

DREAM: HOLISTIC SIMULATION OF DYNAMIC MAINTENANCE OPERATIONS IN AVIATION

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Abstract

Maintenance, Repair and Overhaul (MRO) operations are characterized by intricate interdependencies, stringent resource constraints, and the unique operational state of each component—challenges that traditional, rigid process-planning approaches cannot adequately address. This paper demonstrates the practical applicability of the Dynamic Resource Evaluation and Assembly Model for MRO (DREAM) by systematically defining MRO-specific simulation inputs encompassing component characteristics, hangar resources, and process steps. Functional verification is conducted through two complementary use cases—aircraft inspection and complete repair—optimized for both duration and cost. The results confirm that DREAM correctly interprets complex input schemas and generates logically consistent, optimal process outcomes. By accounting for individualized part states and shared resource constraints, DREAM enables dynamic, data-driven process planning that captures the conditional logic and workflow branching inherent to aviation MRO. Initial scalability challenges are identified and discussed, paving the way for future algorithmic enhancements to further improve computational tractability for large-scale industrial deployment.

Keywords

Process Simulation; Aviation MRO; Maintenance; Repair

1. INTRODUCTION

The global aviation MRO market is experiencing unprecedented growth, with demand reaching \$136 billion in 2025—a 30% increase compared to 2019 [1]. This surge is driven by an aging fleet, with average aircraft age approaching 13 years, compounding supply chain pressures and labor shortages—approximately 41% of certified mechanics in the US are over 60, with 45,000 retirements expected within the decade [1].

Beyond prescriptive maintenance scheduling, reducing turnaround times has emerged as a critical lever for fleet availability. Prior work demonstrated significant potential through optimized process planning [2], though manual analysis limited scalability.

A holistic simulation framework was developed [3,4] and formally described [5] in previous publications, accounting for available human resources, tools, and materials alongside the unique operational state of each aircraft—shaped by age, usage history, and accumulated wear. Given this individuality, the framework dynamically selects optimal process sequences from a pool of available procedures. The mathematical model and scalability analysis were established, yet practical applicability requires realistic, data-driven inputs.

This paper focuses on defining such inputs and demonstrates the approach through an exemplary simulation, bridging theoretical model development and industrial implementation.

2. CONCEPTUAL MODEL AND REVIEW OF RELATED INPUT MODELING APPROACHES

This section outlines the conceptual framework of DREAM and reviews modeling approaches of its three input dimensions - part characterization, hangar modeling, and process description - grounded in academic literature, aviation standards, and industry practice.

2.1. DREAM: Dynamic Resource Evaluation and Assembly Model for MRO

DREAM (Dynamic Resource Evaluation and Assembly Model for MRO) [5] requires three inputs: a component model specifying properties, damage characteristics, and procedural context; a hangar model encoding available resources, their capabilities, and current status; and a modular process catalogue derived from MRO manuals. Each process step defines requirements, start and finish update functions, and objective values (e.g., cost, duration). DREAM initializes a system state and explores the feasible state space by sequentially applying valid process steps, guided by a traversal strategy (breadth-first, depth-first, or Dijkstra), to identify the optimal state satisfying target criteria as shown in Fig. 1.

2.2. Background: Part Modeling

While digital twin and ontology-based frameworks [6–11] effectively link physical components to lifecycle and maintenance data, they typically represent damage as static

