varying time lags (e.g., 3 and 7 years).

Altering the acquisition structure inevitably shifts the magnitude and timing of the maintenance workload waves. For instance, a more balanced ratio (e.g., 30:30) would lower the initial workload peak but significantly amplify the second peak, as the infant mortality of the second batch would substantially overlap with the ongoing maintenance cycles of the first batch. Alternatively, modifying the time lag alters the width of the workload "valley." A shorter gap (e.g., 3 years) would compound the initial shocks, whereas a longer gap (e.g., 7 years) would create a prolonged period of low demand.

However, the fundamental system dynamics and the comparative effectiveness of the capacity adjustment strategies remain structurally robust across these variations. First, regardless of the ratio or gap, split acquisition inherently creates non-linear demand waves. A longer time lag merely deepens the valley between peaks, which would exponentially increase the wasted budget (Unused Resources) if a fixed Level strategy is strictly maintained. Second, the reactive Chase strategy is fundamentally limited by the physical time delay required for workforce training; thus, it consistently fails to defend operational availability whenever a sudden shift occurs, regardless of the exact batch size.

In summary, while specific operational metrics vary with different acquisition structures, the structural imperative for transitioning from reactive (Chase) to proactive (Lead) maintenance capacity planning remains universally valid. The Lead strategy, synchronized with an appropriate review interval, remains the only viable mechanism to optimize both life cycle cost and operational availability.

4.6 Institutional preconditions for implementing the lead strategy

The simulation results highlight the Lead strategy as the optimal mechanism for absorbing the non-linear workload shocks generated by split acquisition. However, applying this proactive strategy in a real-world military context requires specific institutional preconditions, as the model fundamentally assumes the capability to forecast demand accurately and adjust resources in a timely manner. To transition this strategy from a theoretical benchmark to a practical policy, three key institutional conditions must be met.

First, the traditional decision-making silos between the 'Acquisition' (procurement) and 'Logistics' (operation and maintenance) domains must be structurally integrated. In many military bureaucracies, acquisition schedules and maintenance personnel planning (Table of Organization, TO) are managed by separate entities with different timelines. For the Lead strategy to function, acquisition shocks (such as the arrival of a second batch) must be systematically translated into maintenance capacity requirements years in advance, necessitating an integrated Life Cycle Management (LCM) governance framework.

Second, the implementation of a data-driven predictive infrastructure is essential. The Lead strategy relies on accurately anticipating the bathtub-shaped failure curves. In practice, this requires moving beyond static, manual requirement calculations toward Condition-Based Maintenance Plus (CBM+) and predictive analytics. Utilizing integrated military logistics data systems (e.g., the Defense Logistics Integrated Information System) to continuously update failure rate algorithms based on real-time fleet data is a prerequisite for achieving the forecasting accuracy assumed in the model.

Third, institutional flexibility in personnel management must be secured. Military organizations are inherently rigid, often requiring years to approve and train new maintenance technicians. Therefore, the defense planning system (e.g., the Mid-term Defense Plan) must evolve to allow for 'agile capacity chunks'. Instead of fixing personnel numbers for a decade, the system must permit proactive, modular expansions of maintenance flights or shifts tailored to the forecast 5-year workload peaks.

In conclusion, while the Lead strategy represents an idealized operational model within the simulation, it is not an unattainable goal. Rather, it serves as a practical and necessary policy direction that can be realized if supported by the ongoing digital transformation of defense logistics and the synchronization of acquisition-maintenance planning cycles.

5. Conclusion

This study focused on the fact that split acquisition, arising from budget and production constraints as seen in the ROKAF's F-35A introduction, causes non-linear maintenance workload shocks throughout the weapon system's life cycle. The difference in introduction timing, combined with the bathtub-type failure curve, creates unpredictable waves of maintenance demand. Accordingly, this study utilized System Dynamics modeling to derive the optimal maintenance capacity adjustment strategy capable of preventing availability collapse in such a dynamic environment.

