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AutoFlow-MO: An Automated Planning Method of Experimental Process Flows for Multi-Object Demands

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Abstract: The intelligent planning and scheduling of complex Test Support Systems (TSS) are critical for the efficient and safe operation of large-scale experimental facilities. However, traditional manual scheduling and static rule-based paradigms struggle to manage the high-dimensional, non-linear coupling between multi-object concurrent demands and stringent physical resource constraints. To address this NP-hard problem, this paper proposes a novel automated process planning framework driven by multi-dimensional physical constraints and data-driven heuristics. First, a knowledge-driven formalization mechanism utilizing an improved K-Means++ clustering strategy with Mahalanobis distance is established to accurately map heterogeneous, unstructured test demands into computable mathematical models. Subsequently, a hierarchical dependency model and a multi-dimensional resource configuration conflict matrix are constructed. Combined with domain-knowledge-guided heuristic traversal algorithms, this formulation successfully decouples severe spatial-temporal competition and eliminates resource deadlocks among coupled subsystems. Finally, to navigate the massive constraint space, a Space-Time Cooperative A* algorithm integrated with Latin Hypercube Sampling (LHS) is proposed. This approach effectively filters physically infeasible paths and consistently locates Pareto optimal scheduling schemes that balance minimum task response delays with optimal energy consumption. Ultimately, the proposed methodology fundamentally shifts experimental process planning towards a highly autonomous paradigm, providing robust decision-making support for the efficiency and safety enhancement of complex test facility clusters.

Keywords: Automated Process Planning; Resource-Constrained Scheduling; Space-Time Cooperative A Algorithm*; Knowledge-Driven Formalization; Conflict Resolution.

1. Introduction

Large-scale experimental facility clusters play a pivotal role in advancing modern scientific research and industrial engineering [1]. As the core infrastructure supporting these facilities, the TSS is inherently characterized by multi-service objects, interleaved multi-task execution, and highly complex process flows [2]. With the increasing scale and frequency of modern testing requirements, ensuring the efficient and safe operation of the TSS has become a critical challenge in the field of industrial automation and systems engineering [3], [4].

Despite the growing complexity of experimental tasks, the current process planning and scheduling within TSS predominantly rely on manual empirical modes [5]. This conventional approach exhibits significant limitations. On one hand, it frequently leads to the over-allocation of experimental resources, preventing the overall system from reaching its full operational potential [6]. On the other hand, manual scheduling heavily depends on human experience and intuitive judgment, making it fundamentally inadequate to handle intricate process flows. Under multi-dimensional constraints, such empirical methods fail to meet the modern industrial requirements for leanness, high efficiency, and operational safety [7], [8].

The primary bottleneck in overcoming these limitations lies in the immense complexity of coordinating multiple coupled physical resources [9]. A typical TSS involves stringent resource configuration constraints across six major process subsystems: gas supply, exhaust, air pre-treatment, circulating water, fuel and natural gas, and electric power. Effectively mining the constraint rules governing these highly coupled subsystems and dynamically matching them with the concurrent serial and parallel demands of multiple experimental objects remains a significant technical gap in existing research [10], [11].

To address the aforementioned prominent issues, this paper proposes an automated planning method of experimental process flows tailored for multi-object demands. The main contributions and implementations of this study are outlined as follows:

- **Standardized Management Mechanism:** We explore and establish a standardized management mechanism for experimental demands and resources, bridging the gap between physical constraints and algorithmic inputs.
- **Constraint Rule Mining:** We deeply excavate and mathematically model the resource configuration constraint rules of the six core subsystems.
- **Automated Planning for Serial/Parallel Demands:** An automated process planning approach is developed to optimally schedule the complex serial and parallel demands of multiple experimental objects [12].
- **Navigational Scheduling Mode:** We introduce a novel "navigational" process planning and scheduling mode to guide real-time decision-making.

Ultimately, this research provides robust technical support to enhance the leanness, efficiency, and operational safety of experimental process planning, thereby facilitating the quality improvement and efficiency enhancement of large-scale test facility cluster

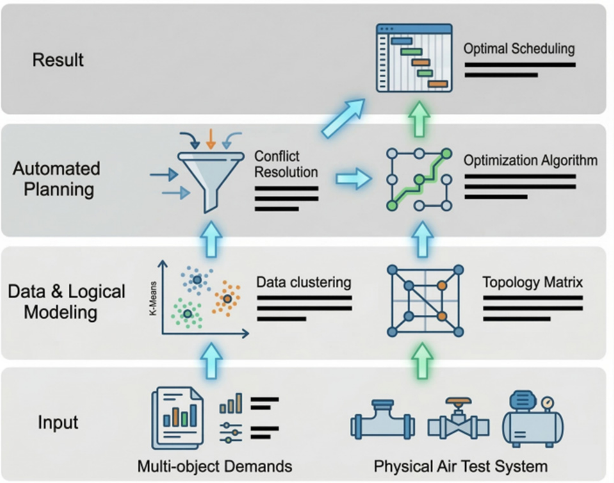


Figure 1. The picture illustrates the framework of the paper.