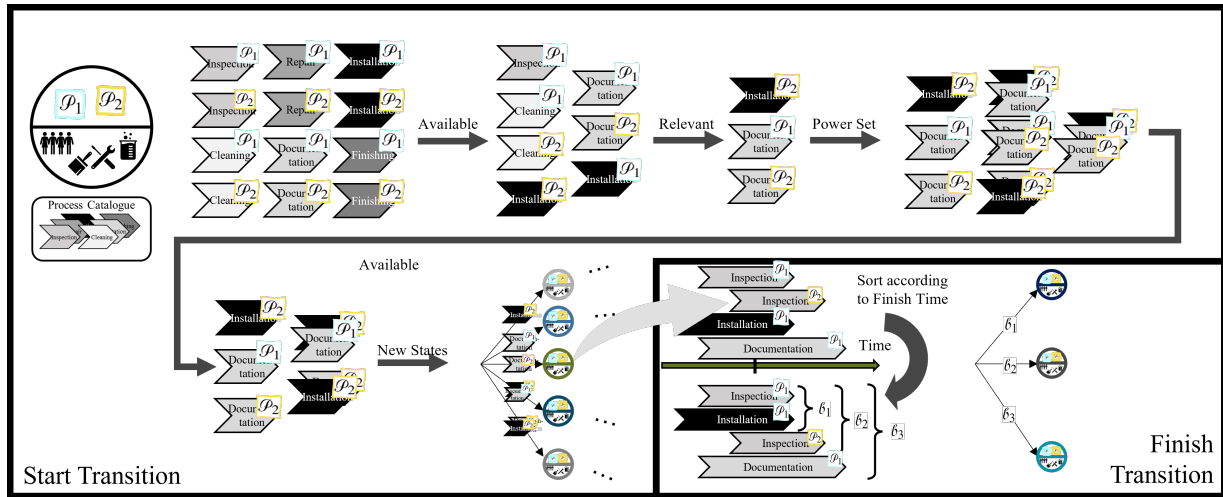


FIG 1. Methodology of DREAM: Iterative Application of Start and Finish Transitions for generating the State Space.

attributes and lack granular modeling of procedural state transitions. Part characterization comprises three inter-related dimensions:

2.2.1. General Part Modeling

Comprehensive part identification relies on unique identifiers (part/serial numbers, CAGE codes), classification systems (ATA chapters, spatial zoning), and structural hierarchies. Reconciling overlapping structural and functional groupings is typically addressed through variant-specific Bill of Materials (BOM) frameworks (EBOM for engineering, MBOM (manufacturing), SBOM (service)) [12–15], though manufacturer implementations diverge (e.g., Airbus unified versus Boeing synchronized EBOM/MBOM architecture) [16,17].

2.2.2. Damage Modeling

Realistic damage modeling requires explicit specification of type, geometry, location, and dimensions. Aviation standards, particularly the Structural Repair Manual (SRM), classify damage into allowable (monitored), repairable, and catastrophic categories. Acceptance criteria are zone-specific and governed by load paths, redundancy, and fatigue sensitivity. Crucially, the geometric relationship of damage to structural features dictates repair feasibility and constrains applicable maintenance methods.

2.2.3. Procedural Description

Procedural states in the DREAM framework capture a component's position within the MRO workflow and could be derived from AMTOSS (Aircraft Maintenance Task Oriented Support System) function codes and ATA references. Modeling these states requires handling hierarchical dependencies and distinguishing between complementary (mutually exclusive, e.g., pressurized/depressurized) and unidirectional states (e.g., inspected/repaired). While complementary pairs often require explicit mutual-exclusion constraints during state updates, unidirectional states do not. Furthermore,

some state relationships are explicitly defined in source systems, while others must be inferentially mapped, adding complexity to interoperable state modeling.

2.3. Modeling of Hangar / Resources

Existing MRO simulation literature exhibits significant fragmentation in the representation of operational entities. Studies typically focus on one or two resource dimensions (human resources, tools, materials), often abstracting the remainder as static bounds or omitting them entirely. Tab. 1 summarizes the modeling scope and computational paradigms across selected publications, ranging from discrete-event simulation (DES) and constraint programming (CP) to mixed-integer linear programming (MILP), metaheuristics, agent-based modeling (ABM), and digital twin (DT)-hybrids. While prior works largely isolate resource dimensions, DREAM explicitly integrates all three core entities within a unified framework.

TAB 1. Resource Modeling in MRO Literature.

Pub.	HR	Tools	Mat.	Modeling Approach
[18]	●	○	○	DES (FlexSim)
[19]	●	○	○	Constraint Programming (CP)
[20]	●	○	○	DES (Arena) – Push/PP/Pull
[21]	●	●	○	Hybrid Metaheuristic (GA)
[22]	●	●	○	DT-based DES
[23]	–	●	–	MILP / Exact MIP
[24]	●	●	–	Multi-Objective GA (NSGA-II)
[25]	●	●	–	Metaheuristic (TLBO+SSGS)
[26]	●	●	–	Agent-Based Simulation
[27]	○	●	–	Queueing Theory + DES
[28]	●	●	–	Binary MIP / Exact Optimization

● = Full/high detail, ○ = Partial/abstracted, – = Not modeled.
 (NS)GA: (Non-dominated Sorting) Genetic Algorithm; TLBO: Teaching-Learning-Based Optimization; SSGS: Serial Scheduling Generation Scheme

2.4. Modeling of Process Steps

MRO procedures, traditionally documented as human-readable prose, require systematic decomposition into modular, machine-processable steps via Process Model Extraction (PME). Although neural network and large language model (LLM)-driven methods [29–31] effectively structure procedural knowledge, they generally lack the explicit causal and temporal dependencies necessary for true modularization. Planning-oriented pipelines [32–34] directly extract atomic actions, pre-conditions, effects, and dependencies, often mapping outputs to formalisms such as PDDL (Planning Domain Definition Language). However, natural language ambiguity, non-linear narratives, and implicit conditions persist as barriers. Consequently, robust, fully automated modularization remains an active research challenge, typically requiring hybrid validation mechanisms or domain-specific constraints to ensure machine-ready step decomposition.