Through the comparative analysis of capacity adjustment strategies, the core message of this study is that split acquisition must not be viewed merely as a budget-phasing tactic but must instead be treated as a long-term maintenance-capacity planning problem. To survive the non-linear waves of maintenance demand, transitioning from reactive (Chase) to proactive, forecast-based decision-making (Lead) is absolutely essential.

However, a critical structural caveat must be emphasized: proactive planning only works well if the review cycle is short enough. Our findings quantitatively demonstrate that extending the decision-making cycle to 10 years neutralizes even the most accurate predictive strategies. Therefore, institutionalizing a flexible personnel management system that synchronizes the maintenance review cycle with the acquisition schedule—specifically within a 5-year horizon, akin to the Mid-term Defense Plan—is the ultimate prerequisite for achieving the availability target.

This study makes the following academic contributions in that it addresses the limitations of existing military maintenance policy research and presents a new theoretical framework:

- Identification of the dynamic linkage between acquisition and maintenance. While existing studies focused on the operational efficiency of already deployed forces, this study identified that the acquisition pattern is the initial condition determining the structure of the life-cycle maintenance workload. This proves that weapon system acquisition policy and operation & support policy are inseparable components of an integrated system.
- Validation of the military applicability of the Lead Strategy. By applying the 'Capacity Lead Strategy' from manufacturing facility investment theory to the military maintenance field, this study theoretically established that proactive decision-making based on 'Perfect Information' is a key mechanism for defending availability even in high-uncertainty defense environments.
- Calculation of the quantitative threshold for organizational flexibility. It was proven that even with accurate predictive information, it is futile if the organization's review cycle cannot support it. In particular, by presenting a specific temporal threshold of 5 years, this study provided empirical evidence for organizational design theory.

Based on the results of this study, the policy recommendations are as follows:

- Institutionalization of 'Maintenance Capacity Lead Strategy' linked with the Mid-term Defense Plan. The reactive Chase strategy failed to absorb the shocks of split acquisition in any case. Therefore, the Air Force must move away from passive planning that reacts to failures after they occur and establish a system that proactively reflects personnel adjustments in the Mid-term Defense Plan (5-year cycle) based on acquisition schedules and failure pattern forecasts.
- Establishment of a maintenance unit review cycle synchronized with the acquisition cycle. The realistic threshold at which availability was maintained in the simulation was the '5-year review'. This suggests that rather than relying on rigid, large-scale unit restructuring every 10 years, a manpower management system capable of flexibly adjusting maintenance lines or shift units at least every 5 years—aligned with acquisition and aging cycles—is essential.
- Transition to a decision-making system based on Total Cost. Simply maintaining maximum maintenance capacity unconditionally to achieve availability is a waste of budget. Data-driven decision-making should be implemented through flexible strategies like the Lead (1) strategy, which expands and reduces capacity only when necessary, thereby achieving both availability and budget efficiency.

This study has the following limitations, and future research should address them:

- Limitation of the single-constraint assumption regarding repair parts. To clearly isolate the dynamic influence of maintenance personnel and facility capacity, this study assumed 100 % availability of repair parts. In reality, global supply chain constraints and part

