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Cost Analysis and Estimation of Avionics Sharing under Multi-Customer and Multi-Fleet Security Conditions

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Abstract This study investigates the cost measurement and optimization of aviation material sharing under multi-client and multi-fleet conditions, and develops a systematic theoretical framework and implementation model. First, using the average annual flight hours of each customer's fleet and a Poisson distribution model, the demand for each part number in the sharing pool is accurately forecast. Based on these forecasts, optimal stock quantities are determined to meet varying protection requirements, thereby maximizing the scale pooling effect and effectively reducing the unit cost of spare parts. Second, the cost structure of aviation material sharing is systematically analyzed, integrating four cost categories—depreciation, capital consumption, labor management, and agreed expenditures—into a unified model. An innovative cost-sharing mechanism is proposed that combines the "flight hour ratio" with the "probability of spare parts consumption," balancing fairness with incentive constraints and effectively preventing "free-riding" behaviors. To validate the method, a software system is designed and developed, integrating parameter setting, data management, preprocessing, calculation execution, and result visualization, thereby automating the process from historical data import to hourly cost output. Case applications demonstrate that the proposed approach significantly reduces hourly costs, greatly improves measurement efficiency in typical sharing scenarios, and achieves further cost savings in the initial coverage stage through multi-location sharing and dual-source supply strategies.

Index Terms aviation material sharing, multi-client multi-fleet, Poisson demand forecasting, cost-sharing mechanism, hourly rate, automated measurement system

I. Introduction

With the rapid growth of the global air transportation industry, airline fleets continue to expand, demand for maintenance and support steadily rises, and the management cost of aviation materials (i.e., aircraft spare parts) increases accordingly [1], [2]. Traditional procurement and inventory models, typically centered on a single customer, a single aircraft type, or a specific route, struggle to adapt to today's complex environment of high capital investment, fluctuating demand, and multi-scenario coordinated support. This results in high capital consumption, inefficient resource allocation, and weak risk-response capability. To address these challenges, the Aviation Material Sharing Mode has emerged [3]. Based on the principle of shared construction and utilization, this model optimizes cash flow, reduces initial capital pressure, and improves spare parts utilization and turnover by establishing a unified parts pool and deploying resources on demand—transforming high one-time procurement costs into ongoing expenditures based on flight-hour billing [4], [5].

In a multi-client and multi-fleet context, however, spare parts sharing faces more complex cost measurement challenges. On one hand, operators differ significantly in fleet composition, flight-hour distribution, parts usage frequency, and service standards [6]. Achieving fair distribution and scientific sharing under a unified platform is key to cost control. On the other hand, managing sudden maintenance peaks and spare parts supply uncertainties requires controlling cost risks while maintaining service levels. Existing research largely focuses on single-entity spare parts management, lacking cost optimization models for joint multi-client support and systematic discussions on cost composition, allocation mechanisms, service level coordination, and risk sharing [7], [8]. This gap calls for a more integrated and collaborative framework.

Scholars worldwide have examined aviation material forecasting and inventory control. Time-series models (e.g., ARIMA, LSTM) can accurately forecast short-term consumption of single parts; Poisson-based inventory models with service-level constraints can determine optimal stock quantities; and cost analyses often focus on depreciation, capital utilization, and shortage risks for single airlines [9]. Although some recent work has explored multi-agency collaborative replenishment, it is mostly supply chain- or game theory-based, emphasizing decentralized vs. centralized decision-making without integrating spare parts demand, cost composition, and rate calculation for multi-customer, multi-fleet conditions [10].

Most inventory optimization models overlook correlations between different fleets and part categories, limiting multi-dimensional, multi-level scheduling. Traditional cost allocation often relies on fleet size or order volume, ignoring key factors such as flight hours, consumption probability, and risk exposure—leading to "free riding" or allocation disputes [11]. While some scholars have proposed hourly rate calculation concepts, they remain largely theoretical, without software implementation or operational verification for multi-customer systems, and struggle to adapt to dynamic scenarios (e.g., fleet changes, sudden demand surges, supply chain disruptions). Parameter deviations can easily distort costs or degrade service levels [12].