3. REPRESENTATIVE SCENARIO DEFINITION AND SYSTEM BOUNDARIES

Building on the independently modeled dimensions, DREAM explicitly integrates parts, process steps, and hangar resources to enable holistic state transitions. This integration is demonstrated through representative inputs that abstract the complexity of the MRO environment into a verifiable conceptual data model, thereby defining the system boundaries for subsequent simulation configurations.

3.1. Part Definition

The part model constitutes the foundational entity, comprising three interdependent information layers: general part attributes, damage characteristics, and procedural workflow states. These layers are specified as follows.

3.1.1. General Part Definition

General part attributes are defined as immutable parameters establishing the component's geometric and material baseline. Each part is assigned a unique type identifier, structural zone classification, and three-dimensional extent (length, width, height in meters). Material composition is discretized into binary indicators for aluminum or composite construction. These parameters remain fixed throughout the simulation and serve as input for damage feasibility and repair method constraints.

3.1.2. Damage Definition

Damage characterization records the defect type, physical shape, location, and dimensions. While the underlying DREAM model is designed to handle a comprehensive taxonomy of damage—including gouges, cracks, burn marks, and non-structural issues like wiring degradation, contamination, or fluid penetration—the current scenario intentionally limits the scope to three representative structural damage types: dents, scratches, and corrosion. This deliberate restriction keeps the focus

on the core state-transition logic and constraint-handling mechanisms without overwhelming the simulation with the full combinatorial complexity of a comprehensive maintenance catalog. Damage morphology is defined using five standard shapes: round/uniform, oval, linear, curved, and random. However, physical and structural constraints mean that not every damage type can occur in every shape. The valid combinations of damage types and shapes for this simulation are formalized in Tab. 2.

TAB 2. Valid Damage Type–Shape Combinations.

	1	2	3	4	5
	Round	Oval	Linear	Curved	Random
1 Dent	•	•	•		•
2 Scratch			•	•	•
3 Corrosion	•		•		•

3.1.3. Procedural State Definition

Procedural states track a component's progress through the MRO workflow and can be derived from AMTOSS function codes or ATA chapter references. While real maintenance procedures often follow hierarchical structures—for instance, distinct cleaning methods grouped under a general preparation step—this simulation uses a simplified, flat set of 17 representative states. Despite

TAB 3. Component Procedural States.

No.	State	U	C
1	Accessible	•	
2	Clean		3
3	Dirty		2
4	Degreased		5
5	Greasy		4
6	Detected	•	
7	Damage shape identified	•	
8	Localized	•	
9	Damage Measured	•	
10	Inspected	•	
11	Dry		12
12	Wet		11
13	Cooled	•	
14	Coated	•	
15	Repaired	•	
16	Painted	•	
17	Certified	•	

U = Unidirectional, C = Complementary.

this abstraction, the model preserves two essential state classifications: unidirectional and complementary. Unidirectional states (e.g., Detected, Inspected, Repaired) are additive and persist once activated. Complementary

pairs (e.g., Clean/Dirty, Dry/Wet) are mutually exclusive, meaning activating one automatically deactivates the other. Process updates respect these types: unidirectional states only turn active without altering existing ones, while complementary states enforce strict switching between paired options. All states are encoded in binary (1 = active, 0 = inactive). Each component starts with specific initial conditions, and the simulation terminates once a specified target state is reached. Tab. 3 lists the 17 states used in this study and marks each as unidirectional (U) or complementary (C).

3.1.4. Simulation Input Configuration

The exemplary configuration defines five distinct parts with varying general, damage, and procedural parameters. All parts share the same type (Aircraft) and zone (Zone 1; no hierarchy modeled), differing in dimensions, material composition, damage type, damage morphology, damage location, and damage dimensions. Initial procedural states are excluded. The complete input dataset is summarized in Tab. 4 as the structured entry point for DREAM's state-space exploration and constraint-based process selection.

TAB 4. Simulation Part Configurations.

Parameter	P1	P2	P3	P4	P5
Type ID	1	1	1	1	1
Zone	1	1	1	1	1
Length (m)	38	40	63	67	38
Width (m)	34	36	60	65	35
Height (m)	11	12	17	18	11
Aluminum (binary)	1	1	0	0	1
Composite (binary)	0	0	1	1	1
Damage Type ID	1	2	3	2	1
Damage Shape ID	2	3	1	4	5
Location Top/Bottom	1	1	2	2	1
Location Front/Back	1	2	1	2	1
Damage Length (mm)	8	35	7	34	6
Damage Width (mm)	3	1	7	1	8
Damage Depth (mm)	1	1	1	1	1

3.2. Resource Definition

Resource modeling extends beyond human personnel to encompass the physical tools, test equipment, and specialized fixtures required for maintenance execution. Each resource is characterized by a unique identifier, functional classification, and dynamic availability status. These attributes define the operational scope of a resource and determine its compatibility with specific process steps. Within the simulation framework, each process step explicitly requests compatible resources based on predefined requirements. Upon successful allocation, resources are temporarily reserved to enforce exclusive usage, and their status is automatically

reset to available upon task completion. This request-and-allocation mechanism enables realistic resource contention modeling while maintaining computational tractability. The subsequent configuration details the resource categories used in the exemplary simulation.