shortages frequently cause significant maintenance delays. If repair parts were constrained in the simulation, the Mean Logistics Delay Time (MLDT) would increase, compounding the capacity shortages to create even higher and longer-lasting maintenance queues. Consequently, the results of this study represent a conservative "best-case baseline." The fact that the reactive Chase strategy fails to defend availability even under this optimistic assumption strongly reinforces the study's core conclusion: proactive capacity planning (the Lead strategy) is absolutely critical to absorbing operational shocks. Future research should construct a multi-constraint model that simultaneously considers both human capacity limitations and supply chain dynamics to analyse these complex ripple effects.
- Limitation of single-fleet analysis. In reality, the Air Force operates multiple aircraft types, such as the F-15K and KF-16, in addition to the F-35A. Analyzing the portfolio effect of sharing maintenance resources among aircraft types could help identify measures to improve the maintenance efficiency of the entire military.
- Data limitations and roadmap for empirical validation. Due to security classifications and the relatively recent deployment of the F-35A fleet, this study utilized empirical data from public DoD reports rather than classified operational logs. To transition this study from a theoretical modeling framework to a fully verified decision-support tool, a more explicit roadmap for empirical validation is required. Future research will achieve this through a structured three-phase approach:
- Phase 1: Longitudinal Data Accumulation. As the fleet matures, actual operational and maintenance logs must be continuously extracted from the Defense Logistics Integrated Information System (DELIS). Five to ten years of data are required to capture the true shape of the fleet's infant mortality and the transition into steady-state failure rates.
- Phase 2: Parameter Calibration. The current theoretical Weibull distribution assumptions and public parameter values will be replaced with actual MTBF (Mean Time Between Failure) and MTTR (Mean Time To Repair) data. This calibration will reflect the unique operational intensity and environmental factors specific to the ROKAF.
- Phase 3: Ex-post Cross-Validation. Once sufficient historical data is accumulated, the simulation’s past predictions regarding 'Queue for Repair' and 'Availability' will be statistically compared against actual historical records. The model's forecasting accuracy will be validated using error metrics such as Mean Absolute Percentage Error (MAPE) or Root Mean Square Error (RMSE), and its internal algorithms will be refined accordingly.

This empirical validation roadmap will continuously improve the model's fidelity, ensuring its practical utility for long-term military logistics planning.

Acknowledgement

This work was supported by the Defense Acquisition Program Administration (DAPA) Research Fund (Project Title: "An Analysis of the Minor Performance Improvement Program for the E-737").

References

[1] Ebeling, C.E. (2019). *An introduction to reliability and maintainability engineering*, 3rd edition, Waveland Press, Long Grove, USA.

[2] Nowlan, F.S., Heap, H.F. (1978). *Reliability-centered maintenance*, Report No. AD-A066579, United Airlines, San Francisco, USA.

[3] Choi, J., Moon, S. (2022). Rare event simulation by combining trend and probability: An application to naval ship critical failures, *Industrial Engineering & Management Systems*, Vol. 21, No. 1, 128-136, doi: 10.7232/iems.2022.21.1.128.

[4] De Pater, I., Reijns, A., Mitici, M. (2022). Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics, *Reliability Engineering & System Safety*, Vol. 221, Article No. 108341, doi: 10.1016/j.ress.2022.108341.

[5] Jin, H., Song, X., Xia, H. (2023). Optimal maintenance strategy for large-scale production systems under maintenance time uncertainty, *Reliability Engineering & System Safety*, Vol. 240, Article No. 109594, doi: 10.1016/j.ress.2023.109594.

[6] Pyles, R.A. (2003). *Aging aircraft: USAF workload and material consumption life cycle patterns*, RAND Corporation, Santa Monica, USA.

[7] Dixon, M.C. (2006). *The maintenance costs of aging aircraft: Insights from commercial aviation*, RAND Corporation, Santa Monica, USA.

[8] Kim, K.-R., Kim, H.-W., Jeong, J., Cha, J.-H., Jeong, D.-S. (2020). Simulation study on the calculation of weapon system's operating maintenance costs to develop LCS-P, *Journal of the Korea Academia-Industrial Cooperation Society*, Vol. 21, No. 9, 82-91, doi: 10.5762/KAIS.2020.21.9.82.

[9] Keating, C., Rogers, R., Unal, R., Dryer, D., Sousa-Poza, A., Safford, R., Peterson, W., Rabadi, G. (2003). System of systems engineering, *Engineering Management Journal*, Vol. 15, No. 3, 36-45, doi: 10.1080/10429247.2003.11415214.