In response to these challenges, this paper develops a systematic aviation material sharing cost analysis framework for multi-agent collaboration. Based on Poisson distribution demand forecasting and annualized consumption calculations, the flight hours of all participating customers are aggregated to derive the overall demand distribution of each part number in the shared pool. This approach preserves the individual characteristics of each customer while achieving significant unit cost reductions through economies of scale [13]. The cost structure—covering depreciation, capital occupation, labor and management, and service agreement costs—is examined in detail, and a sharing mechanism is proposed that combines the proportion of flight hours, spare parts consumption probability, and a risk-adjustment factor to ensure fairness, transparency, and incentive alignment, while encouraging all parties to improve service levels through contractual arrangements. Furthermore, a software system is designed with modules for parameter presetting, data management, preprocessing, calculation, and result output, enabling full automation from historical data import to cost result generation. Case studies verify the feasibility of the proposed method, demonstrating its efficiency gains and cost optimization benefits in multi-customer, multi-fleet hourly rate calculations.

II. Basic Model

This paper takes aviation material sharing as the background and constructs a supply chain cost decision model suitable for multi-customer and multi-fleet environments. Considering the procurement, storage, allocation, and service pricing of aviation materials in the sharing pool, the decision models of centralized and decentralized supply chains are established to explore optimization strategies for cost and benefit under different organizational models [14].

II. A. Centralized Supply Chain Decision

In a centralized supply chain structure, the supplier and service providers (i.e., the aviation parts provider and the airline customers) are treated as a unified decision-making entity. The primary goal is to maximize the overall profit of the entire supply chain through coordinated operations and integrated planning [15]. Under this mode, aviation material sharing is managed through a centralized platform that makes joint decisions regarding demand forecasting, inventory levels, and pricing, ensuring efficient resource allocation and minimizing opportunistic behaviors.

The profit function for the centralized supply chain can be expressed as:

$$\Pi_{\text{centralized}} = \sum_{i=1}^{N} pD_i - cS - hS - K. \tag{1}$$

Here, D_i represents the annual demand of customer i (estimated by flight hours); p is the uniform hourly service rate; c is the unit procurement cost of spare parts; h is the unit inventory holding cost; K is the fixed operating cost of the shared pool; S is the total procurement volume of spare parts; and N is the number of participating customers. The term $\sum_{i=1}^{N} pD_i$ represents the total revenue collected from customers based on flight hours, cS is the total cost of procuring spare parts, hS is the inventory holding cost, and K accounts for system-wide fixed costs.

The objective of centralized decision-making is to determine the optimal procurement quantity S^* and service rate p^* that maximize the overall profit $\Pi_{\text{centralized}}$, while satisfying each customer's required service level. Compared to a decentralized model, the centralized structure facilitates the realization of scale economies and improves the overall efficiency of resource utilization. It also enhances the responsiveness and cost-effectiveness of the spare parts support system, laying a solid foundation for fair cost allocation and dynamic pricing strategies in the later stages.

II. B. Decentralized Supply Chain Decision Model

In a decentralized supply chain model, participants such as suppliers and retailers in the aviation material sharing system act as independent decision-makers, each aiming to maximize their own profit. The decision-making follows a sequential structure that reflects real-world strategic interactions under multi-party collaboration [16].

First, the supplier determines the wholesale price w and the effort level e invested in ensuring material availability (such as maintenance responsiveness or part freshness). Next, based on the supplier's decisions regarding w and e, the retailer sets the selling price p, determines the value-added service level s, and decides the order quantity Q.

The retailer's profit function Π_r is defined as:

$$\Pi_r = (p - w) \cdot \mathbb{E}[\min(Q, D)] - c_s(s) \cdot Q, \tag{2}$$

where $\mathbb{E}[\min(Q, D)]$ is the expected demand satisfied, and $c_s(s)$ is the unit cost of providing service level s, where $c_s'(s) > 0$.

The supplier's profit function Π_w is given by:

$$\Pi_w = (w - c) \cdot \mathbb{E}[\min(Q, D)] - c_e(e), \tag{3}$$

where c is the unit production or procurement cost, and $c_e(e)$ is the cost associated with effort level e, where $c_e'(e) > 0$.

In this structure, the supplier acts as the Stackelberg leader, anticipating the retailer's optimal responses in terms of p, s, and Q, and determining the optimal w and e accordingly. The retailer then responds optimally to the supplier's decisions. Using backward induction, the optimal strategy set $(w^*, e^*, p^*, s^*, Q^*)$ for the decentralized supply chain is obtained. The resulting equilibrium is compared with the centralized model to evaluate differences in total system profit and resource allocation efficiency.