3.2.1. Human Resources

Human resources are modeled as a role-constrained resource pool, where each individual is assigned a unique identifier and a specific occupational role that restricts the set of permissible process steps. In practical MRO environments, personnel qualification follows multi-level certification hierarchies (e.g., NDT Levels 1–3), enabling differentiated responsibilities such as inspection execution, report certification, or maintenance strategy definition. To preserve computational tractability while maintaining functional realism, this study abstracts certification hierarchies into discrete, non-hierarchical role categories. Resource allocation is governed by a demand-driven availability rule: each process step specifies the required quantity and role type. If sufficient personnel of the designated role are currently idle, they are dynamically assigned to the task; upon task completion, their status is automatically reset to available. This approach ensures traceable resource utilization without requiring explicit scheduling optimization. The exemplary configuration employs five representative roles, each supported by an identical pool of four personnel, as summarized in Tab. 5.

TAB 5. Human Resource Pool Configuration.

Role	Available Personnel
Mechanic	4
NDT Staff	4
Painter	4
Composite Certifying Staff	4
Aluminum Certifying Staff	4

3.2.2. Tools

Each tool is characterized by a unique identifier and a defined capability set that determines compatibility with specific MRO operations. In practical MRO environments, tool management includes additional constraints such as personnel-specific assignment, calibration validity periods, and specialized handling requirements. For computational tractability, this simulation assumes a standardized pool of calibrated tools and abstracts personal tool ownership. Resource allocation follows a demand-driven logic: when a process step requires a tool of a specific capability, the system checks current availability. If sufficient units are idle, they are allocated to the task. Upon completion, tools are either returned to the general pool or flagged as "Leave at Part" (e.g., access platforms), rendering them temporarily unavailable for subsequent tasks until explicitly reset. The available tool inventory and quantities are summarized in Tab. 6.

TAB 6. Tool Inventory.

ID	Tool	Quantity
T1	Access Platform 3 M	2
T2	Access Platform 6 M	2
T3	Access Platform 8 M	2
T4	NDT Kit	1
T5	Profile Gauge	5
T6	3D Scanning Tool	1
T7	Measurement Kit	5
T8	2D Camera	2
T9	Blending Equipment	3
T10	Machining Equipment	3
T11	Grinding Equipment	3
T12	Coating Equipment	3
T13	Painting Equipment	2

TAB 7. Material Inventory.

ID	Material	Initial Stock
M1	Aluminum Cleaning Material	10000
M2	Aluminum Degreasing Material	10000
M3	Composite Cleaning Material	10000
M4	Composite Degreasing Material	10000
M5	Aluminum Blending Material	10000
M6	Composite Machining Material	10000
M7	Aluminum Machining Material	10000
M8	Composite Grinding Material	10000
M9	Aluminum Grinding Material	10000
M10	Composite Coating Material	10000
M11	Aluminum Coating Material	10000
M12	Mixing Material	10000
M13	Composite Painting Material	10000
M14	Aluminum Painting Material	10000

3.2.3. Material / Spare Parts

Unlike human resources and tools, which are temporarily allocated and returned to the resource pool upon task completion, materials and spare parts operate as consumable assets. Once deployed in a maintenance process, they are permanently deducted from the inventory rather than recycled. In practical MRO environments, material management involves complex logistical considerations, including inventory optimization to balance availability against storage constraints, shelf-life monitoring, manufacturer return requirements, controlled storage conditions (e.g., temperature and humidity), and batch/lot tracking. To maintain computational tractability while preserving the core depletion dynamics, this simulation abstracts these complexities into a simplified, static consumable inventory. Each process step explicitly requests specific materials, triggering a permanent reduction in stock levels. Replenishment mechanisms and time-dependent expiration tracking are excluded from this baseline configuration. The initial inventory of consumable materials and their respective quantities are detailed in Tab. 7.