2. Related Work

The intelligent planning and scheduling of process flows within complex TSS, particularly in the aviation power testing domain, are critical for enhancing testing efficiency and reducing operational costs. Given the multi-model, multi-task, and multi-condition characteristics of modern experimental objects, conventional scheduling paradigms based on manual experience or static rules struggle to manage the high-dimensional, non-linear coupling between dynamic demands and resources. Recent literature has broadly explored this area, transitioning from pure digitalization to intelligent, multi-objective collaborative decision-making.

(1) Process Knowledge Mining and Model Construction

In the domain of process knowledge mining, the focus has shifted from traditional rule-based reasoning (RBR) to hybrid data-driven approaches. While recent advancements utilizing knowledge graphs, Graph Neural Networks (GNNs), and Generative Adversarial Networks (GANs) have significantly improved process generation and parameter optimization in discrete manufacturing, their application in continuous-discrete hybrid systems—such as aviation high-altitude test facilities—remains limited. Existing research predominantly focuses on isolated data processing, lacking an integrated, closed-loop mechanism that links fundamental data cleaning to relationship mapping. Consequently, current models exhibit insufficient generalization and robustness when confronted with the highly dynamic, multi-physics coupled experimental demands inherent in modern TSS.

(2) Automated Planning Methods for Multi-Task Process Flows

Addressing the Multi-mode Resource-Constrained Project Scheduling Problem (MRCPSP) within process planning, researchers have increasingly adopted reinforcement learning (RL) and hybrid heuristic algorithms to overcome the NP-hard bottlenecks of traditional operations research. However, existing methods often employ staged optimization strategies that isolate tightly coupled subsystems, frequently leading to resource deadlocks and suboptimal efficiency in continuous-flow environments. To achieve global synergy in multi-task serial-parallel scheduling, there is a critical need for advanced spatial exploration and optimization mechanisms—such as the integration of LHS with A* graph search. This integration is essential to rapidly locate global optima within massive, tightly coupled resource constraint spaces while strictly adhering to the rigorous safety constraints of aviation testing.

(3) Intelligent Scheduling and Conflict Resolution

Regarding intelligent scheduling and conflict resolution, recent literature highlights the integration of robust Markov Decision Processes (MDP), many-objective optimization algorithms, and visual analytics to maintain system stability under dynamic disturbances. Despite these theoretical strides, current applications predominantly rely on offline simulations and lack a multi-scale linkage between micro-level equipment control and macro-level task scheduling. For high-cost and high-risk environments like aviation testing, a significant gap remains in developing comprehensive, visually-supported decision tools capable of dynamically balancing testing success rates, energy consumption, and cycle times to ensure robust system operation.

3. Knowledge-Driven Formalization of Experimental Demands and Equipment

(1) Data Formalization and Feature Representation

To achieve optimal scheduling and maximize resource utilization within the test support system, the primary task is to extract and fuse experimental demand and planning data based on an expert rule base. By systematically screening and revising descriptive test tasks, a multi-dimensional data model is constructed to transform unstructured requirements into structured data suitable for algorithmic processing. This model encapsulates all critical attributes into a unified data object, integrating basic information, object attributes, core parameters, critical time constraints, and derived test categories. This standardized model serves as the fundamental prerequisite for optimal path planning, conflict detection, and dynamic scheduling. For instance, in high-altitude chamber testing, demands are extracted based on flow, temperature, and pressure, which are systematically categorized into five distinct types: low-pressure direct supply, medium-pressure direct supply, dry supply, negative-temperature supply, and high-temperature supply.