[10] Safaei, N., Banjevic, D., Jardine, A.K.S. (2011). Workforce-constrained maintenance scheduling for military aircraft fleet: A case study, *Annals of Operations Research*, Vol. 186, No. 1, 295-316, doi: 10.1007/s10479-011-0885-4.

[11] Aramon Bajestani, M., Beck, J.C. (2013). Scheduling a dynamic aircraft repair shop with limited repair resources, *Journal of Artificial Intelligence Research*, Vol. 47, 35-70, doi: 10.1613/jair.3902.

[12] Mattila, V., Virtanen, K. (2014). Maintenance scheduling of a fleet of fighter aircraft through multi-objective simulation-optimization, *Simulation*, Vol. 90, No. 9, 1023-1040, doi: 10.1177/0037549714540008.

[13] Zhang, Q., Liu, Y., Xiahou, T., Huang, H.-Z. (2023). A heuristic maintenance scheduling framework for a military aircraft fleet under limited maintenance capacities, *Reliability Engineering & System Safety*, Vol. 235, Article No. 109239, doi: 10.1016/j.ress.2023.109239.

[14] Vollmann, T.E., Berry, W.L., Whybark, D.C., Jacobs, F.R. (2005). *Manufacturing planning and control systems for supply chain management*, 5th edition, McGraw-Hill, New York, USA.

[15] Olhager, J., Rudberg, M., Wikner, J. (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning, *International Journal of Production Economics*, Vol. 69, No. 2, 215-225, doi: 10.1016/S0925-5273(99)00098-5.

[16] Bunecke, K., White, E.D., Ritschel, J.D., Bush, B.A. (2018). Evaluating annual fixed wing maintenance costs, *Defense Acquisition Research Journal*, Vol. 25, No. 3, 244-263, doi: 10.22594/dau.18-797.25.03.

[17] Blanchard, B.S. (2004). *System engineering management*, 3rd edition, John Wiley & Sons, New York, USA.

[18] Kullstam, P. (1981). Availability, MTBF and MTTR for repairable M out of N system, *IEEE Transactions on Reliability*, Vol. R-30, No. 4, 393-394, doi: 10.1109/TR.1981.5221134.

[19] Sharma, R.K., Kumar, S. (2008). Performance modeling in critical engineering systems using RAM analysis, *Reliability Engineering & System Safety*, Vol. 93, No. 6, 913-919, doi: 10.1016/j.ress.2007.03.039.

[20] Bányai, Á. (2023). Impact of agile, condition-based maintenance strategy on cost efficiency of production systems, *Advances in Production Engineering & Management*, Vol. 18, No. 3, 317-326, doi: 10.14743/apem2023.3.475.

[21] Peng, J., Liu, B., Liu, Y., Xu, X. (2020). Condition-based maintenance policy for systems with a non-homogeneous degradation process, *IEEE Access*, Vol. 8, 81800-81811, doi: 10.1109/ACCESS.2020.2991590.

[22] Chen, Y., Gong, W., Xu, D., Kang, R. (2018). Imperfect maintenance policy considering positive and negative effects for deteriorating systems with variation of operating conditions, *IEEE Transactions on Automation Science and Engineering*, Vol. 15, No. 2, 872-878, doi: 10.1109/TASE.2017.2675405.

[23] Alrabghi, A. (2025). A modelling approach for asset degradation: Advancing digital twin in maintenance, *International Journal of Simulation Modelling*, Vol. 24, No. 1, 76-86, doi: 10.2507/IJSIMM24-1-715.

[24] Jeang, A., Ko, C.P., Chung, C.-P., Chen, Y.-J., Lin, I. (2019). Optimal availability for determining choice and repair policy of system components, *International Journal of Quality & Reliability Management*, Vol. 36, No. 3, 347-357, doi: 10.1108/IJQRM-12-2017-0255.