3.3. Process Step Definition

Maintenance procedures documented in the Aircraft Maintenance Manual (AMM), Structural Repair Manual (SRM), and Component Maintenance Manual (CMM) are traditionally expressed in human-readable prose. For computational modeling within the DREAM framework, these procedures are formalized into discrete, machine-readable process steps. Each step comprises three core elements: requirements, specifying the necessary human resources, tools, materials, and part-state prerequisites; start and finish updates, detailing state transitions for both the hangar environment and the component upon step initiation and completion; and parameters, primarily duration and cost, used to evaluate simulated process flows. Fig. 2 illustrates an exemplary process catalogue used for model verification. To capture the complexity of realistic MRO operations, individual process steps are

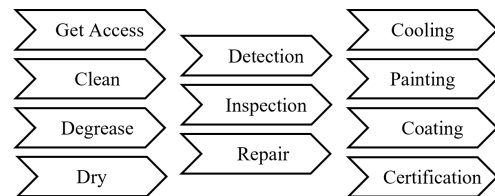


FIG 2. Exemplary Process Catalogue.

parameterized into multiple condition-driven instances. For example, the "Get Access" step is differentiated into four variants based on aircraft size and damage location (e.g., top/bottom access for small/large aircraft). Similarly, cleaning, degreasing, painting, coating, and certification procedures are material-specific (aluminum vs. composites), reflecting distinct tooling, consumable, and workforce certification requirements. Detection, inspection, and repair steps are further stratified by material, damage type, geometry, location, and dimensional limits—such as applying blending for shallow defects versus machining for deeper anomalies as exemplarily shown in Fig. 3.

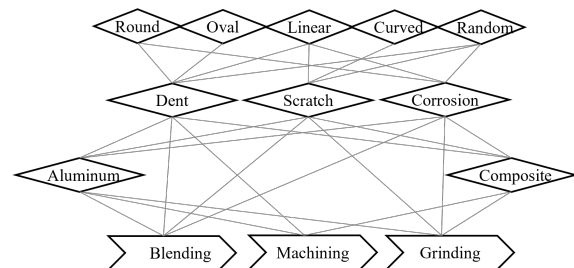
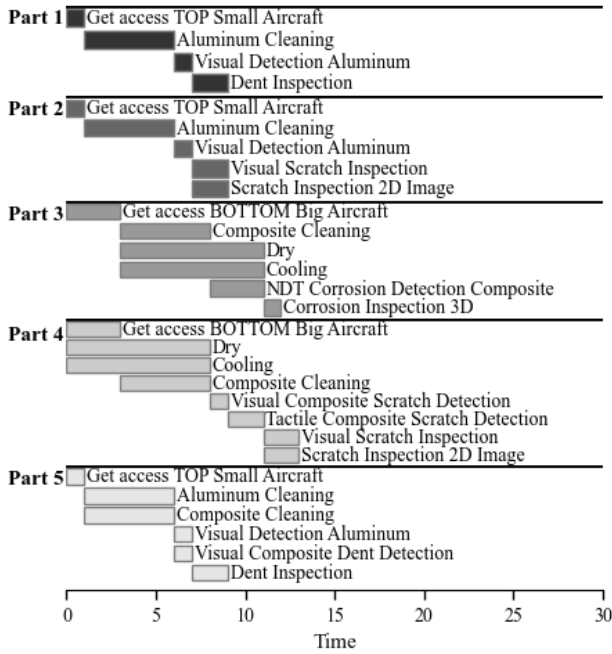
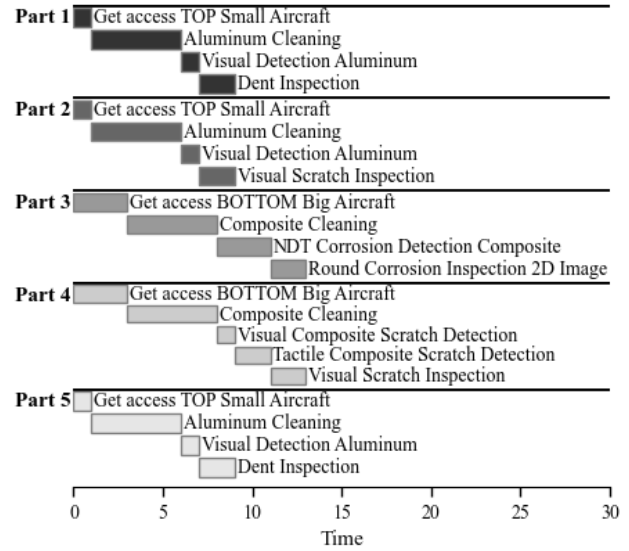


FIG 3. Decision Criteria for Repair Procedures.

This condition-dependent structure directly mirrors the task-specific organization of standard aviation maintenance manuals. Tab. 8 provides a comprehensive overview of the defined step instances, including their respective counts, parameter values (duration and cost), resource dependencies, state transitions, and the decision logic governing instance selection.



(a) Simulated duration-optimal inspection processes.