The retailer's optimal decisions satisfy:

$$\Pi_r = (p - w) \cdot \mathbb{E}[\min(Q, D(p, s, e))] - C_s(s), \tag{4}$$

where $D(p, s, e)$ represents the demand function, typically decreasing in p and increasing in s and e, and $C_s(s)$ represents the cost function for value-added services, where $c_s'(s) > 0$. Applying the first-order conditions yields the optimal retail price p^*, service level s^*, and order quantity Q^*.

Given the retailer's optimal responses (p^*, s^*, Q^*), the supplier then chooses w and e to maximize:

$$\Pi_w = (w - c) \cdot \mathbb{E}\left[\min(Q^*, D(p^*, s^*, e))\right] - C_e(e), \tag{5}$$

where $C_e(e)$ represents the freshness effort cost function, with $c_e'(e) > 0$. The optimal freshness effort level e^* and wholesale price w^* are then determined.

Therefore, in a decentralized supply chain, the supplier's optimal decisions are w^* and e^*, and the retailer's optimal decisions are p^*, s^*, and Q^*. This strategy combination constitutes the Nash equilibrium in a decentralized game. Without a coordination mechanism, this equilibrium often fails to achieve the optimal overall supply chain benefit, leading to the double marginalization effect. Contract mechanisms or cost compensation strategies should be considered to achieve coordinated optimization.

II. C. Bilateral Revenue Sharing and Cost Sharing Contract

In a decentralized supply chain, the "double marginalization" problem in the traditional model can be overcome through a bilateral revenue sharing and cost sharing contract (Revenue Sharing Contract, RSC). This contract enables all parties in the supply chain (suppliers and sellers) to achieve overall optimization by sharing profits and costs, thereby improving the overall efficiency of the supply chain.

Under a bilateral revenue sharing contract, suppliers and sellers share revenue and costs by setting a predetermined sharing ratio. The core idea of this contract is as follows:

1) Supplier's goal: maximize its own profits while increasing the seller's profits through appropriate prices and effort levels, thereby maximizing the overall benefits of the supply chain.
2) Seller's goal: maximize its own profits by setting retail prices and value-added service levels, obtaining the highest possible sales revenue while bearing the corresponding costs.

In the bilateral revenue sharing and cost sharing model, the decision-making process of the aviation material sharing supply chain involves close cooperation between suppliers and sellers to ensure the sharing of both benefits and costs. The specific process is:

1) The supplier sets a relatively low wholesale price w to motivate sellers to purchase and sell.
2) After product sales, the seller returns an agreed proportion of sales revenue to the supplier as compensation, ensuring cooperation and alignment between both parties.
3) This mechanism reduces the supplier's initial investment risk, while enabling sellers to obtain more favorable purchasing terms, thereby improving the efficiency of the entire supply chain.

The supplier's profit consists of two components:

(a) Sales revenue from selling products to the seller at wholesale price w.
(b) Return compensation — a portion of the sales revenue returned by the seller according to the agreed ratio.

The supplier's profit function is:

$$\Pi_W = (w - c) \cdot Q - C_e(e) + \gamma \cdot R, \tag{6}$$

where w is the wholesale price, c is the unit production cost, Q is the sales volume, $C_e(e)$ is the preservation effort cost function, $\gamma \cdot R$ is the revenue returned by the seller, and R is the total sales revenue.

The seller's profit also consists of two parts:

(a) Sales revenue from selling products at retail price p.

(b) Cost expenditure, including payments to the supplier for wholesale purchases and the cost of value-added services.

The seller's profit function is:

$$\Pi_r = (p - w) \cdot Q - C_s(s) + \gamma \cdot R, \tag{7}$$

where p is the retail price, w is the wholesale price, $C_s(s)$ is the value-added service cost, and $\gamma \cdot R$ is the agreed proportion of revenue returned to the supplier.

Through this model, suppliers and sellers achieve common benefit sharing and synergistic growth via coordinated pricing and revenue-sharing agreements. Suppliers share sales risks with sellers and obtain part of the sales revenue, while sellers profit through optimal retail prices and service levels, returning an agreed proportion to suppliers. This ensures fairness in profit and cost sharing, enhancing supply chain efficiency.