To facilitate automated processing, historical task data are preprocessed into feature vectors. Equipment information is converted into numerical features, while environmental requirements are quantitatively processed. Formally, the set of experimental demands is defined as $\mathrm{D} = \{\mathrm{d}_1, \mathrm{d}_2, \ldots, \mathrm{d}_\mathrm{n}\}$, where each specific demand d_i is mapped into an \$m\$-dimensional feature vector$\mathrm{x}_\mathrm{i} \in \mathrm{R}^\mathrm{m}$:

$$x_i = [P_i, T_i, Q_i, \tau_i, \ldots]^T$$

Where $\mathrm{P}_\mathrm{i}$denotes the test pressure (kPa.A), $\mathrm{T}_\mathrm{i}$represents the test temperature (°C), $\mathrm{Q}_\mathrm{i}$is the air mass flow rate (kg/s), and τ_i signifies the test duration or temporal characteristics. Given the massive dimensional discrepancies—where pressure can reach thousands of kPa while flow may only be tens of kg/s—direct distance calculations would allow large-value features to dominate the clustering results. Therefore, a Z-Score standardization is strictly applied before algorithmic input, mapping the heterogeneous data into a unified distribution space with a mean of 0 and a standard deviation of 1.

(2) Knowledge-Driven Clustering and Mapping

Mechanism

To autonomously construct the mapping relationship between experimental demands and test equipment, an improved K-Means clustering algorithm is employed. To ensure the algorithm converges to a global optimum and to eliminate the drawbacks of random initialization, the K-Means++ strategy is adopted. The core concept is to maximize the distance between initial cluster centers. The probability $\mathrm{P(x)}$ of a new center $\mathrm{c_k}$ being selected is proportional to the square of its shortest distance $\mathrm{D(x)}$ to the currently selected centers:

$$P(x) = \backslash fracD(x)^2 \sum_{x \in X} D(x)^2$$

This initialization strategy is particularly crucial in multi-object serial-parallel scenarios, as it ensures the initial prototypes cover significantly varied working conditions and avoids the skewness of clustering results.

Furthermore, considering the strong physical correlation among test parameters, the Mahalanobis distance is introduced to replace the traditional Euclidean distance as the similarity metric. By incorporating the inverse covariance matrix Σ^{-1}, the Mahalanobis distance effectively corrects for data correlations:

$$d_M(x_i, c_k) = (x_i - c_k)^T \Sigma^{-1} (x_i - c_k)$$

This pivotal modification allows the algorithm to identify elliptical distribution clusters that comply with underlying physical laws, rather than mechanically carving out spherical clusters, thereby categorizing experimental demands with similar physical characteristics much more accurately. The ultimate objective of the algorithm is to minimize the sum of squared clustering errors J to locate K optimal experimental pattern prototypes:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} d_M(x_i, c_k)^2$$

Through this mapping mechanism, the system can rapidly determine the test category for different objects, allocate required resources and accurately lock specific equipment and main pipelines.

4. Mathematical Modeling and Data Representation of Resource Constraints

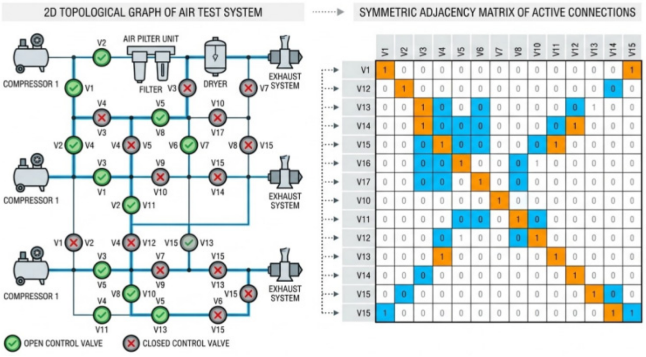
(1) Hierarchical Dependency Model of Physical Resources

To achieve the refined management and automated scheduling of test system resources, it is imperative to construct a data model capable of accurately mapping physical equipment entities, their performance capabilities, and their complex interconnections. In this paper, a Hierarchical Dependency Model is formulated to systematically digitize all equipment resources. The core philosophy lies in deconstructing the massive test system into logically clear and computable objects, abstracting all physical resources into two core categories: basic equipment units and composite equipment systems.

By employing a bottom-up hierarchical modeling approach, a static and intricately connected physical equipment network is transformed into a dynamic data model with clear structures, rigorous logic, and real-time state inferencing capabilities. This model provides the scheduling engine with a multi-resolution view. It enables the rapid matching of system-level aggregated capacities from a macroscopic perspective, while allowing downward drilling to the component level to verify the current status of any foundational unit. Furthermore, to handle the heterogeneous data formats and variable operating conditions, a universal equipment resource encoding method based on an Attribute-Value semi-structured data paradigm is adopted to achieve a full-element digital mapping of the physical entities.