(b) Simulated cost-optimal inspection processes.

FIG 4. Comparison of duration- and cost-optimal Inspection Processes for individual parts.

4. FUNCTIONAL VERIFICATION OF DREAM

A functional verification of the simulation engine assesses end-to-end process integrity, ensuring correct input interpretation and logically consistent outcomes. Two use cases—aircraft inspection and complete repair—are used to evaluate isolated and, for inspection, parallel process simulation with shared resources. Optimization considers both cost and duration to address diverse customer requirements.

4.1. Use Case 1: Aircraft Inspection

The objective of this use case is to evaluate both isolated simulation of individual aircraft and integrated simulation of parallel processes, assessing DREAM's capability to optimize for duration and cost, respectively.

4.1.1. Results

Fig. 4 shows the duration- and cost-optimal inspection processes for each individual part. All optimizations converge successfully. Based on these single-part results, Fig.

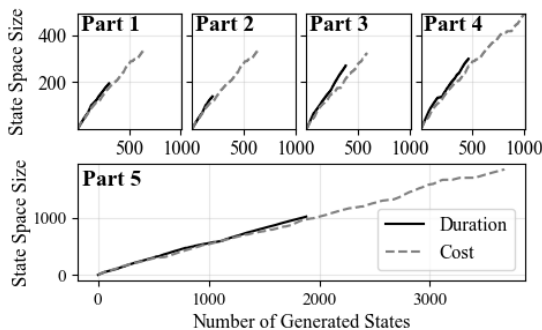
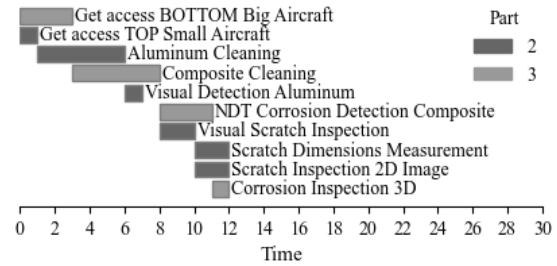
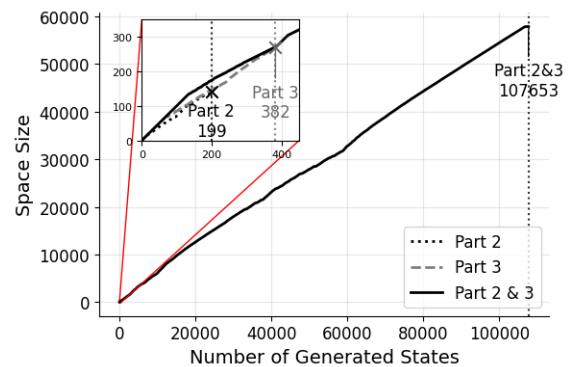


FIG 5. State space growth for processes from Fig. 4.

5 compares the computational effort of the two optimization objectives in terms of the number of states that must be calculated until the optimal process is returned. For the two-part scenario, Fig. 6a illustrates how parallel processes are scheduled under duration optimization, while Fig. 6b quantifies the corresponding state-space growth of this process.

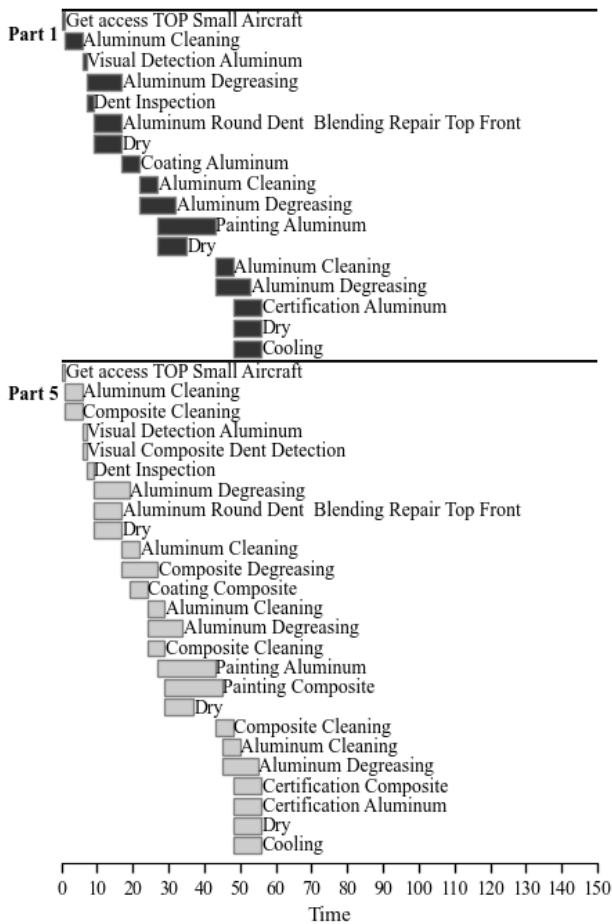


(a) Duration-optimal process for 2 parts.