When the parameters of this collaborative contract — including wholesale prices, retail prices, and return ratios — are set to specific optimal values, decentralized supply chain decisions can be improved. These parameters affect both the distribution of benefits and the allocation of resources, ensuring maximization of overall supply chain performance. Proper configuration promotes efficiency gains while respecting each party's interests.

For Pareto optimization, key parameters such as return ratio, wholesale price, and retail price must meet specific conditions so that all parties' interests are protected. Under these conditions, suppliers and sellers maximize social welfare and achieve a win–win outcome through rational resource allocation. Even in the presence of demand fluctuations or market uncertainties, proper parameter settings prevent "free riding" and safeguard long-term cooperation.

This bilateral revenue and cost sharing arrangement also enables value co-creation. By sharing both risks and profits, suppliers and sellers can allocate resources more effectively, improving operational efficiency, increasing collective benefits, enhancing competitiveness, and strengthening long-term collaboration.

II. C. 1) Supplier Profit Function

If the supplier sets wholesale price w, production cost c, and provides a given service level, profit is:

$$\pi_S = (w - c) \cdot x - F_S, \tag{8}$$

where F_S is the fixed cost.

II. C. 2) Retailer Profit Function

The retailer's profit is:

$$\pi_R = (p - w) \cdot x - F_R, \tag{9}$$

where F_R is the fixed cost.

II. C. 3) Revenue Sharing Mechanism

In the bilateral contract, the retailer shares a fraction γ of sales revenue with the supplier. If total revenue is $p \cdot x$, the amount returned to the supplier is:

$$C_S = (1 - \gamma) \cdot p \cdot x, \tag{10}$$

and the retailer retains:

$$C_R = \gamma \cdot p \cdot x. \tag{11}$$

The optimal wholesale price w^* for the supplier maximizes:

$$\pi_S(w, p) = (w - c) \cdot x(w, p) - F_S, \tag{12}$$

subject to:

$$\frac{\partial \pi_S}{\partial w} = 0. \tag{13}$$

The optimal retail price p^* for the retailer maximizes:

$$\pi_R(w, p) = (p - w) \cdot x(w, p) - F_R, \tag{14}$$

subject to:

$$\frac{\partial \pi_R}{\partial p} = 0. \tag{15}$$

The final objective is to adjust w, p, x, and γ to maximize joint profits while balancing the interests of all parties. This eliminates free-rider behavior, ensures Pareto improvement, and fosters long-term value co-creation in the supply chain.

III. Cost Analysis of Spare Parts Sharing under Multi-Fleet and Multi-Customer Conditions

III. A. Construction of a Shared Spare Parts Pool

In a spare parts support system involving multiple fleets and customers, establishing a shared spare parts pool has become a key strategy to improve resource utilization and reduce redundant inventory costs. This pool is jointly shared by multiple customers and managed in a centralized manner by the supplier. To scientifically determine the required inventory level, the Poisson distribution can be used to model spare parts demand based on historical failure data.

Let the demand for a specific spare part by customer i within a unit time period follow a Poisson distribution with rate λ_i, then the total demand across all customers can be expressed as:

$$D = \sum_{i=1}^{n} D_i, \quad D_i \sim Poisson(\lambda_i). \tag{16}$$

Thanks to the additive property of the Poisson distribution, the aggregated demand still follows a Poisson distribution:

$$D \sim Poisson\left(\lambda = \sum_{i=1}^{n} \lambda_i\right). \tag{17}$$

Accordingly, the required number of spare parts S in the shared pool can be calculated based on a target service level α:

$$P(D \leq S) \geq \alpha. \tag{18}$$

That is, the minimum inventory S that satisfies the cumulative probability corresponding to service level α can be determined using a Poisson distribution table or simulation.

To account for emergency demand, a safety stock strategy can also be incorporated:

$$S = \lambda + z \cdot \sqrt{\lambda}, \tag{19}$$

where λ is the average demand of the spare part, and z is the standard normal distribution quantile corresponding to the desired service level.

This model provides theoretical support for capacity planning of a shared spare parts pool, helping reduce overall redundancy while improving coordinated system responsiveness.