(2) State Encoding and Matrix Representation of Network Topology

Based on the functional classification of test equipment, the operational states of critical components—such as compressor units, turbines, wave rotors, and heaters—are discretely encoded. Specifically, inactive, and debugging/maintenance states are digitally encoded as1, 0, and−1, respectively. These numerically encoded demands and equipment states are structurally stored to provide a solid data foundation for subsequent querying, statistical analysis, and automated plan generation.



	V1	V2	V3	V4	V5	V6	V7	V8	V10	V11	V12	V13	V14	V15
V1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
V12	0	1	0	0	0	0	0	0	0	0	0	0	0	0
V13	0	0	1	0	0	0	0	0	0	0	0	1	0	0
V14	0	0	1	0	0	0	0	0	0	0	1	0	0	0
V15	0	0	0	1	0	0	0	0	0	1	0	0	0	0
V16	0	0	0	0	1	0	0	0	1	0	0	0	0	0
V17	0	0	0	0	0	1	0	0	0	0	0	0	0	0
V10	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V11	0	0	0	0	0	0	0	1	0	0	0	0	0	0
V12	0	0	0	0	1	0	0	0	1	0	0	0	0	0
V13	0	0	0	1	0	0	0	0	0	1	0	0	0	0
V14	0	0	0	0	0	0	0	0	0	0	1	0	0	0
V15	0	0	0	0	0	0	0	0	0	0	0	1	0	0
V15	1	0	0	0	0	0	0	0	0	0	0	0	1	1

Figure 2. Topology & Matrix Encoding

To efficiently handle data operations during the state monitoring and updating phases, a highly intuitive matrix encoding scheme based on graph theory is utilized for the pipeline and valve topology. In this topological model, each control valve within the pipeline is defined as a real node, while each pipeline intersection is treated as a virtual node. The open and closed states of the real nodes are denoted by boolean values. The flow connection relationships are represented as adjacent nodes, where a pair of adjacent nodes constitutes a specific pipeline segment. Consequently, the complex topological relationships among n control nodes are comprehensively captured using an $n \times n$ symmetric adjacency matrix. In this matrix, the rows and columns correspond strictly one-to-one with the n valves. This symmetric structure significantly facilitates the unified computational processing of mutual relationships, effectively characterizing both their independent switching states and their interactive connectivity and potential spatial conflicts during concurrent serial-parallel testing.

5. The Proposed Automated Planning Method for Multi-Object Demands

(1) Ontology-Based Association Rule Mining and Evolution

Addressing the highly non-linear mapping challenges between heterogeneous test demands and bottom-up hardware resources, this section establishes a semantic association graph covering full temporal-spatial and operational conditions through ontology modeling. To avoid the limitations of pure empirical methods, a dual-driven mining algorithm system based on an expert rule base and massive historical operational data is proposed.

Due to the extreme sparsity and heterogeneity of test data, a modified heuristic association rule mining strategy is applied. By searching for frequent itemsets layer by layer, high-confidence correlation patterns are extracted from complex configuration logs and solidified into a standardized association rule matrix. To ensure continuous adaptation to hardware iterations and novel test demands, a RL framework is integrated to provide the rule base with closed-loop learning capabilities. Efficiency metrics, safety boundaries, and resource consumption data collected post-execution serve as feedback signals to automatically adjust the confidence weights of the association rules, fundamentally shifting the process planning from experience-dependent to data-driven.

(2) Hierarchical Dependency Model of Physical Resources

In scenarios featuring multiple test objects and concurrent test categories, the strong coupling and spatial-temporal positional competition of internal resources create significant bottlenecks for scheduling efficiency. To break through the traditional static resource checking paradigm, a multi-dimensional heterogeneous resource configuration conflict matrix is constructed based on topological parsing. This matrix quantitatively captures comprehensive conflict factors, including control valve states, pipeline occupation, and the operational statuses of key equipment.

When identifying potential conflicts in massive concurrent tests, exhaustive methods inevitably lead to combinatorial explosion. Therefore, a domain-knowledge-guided heuristic traversal algorithm is proposed. This algorithm profoundly fuses the connectivity probing capability of Depth-First Search (DFS) with the hierarchical expansion characteristics of Breadth-First Search (BFS), embedded with a physical-rule-based pruning strategy. Taking the current test plan sequence P_{plan} and real-time equipment state vector S_{curr} as inputs, the algorithm efficiently outputs the precise conflict set $Set_{conflict}$.