[25] Fadaeefath Abadi, M., Bordbari, M.J., Haghighat, F., Nasiri, F. (2025). Dynamic maintenance cost optimization in data centers: An availability-based approach for K-out-of-N systems, *Buildings*, Vol. 15, No. 7, Article No. 1057, doi: 10.3390/buildings15071057.

[26] Albino, V., Carella, G., Okogbaa, O. (1992). Maintenance policies in just-in-time manufacturing lines, *International Journal of Production Research*, Vol. 30, No. 2, 369-382, doi: 10.1080/00207549208942900.

[27] Selech, J., Matijosius, J., Kilikevicius, A., Marinkovic, D. (2025). Reliability analysis and the costs of corrective maintenance for a component of a fleet of trams, *Tehnički Vjesnik – Technical Gazette*, Vol. 32, No. 1, 205-216, doi: 10.17559/TV-20241121002144.

[28] Al-Turki, U. (2011). A framework for strategic planning in maintenance, *Journal of Quality in Maintenance Engineering*, Vol. 17, No. 2, 150-162, doi: 10.1108/13552511111134583.

[29] Turan, H.H., Elsawah, S., Ryan, M.J. (2020). A long-term fleet renewal problem under uncertainty: A simulation-based optimization approach, *Expert Systems with Applications*, Vol. 145, Article No. 113158, doi: 10.1016/j.eswa.2019.113158.

[30] Adamides, E.D., Stamboulis, Y.A., Varelis, A.G. (2004). Model-based assessment of military aircraft engine maintenance systems, *Journal of the Operational Research Society*, Vol. 55, No. 9, 957-967, doi: 10.1057/palgrave.jors.2601756.

[31] Park, J., Moon, S., Choi, J. (2022). Planned maintenance queue simulation based on failure probability: Focused on the naval battleship, *Journal of the Korean Institute of Industrial Engineers*, Vol. 48, No. 1, 105-116, doi: 10.7232/jkiie.2022.48.1.105.

[32] Forrester, J.W. (1969). *Urban dynamics*, MIT Press, Cambridge, USA.

[33] Sterman, J.D. (2000). *Business dynamics: Systems thinking and modeling for a complex world*, McGraw-Hill, New York, USA.