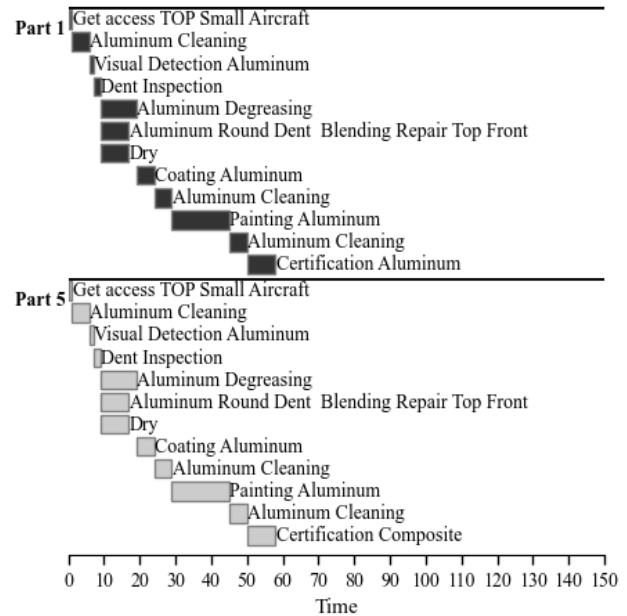


(b) State space growth: Joint vs. isolated optimization.

FIG 6. Joint inspection simulation of two parts.



(a) Duration-Optimal Repair Processes.



(b) Cost-Optimal Repair Processes.

FIG 7. Comparison of duration- and cost-optimal Repair Processes for individual parts.

4.1.2. Discussion

The framework correctly interprets the input schema and generates logically consistent process outcomes. However, the optimization objectives yield distinct process characteristics: duration optimization preferentially executes additional parallel steps not strictly required for the critical path, while cost optimization results in processes with only the minimum necessary steps executed sequentially.

Duration optimization converges substantially faster than cost optimization, likely due to DREAM's preference for parallel step execution, which aligns naturally with minimizing duration but conflicts with the objective of minimizing total cost. The simulation for Part 5 generates a disproportionately big state space due to its dual-material definition, and future work should investigate whether such parts should be hierarchically decomposed into single-material sub-parts (Fig. 5).

When multiple parts are optimized jointly, only a single critical path is minimized, potentially under-optimizing parts with shorter processing times. Since parts may belong to different customers, a multi-objective optimization approach with individual optimization per part may be preferable—not only to ensure fair treatment of all customers, but also to mitigate the trade-off between duration optimization, which tends to add unnecessary

parallel steps, and cost optimization, which may neglect potential time savings from parallelization.

The most critical observation concerns scaling behavior: individual simulation of Parts 2 and 3 converges rapidly (only 199 and 382 states must be generated, respectively), yet combined optimization requires simulating 107,653 states—substantially more than the product of individual computations (see Fig. 6b). This exponential growth necessitates a fundamental trade-off: either accept computationally feasible individual optimizations per part followed by manual integration—which may yield suboptimal solutions, since globally optimal processes can include locally suboptimal parts that collectively outperform individually optimized solutions—or invest substantially more computational resources to guarantee the true global optimum while exploiting DREAM's core advantage of shared resource optimization. Future work must determine which approach strikes the best balance between solution quality and computational tractability for realistic use cases.

4.2. Use Case 2: Aircraft Repair

Due to the combinatorial growth of parallel processes, only individual part optimization is shown for this use case. Results for Parts 1 and 5 are presented for both optimization objectives.

4.2.1. Results

Fig. 7a shows the duration-optimal processes for Parts 1 and 5, while Fig. 7b presents the corresponding cost-optimal results. Fig. 8 compares the state space scaling behaviour between both optimization objectives.

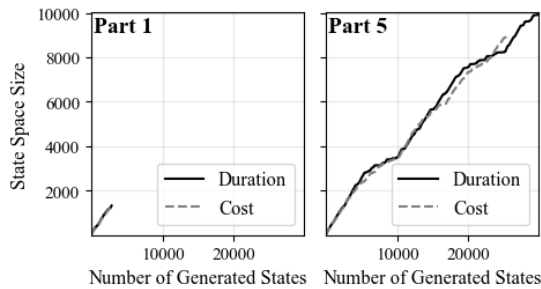


FIG 8. State space growth for processes from Fig. 7.