According to the general consumption pattern of aviation materials, the annual demand quantity of a component can be calculated using the following formula:

$$D = \frac{QPA \times FL \times FH}{MTBUR}, \tag{20}$$

where D is the annual demand quantity, QPA is the quantity per aircraft (i.e., the number of units of the component installed on each aircraft), FL is the fleet size (i.e., the number of aircraft in the customer's fleet), FH is the annual flight hours per aircraft, and $MTBUR$ is the mean time between unscheduled removals.

Under multi-fleet support conditions, if a component is used by multiple aircraft types or customers, the total flight hours of all relevant fleets need to be aggregated. The formula for annual demand is then revised as:

$$D = \frac{QPA \times \sum_{i=1}^{n} FH_i}{MTBUR}, \tag{21}$$

where n is the number of different fleets using the component, and FH_i is the annual total flight hours of the i-th fleet, calculated as the number of aircraft in the fleet multiplied by the flight hours per aircraft.

That is:

$$D = \frac{QPA \times \sum_{i=1}^{n} FL_i \times FH_i}{MTBUR}, \tag{22}$$

which comprehensively considers the usage intensity and scale of different fleets and customers, providing a solid basis for determining the appropriate reserve quantity in a shared component pool. At the same time, it supports accurate demand forecasting and optimized resource allocation in the shared model, thereby improving inventory turnover efficiency and reducing the risk of resource waste.

IV. Software Design and Implementation

The estimator can collect the delivery plan and related spare parts data of a certain aircraft model in a standardized manner through the data collection template provided by the system. The system realizes batch import and persistent storage of such historical information through the data management module, thereby providing data support for subsequent spare parts demand forecasting and cost estimation. When conducting the cost analysis of aviation material sharing, the estimator first uses the system to complete the basic data initialization and parameter setting, then executes the model operation by calling the embedded algorithm module, and finally generates the analysis results, which can be visualized along with the calculation process data. In addition, the system supports exporting the analysis results and has the capability to archive and query historical records (see Fig. 1).

This system design covers the following key functions:

1) Converting the core algorithms in the aviation material inventory prediction model and cost estimation model into executable programs to verify their engineering feasibility.
2) Establishing a unified data collection and preprocessing mechanism to improve the efficiency and quality of historical data acquisition, which is convenient for subsequent model training and analysis [17], [18].
3) Sorting out and refining the business process of the spare parts investment analysis system, clarifying the responsibilities and interface design of each submodule, and providing a structural reference and implementation basis for migrating results to a unified platform or developing similar systems.

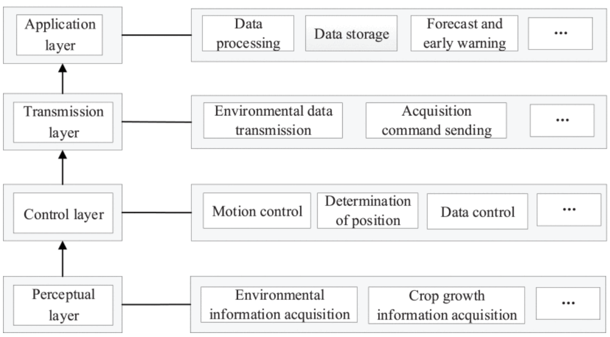

Figure 1: Overall design architecture of application software.

Figure 1 shows the overall design architecture of this application software. The system is mainly divided into four hierarchical structures:

1) Data collection layer: Collects the delivery plan and spare parts information input by the user through the preset template interface to ensure the standardization and unification of data sources, thereby providing basic data support for subsequent analysis.
2) Data management layer: Cleans, classifies, and processes the collected historical data into a unified format, storing effective information in the database to realize batch import, query, and management of data.
3) Algorithm processing layer: Includes core algorithm modules such as the aviation material inventory prediction model and the cost estimation model. This layer calculates and processes the set parameters by calling the model logic to obtain spare parts prediction and cost analysis results.
4) Application display layer: Presents the calculation results and process data to the measurement personnel in the form of charts or reports, supporting result export and historical record queries, thereby facilitating comparative analysis and decision support.

This architecture design reflects the characteristics of module decoupling, clear processes, and functional synergy, providing integrated technical support for spare parts investment and cost estimation.