Appendix A. Key variables and equations

Table A1 Specification of model variables and equations

Variable Name	Description	Initial Value / Equation	Type	Unit
Adopted Equipment	Cumulative number of fighters introduced according to the acquisition strategy	0 / Adoption Rate - Abandon Rate - Start of CBM + Return from CBM	Stock	unit
CBM Equipment	Number of fighters undergoing Condition-Based Maintenance (CBM)	0 / Start of CBM - Return from CBM	Stock	unit
Abandoned Equipment	Cumulative number of fighters discarded due to accidents or retirement	0 / Abandon Rate	Stock	unit
Equipment in Field	Number of fighters currently operating in the field	0 / Return from Repair Rate - Exit Rate - Failure Rate - Go for CBM + New Equipment Rate + Return from CBM Repair Shop	Stock	unit
Queue for Repair	Number of fighters waiting for maintenance due to capacity constraints	0 / Failure Rate - Entrance Rate	Stock	unit
Equipment in Repair	Number of fighters currently undergoing base-level maintenance	0 / Entrance Rate - Return from Repair Rate	Stock	unit
Adoption Rate	Number of fighters introduced per day according to acquisition strategy	Adoption Strategy	Flow	unit/ day
Abandon Rate	Number of fighters retired or lost due to accidents	Retire Rate + Accident Rate	Flow	unit/ day
Start of CBM	Number of fighters entering Condition-Based Maintenance (CBM)	IF THEN ELSE(Second Adoption=0, IF THEN ELSE(Time<=CBM Cycle:OR:Time>=(365 * 30 - 913), 0, MAX(0, Adopted Equipment/CBM Cycle)), IF THEN ELSE(Time<=CBM Cycle:OR:Time>=(365 * 35 - 913), 0, MAX(0, Adopted Equipment/CBM Cycle)))	Flow	unit/ day
Failure Rate	Number of failures occurring per day according to the failure rate function	(Equipment in Field - Exit Rate - Go for CBM) * Failure Ratio	Flow	unit/ day
Life Cycle	Fighter's Life Cycle	10,950	Auxiliary	day
Retire Rate	Determination of fighter retirement volume considering life cycle, accident rate, and retirement rate	IF THEN ELSE(Time=Life Cycle, (Adopted Equipment - Accident Rate - Start of CBM)/2, IF THEN ELSE(Time>=Life Cycle + 365 * 5, (Adopted Equipment - Accident Rate), 0))	Auxiliary	unit
Accident Probability	Setting of fighter accident probability.	2.28/10^6	Auxiliary	-
Failure Function	Setting of Lookup function based on failure rate data	[(0,0)-(12775,0.125)], (0, 0.125), (180, 0.1175), (365, 0.11), (730, 0.1025), (1095, 0.095), (1460, 0.0875), (1825, 0.08), (2190, 0.0725), (2555, 0.065), (2920, 0.0575), (3285, 0.05), (3650, 0.05), (7665, 0.0575), (8030, 0.065), (8395, 0.0725), (8760, 0.08), (9125, 0.0875), (9490, 0.095), (9855, 0.1025), (10220, 0.11), (10585, 0.1175), (10765, 0.125), (10950, 0.125), (11315, 0.095), (11680, 0.1025), (12045, 0.11), (12410, 0.1175), (12590, 0.125), (12775, 0.125)	Lookup	-
Base Repair Capacity	Set amount of Base Repair Capacity	12	Auxiliary	unit
Review Interval	Review interval for maintenance capacity adjustment	IF THEN ELSE(Scenario 1=1, 365 * 3, IF THEN ELSE(Scenario 2=1, 365 * 5, 365 * 10))	Auxiliary	day
Review Signal	Signal for maintenance capacity adjustment	IF THEN ELSE(Time<10950, PULSE TRAIN(IF THEN ELSE (Scenario 1=1, 365 * 3, IF THEN ELSE(Scenario 2=1, 365 * 5, 365 * 10)), 1, Review Interval, 10950), 0)	Auxiliary	-
Candidate Repair Capacity	Calculated maintenance capacity for the next cycle reflecting the current status and adjustment signal	IF THEN ELSE(Is Lead=1, IF THEN ELSE(Time<3650, IF THEN ELSE(Switch = -1, Previous Required Repair Capacity, Previous Required Repair Capacity + (1 - Is Level) * Repair Adjustment Signal * Switch * Repair Chunk), Previous Required Repair Capacity + (1 - Is Level) * Repair Adjustment Signal * Switch * Repair Chunk), Previous Required Repair Capacity + (1 - Is Level) * Repair Adjustment Signal * Switch * Repair Chunk	Auxiliary	unit
Repair Chunk	Unit of resource increment/decrement available per adjustment	MIN(Required Units, Max Chunk)	Auxiliary	unit
Repair Gap	Calculation of maintenance capacity shortage	Queue for Repair - Adopted Repair Capacity	Auxiliary	unit
Switch	Trigger to determine capacity increase/decrease in Chase and Lead strategies	IF THEN ELSE(Is Lead=1, IF THEN ELSE(Lead Gap>0, -1, IF THEN ELSE(Lead Gap<0, 1, 0)), IF THEN ELSE (Chase Gap>0, -1, IF THEN ELSE(Chase Gap<0, 1, 0)))	Auxiliary	-
Availability of Equipment	Calculation of actual availability of fighters introduced in the model	XIDZ(Equipment in Field, Total Equipment, 1)	Auxiliary	unit
Difference of Availability	Difference between target availability and actual availability	ABS(Target Availability - Availability of Equipment)	Auxiliary	-