4.2.2. Discussion

In contrast to the shorter inspection processes, no clear tendency is observed between cost and duration optimization regarding the number of explored states. This is likely because the complete repair processes are defined such that almost all steps must be executed anyway, leaving little room for optimization—hence, the choice of optimization objective becomes less influential on computational complexity. Part 5 requires substantially higher state space size than Part 1, likely due to its dual-material definition, which permits nearly all process steps without exclusion by material constraints. Consistent with Use Case 1, cost optimization avoids unnecessary steps, resulting in more compact process definitions compared to duration optimization.

5. CONCLUSION

This paper demonstrated the practical applicability of the DREAM framework through a comprehensive input schema definition and functional verification on realistic MRO scenarios. The results confirm that DREAM correctly interprets the multi-dimensional input model—encompassing part characteristics, hangar resources, and process steps—and reliably generates optimal process sequences for both isolated and parallel operations. However, the identified challenges, particularly the exponential state space growth in joint multi-part optimization and the computational asymmetry between duration and cost objectives, highlight critical scalability limitations that must be addressed. Given the growing MRO demand driven by an aging fleet, intensifying labor shortages, and mounting pressure on turnaround times, DREAM's capability to dynamically optimize maintenance processes while accounting for individualized part states and shared resource constraints holds significant practical potential. Currently, DREAM exclusively targets efficiency objectives (duration and cost), yet real-world MRO operations frequently face conflicting priorities such as process robustness, resilience to disruptions, or risk minimization. Future work will extend the optimization framework to incorporate such stability-oriented criteria, enabling planners to balance efficiency against operational resilience and disturbance tolerance. Algorithmic enhancements to mitigate state space explosion, hierarchical decomposition strategies for multi-material components, and multi-objective optimization approaches that balance duration, cost, and fairness across customer-differentiated workflows will further advance industrial applicability.

TAB 8. Process Catalogue Parameters.

Step	#	Dur.	Cost	Role (Amount)	Tool (Amount)	Material (Amount)	Procedural Requirements	Procedural Update	Decision Criteria
Get Access	4	1–3	100–300	R1 (1)	T1, T2, T3 (1)	–	–	–	Part Size, Dam. Location
Cleaning	2	5	100	R1 (1)	–	M1/M3 (100)	1	3 → 2	Material
Degreasing	2	10	200	R1 (1)	–	M2/M4 (200)	1	3 → 2, 5 → 4	Material
Detection	1	1	80	R1 (1)	–	–	1, 2	6, 7, 8	–
Aluminum									
Visual Det.	2	1	80	R1 (1)	–	–	1, 2	6, 8	Dam. Type
Composite									
Tactile Det.	2	2	160	R1 (1)	–	–	1, 2, 6, 8	7	Dam. Type
Composite									
NDT Corr.	1	3	500	R2 (1)	T4 (1)	–	1, 2	6, 7, 8, 9	–
Det. Comp.									
Inspection	8	1–2	160–400	R1 (1)	T5, T6, T7, T8 (1)	–	1, 2, 6, 7, 8 (10)	9, 10	Dam. Type, Dam. Size
Blending	40	8–10	1000–1800	R1 (2)	T9 (1)	M5 (30–50)	1, 2, 9, 10	2 → 3, 4 → 5, 11 → 12, 15	Dam. Type, Dam. Shape, Dam. Location, Dam. Size
Repair									
Machining	32	16–20	3000–4000	R1 (2)	T10 (1)	M6, M7 (1)	1, 2, 9, 10, 11, 13	2 → 3, 4 → 5, 11 → 12, 15	Material, Dam. Type, Dam. Shape, Dam. Loc., Dam. Size
Repair									
Grinding	48	12–24	1500–4000	R1 (2)	T11 (1)	M8, M9 (1)	1, 2, 9, 10, 11, 13	2 → 3, 4 → 5, 11 → 12, 15	Material, Dam. Type, Dam. Shape, Dam. Loc., Dam. Size
Repair									
Coating	2	5	500–800	R1 (2)	T12 (1)	M10/M11 (50), M12 (1)	1, 2, 4, 11, 15	2 → 3, 4 → 5, 11 → 12, 14	Material
Painting	2	16	1000–1200	R3 (1)	T13 (1)	M12 (1), M13/M14 (100)	1, 2, 4, 11, 14, 15	2 → 3, 4 → 5, 11 → 12, 16	Material
Composite									
Certification	1	8	400	R4 (1)	–	–	1, 2, 11, 14, 15, 16	17	–
Aluminum									
Certification	1	8	400	R5 (1)	–	–	1, 2, 11, 14, 15, 16	17	–
Dry	1	8	10	R1 (1)	–	–	–	12 → 11	–
Cooling	1	8	10	R1 (1)	–	–	–	13	–
Replacement	1	720	10 ⁷	R1 (1)	–	–	–	–	Exception case

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