(3) Space-Time Cooperative A* Algorithm with LHS Optimization

To achieve optimal process routing across complex test scenarios, the process planning problem is abstracted into a high-dimensional non-linear combinatorial optimization model. A Space-Time Cooperative A* Algorithm, deeply integrated with heuristic search and random sampling techniques, is proposed to achieve global optimization under dynamic resource constraints.

Initially, the process parameter space is defined as$S \in R^D$. The state vector x is constructed by selecting critical dimensions:

$$x = [w, T_{exec}, Q]^T$$

where $w \in [0,1]$ represents the resource allocation weight , T_{exec} denotes the core execution period , and Q is the medium flow regulation range. To prevent the dimensional disaster typically caused by traditional grid sampling and the sample clustering issues of simple random sampling, the LHS algorithm is introduced to cover the multi-dimensional process space.

The automated planning logic follows a progressive filtering and optimization mechanism:

a. **Candidate Generation:** Based on the association rule base, initial candidate process paths satisfying the test working conditions are identified.

b. **Conflict Reduction:** The x paths are mapped into the multi-tester resource configuration conflict matrix. By cross-referencing real-time valve and equipment state conflict matrices, y paths that are physically or logically infeasible are automatically eliminated.

c. **Global Optimization:** The remaining feasible paths, denoted as Z where $Z = x - y$, are subsequently inputted into the Space-Time Cooperative A* Algorithm.

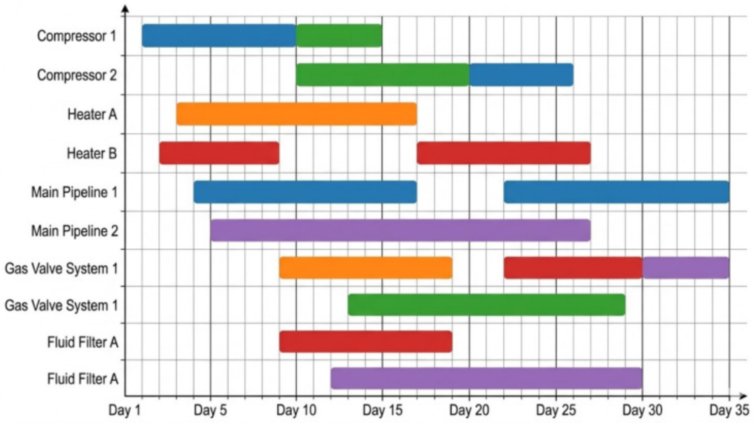


Figure 3. Multi-objective Spatiotemporal Collaborative Scheduling Execution Window Timing Diagram

Ultimately, the algorithm pinpoints the global optimal path featuring the shortest task response delay and the most balanced energy consumption among the Z candidates. This systematic methodology comprehensively transcends the limitations of manual trial-and-error, providing a deterministic and scientifically rigorous decision-making foundation for complex system scheduling.

6. Conclusion

The efficient and safe operation of large-scale TSS under multi-object concurrent demands is a critical bottleneck in modern aviation and industrial engineering. To overcome the inherent limitations of traditional manual scheduling and static rule-based paradigms, this paper proposes a novel automated process planning framework driven by both multi-dimensional physical constraints and data-driven heuristics.

The core contributions and findings of this study are summarized as follows:

- **Knowledge-Driven Demand Formalization:** A standardized mapping mechanism was established. By utilizing an improved K-Means++ clustering strategy with Mahalanobis distance, the highly heterogeneous and sparse unstructured test demands were successfully transformed into computable mathematical models, significantly enhancing the adaptability of the system to complex physical working conditions.
- **High-Resolution Resource Modeling and Conflict Resolution:** A hierarchical dependency model and a symmetric adjacency matrix were constructed to digitally map the topological network of massive physical resources. The proposed multi-dimensional resource configuration conflict matrix, combined with heuristic traversal algorithms, successfully decoupled the severe spatial-temporal competition among six major subsystems, thereby completely eliminating potential resource deadlocks and operational safety hazards.
- **Global Optimization via Space-Time Cooperative A*:** The integration of LHS with the proposed Space-Time Cooperative A* algorithm effectively solved the high-dimensional non-linear combinatorial optimization problem. This method thoroughly filters out physically infeasible paths and consistently locates the Pareto optimal scheduling schemes, balancing minimum task response delays with optimal energy consumption under stringent safety boundaries.

Ultimately, the proposed methodology fundamentally shifts the experimental process planning from an empirical-dependent mode to a highly autonomous, data-driven paradigm. It provides robust, deterministic, and scientifically rigorous decision-making support for the quality improvement and efficiency enhancement of complex test facility clusters.

Acknowledgments

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