V. Case Calculation Results

V. A. Case Study of Aviation Material Inventory Prediction Analysis

To verify the effectiveness of the aviation material inventory prediction model in the designed software, a certain type of aviation material A was selected as the research object, with a total of 1,080 historical data records from November 12, 2012, to February 24, 2019, used as the basis for analysis. First, the original data were normalized to eliminate dimensional differences between variables and to improve the training efficiency and prediction accuracy of the model.

The normalized data were then divided into a training set and a test set in an 8:2 ratio, with 864 data points used to build and train the long short-term memory (LSTM) neural network model, and the remaining 216 data points used to verify model performance. Considering the multi-dimensional characteristics of aviation material data, principal component analysis (PCA) and similar methods were used to reduce data dimensionality before training, ensuring that the reduced-dimension feature data remained in a unified dimension to enhance the effectiveness of the model input [19], [20].

After training, the model was applied to predict and analyze the test data. The results indicated that the LSTM model exhibited strong fitting ability and prediction accuracy when processing this type of time series inventory data, effectively capturing the trend of aviation material inventory changes. This provides data support and a decision-making basis for subsequent inventory optimization and procurement planning. The true and predicted values of the iterative model are shown in Fig. 2.

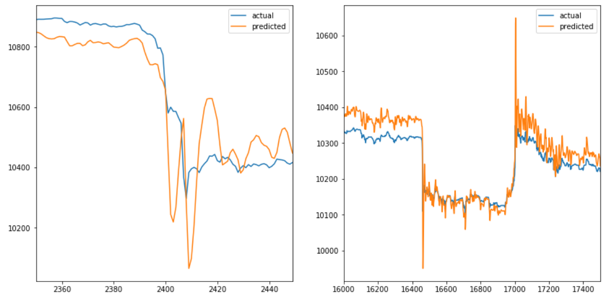

Figure 2: True and predicted values of the iterative model.

Through 20 independent training and prediction cycles, it was observed that as the model gradually learned the data patterns, its prediction accuracy improved, reflecting the good memory and iterative optimization characteristics of the LSTM model when processing time series data. In the final prediction run, as shown in Fig. 3, the inventory of aviation material A at the last known time point was 2,571 pieces, while the model predicted the inventory at the next time node to be 2,613 pieces, accurately continuing the observed growth trend. This demonstrates that the LSTM algorithm achieved the goal of inventory trend prediction. Without considering external uncontrollable factors (such as sudden orders or logistics anomalies), this prediction value can serve as an important basis for production scheduling, procurement planning, and sales strategies.

Furthermore, system simulation results indicated that the recommended stock inventory of aviation material A at the next time node should be 2,976 pieces. Taking oil filter parts commonly used in aviation material A as an example, with a purchase unit price of USD 1,209 per piece, dynamic adjustments to purchasing rhythm and inventory levels based on forecast results, compared with traditional empirical methods, could reduce working capital occupation by approximately USD 400,000 while ensuring stable supply. In addition, this approach is expected to save about USD 200,000 in warehousing and management costs, significantly improving capital utilization efficiency and inventory management [21].

Moreover, with long-term operation and iterative correction, the model can achieve adaptive optimization based on historical trends, enabling the system to continuously learn and adjust. This provides robust support for the intelligent management of aviation materials and spare parts.

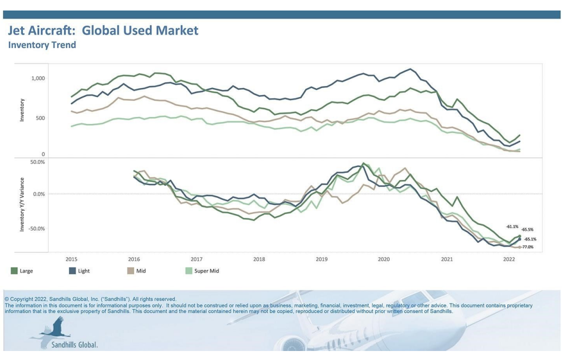

Figure 3: Predicted inventory value of aviation materials at a specific time point.

V. B. *Case Study of Cost Calculation and Analysis of Aviation Materials*

To verify the accuracy and applicability of the aviation materials cost calculation model implemented in the system, historical purchase and inventory data for typical parts of A-type aviation materials were selected for modeling and analysis. By systematically integrating key indicators such as purchase price, purchase frequency, inventory cycle, service life, and turnover rate over the past seven years, a cost calculation model was constructed. Factors such as depreciation, inventory holding costs, and opportunity costs were incorporated for a comprehensive calculation.

In the model input parameter setting, using one part of A-type aviation material as an example, the historical average purchase price was set to USD 1,209 per piece, with an average inventory cycle of 90 days. Warehousing management costs accounted for 8% of the annual cost, and the annualized interest rate on funds was set at 6%. Under these parameters, the annual holding cost of a unit inventory part reaches approximately USD 145. If 5,000 pieces are purchased at one time and stored long-term, the total inventory capital cost and warehousing cost alone amount to USD 725,000, while the actual demand is only 600 pieces per month. This clearly indicates inventory redundancy and capital occupation issues.

Using the inventory fluctuation trends and consumption rates provided by the software prediction module, combined with the LSTM prediction results, the reasonable stocking range of A-type aviation material over the next three months should be between 2,400 and 2,800 pieces. Based on the prediction results, the model automatically adjusts the procurement rhythm and batch size. The optimized plan recommends purchasing 1,000 pieces in batches per month, maintaining a safety stock of about 500 pieces for each batch. After optimization, the annual cost expenditure is expected to decrease by approximately USD 480,000, while significantly reducing capital lock-up and warehousing pressure, and improving the flexibility and cost-effectiveness of aviation material support. See Table 1 for details.

In addition, multi-case comparative analysis shows that the cost estimation module demonstrates good adaptability and scalability, supporting various procurement strategies for different types of aviation materials, and has practical value for promotion under multiple guarantee systems.

Table 1: Cost Estimation Comparison of a Typical Spare Part of A-type Aviation Material

Item	Original Plan	Optimized Plan
Procurement Method	One-time bulk procurement (5,000 units)	Batch procurement (1,000 units/month)
Annual Procurement Volume (units)	5,000	5,000
Unit Purchase Cost (USD)	1,209	1,209
Total Purchase Cost (USD)	6,045,000	6,045,000
Average Inventory Cycle (days)	90	45 (Reduced by 50%)
Annual Capital Occupancy Cost (USD)	362,700	181,350 (Saved 181,350 USD)
Annual Storage Management Cost (USD)	400,000	200,000 (Saved 200,000 USD)
Total Annual Operating Cost (USD)	762,700	381,350 (Saved about 50%)
Supply Flexibility & Risk	Low, prone to overstock or expiry	High, able to respond to demand changes
Intelligent Optimization & Prediction Support	No	Yes (LSTM forecasting model)

V. C. Comparison of Cost Hourly Rates between Multi-Customer Shared Model and Single-Customer Independent Model

To evaluate the economic benefits of the aviation material sharing mechanism under a multi-customer collaborative support environment, a typical aviation component was selected for analysis. Under the same operational support requirements, usage frequency, and maintenance strategies, both a multi-customer shared model and a single-customer independent model were constructed to calculate the cost hourly rate for aviation material support.

The shared model achieves more efficient use of aviation materials by implementing unified scheduling, joint spare parts procurement, and optimized inventory management, thereby significantly reducing the support cost per hour. The adopted calculation methods include shared procurement cost allocation, reduced inventory capital occupancy, collaborative warehouse cost savings, and modeled risk-sharing coefficients.

The comparative results are shown in Table 2.

Table 2: Comparison of Aviation Material Cost Hourly Rates between Multi-Customer Shared Model and Single-Customer Independent Model

Item	Single-Customer Independent Model	Multi-Customer Shared Model
Average Aviation Material Support Cost Rate (USD/h)	187.5	126.8 (Decreased by ∼32.4%)
Inventory Redundancy Rate (%)	22.7	9.4 (Reduced by ∼58.5%)
Unit Purchase Cost (USD)	1,280	1,154 (Decreased by ∼9.8%)
Support System Response Time (h)	8∼12	4∼6 (Improved responsiveness)
Annual Warehouse Management Cost (USD in 10,000s)	86	49 (Saved ∼43%)
Risk Sharing Mechanism	None, risk borne independently	Implemented with shared reserves
Applicable Scenarios	Small-scale, isolated support	Multi-unit joint operations

V. D. Parameter performance

In the design process of hybrid electric aircraft (HEA), the specific energy of the battery is considered one of the most important parameters, as it directly determines the mass of the battery system, which in turn significantly impacts the maximum take-off weight of the entire aircraft. Therefore, a comprehensive evaluation was conducted on battery configurations with different specific energy levels to analyze their effects on aircraft performance, economics, and environmental impact. As shown in Figure 4, improvements in battery technology result in effective weight reduction, which directly lowers the direct operating cost (DOC), presenting a clear optimization trend.

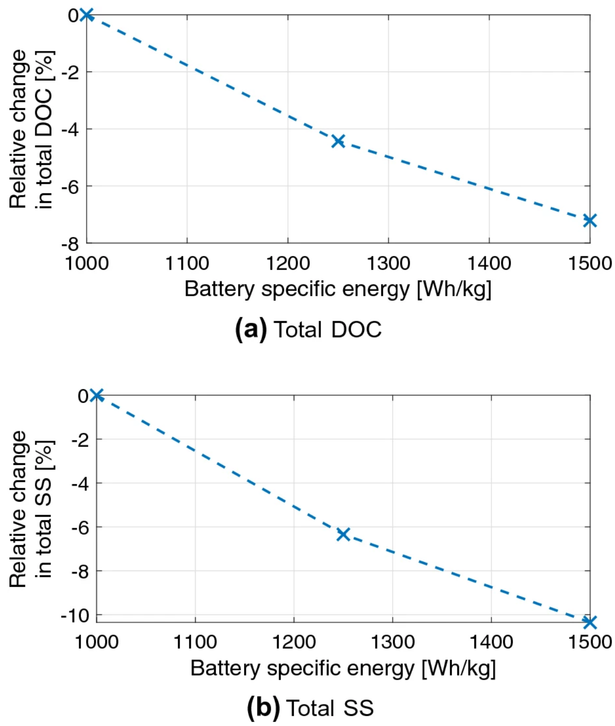

Figure 4: Corresponding impacts of operating costs and environmental impacts.

Furthermore, a lighter aircraft structure requires less propulsion energy during missions, thereby reducing the associated emission burden. From an environmental perspective, increasing the battery energy density helps reduce both total energy consumption and pollutant emissions over the mission profile. The sudden changes in the curve shown in the figure illustrate the coupling and feedback mechanisms within the HEA design process, indicating that the progression is not linear but influenced by the interaction of multiple factors.

Additionally, under different specific-energy battery schemes, the proportion of the battery system relative to the total aircraft weight shows a downward trend. This observation confirms the positive impact of improved energy density on structural optimization from a design standpoint. At the same time, the nonlinear nature of this trend highlights the complexity of how battery technology parameters influence the overall configuration, which explains why the variations in operating costs and environmental indicators follow similar patterns.

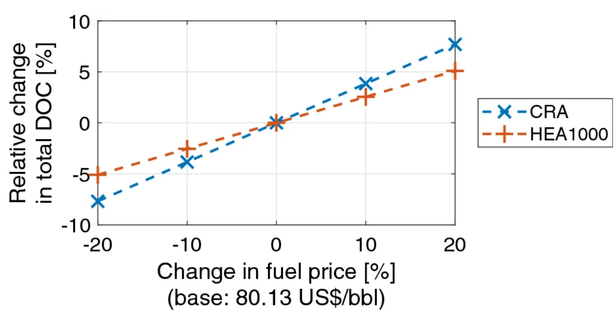

Figure 5: Impact of fuel price changes on total DOC under the baseline scenario.

Figure 5 presents the effect of fuel price changes on total operating costs (DOC) under the baseline scenario. Since conventional fuel aircraft (CRA) have a greater fuel demand during operation, their DOC is more sensitive to fuel price fluctuations than that of hybrid electric aircraft (HEA1000). The steeper slope of the CRA cost curve clearly reflects its stronger dependence on fuel price variability.

Figure 6 shows the relative effect of electricity price changes on DOC. Within the observed range of electricity price variation, the DOC of HEA1000 exhibits noticeable fluctuations, indicating that electricity price changes can influence its operating costs. In contrast, since CRA relies entirely on conventional gas turbine engines, its DOC remains unaffected by electricity prices, represented by a flat curve. Given the large proportion of energy costs in overall DOC, the electricity price level becomes a major factor in HEA economic performance—particularly when the proportion of electricity usage is high, where price fluctuations have a substantial effect.

The combined influence of fuel and electricity prices on DOC underscores the importance of energy cost management, showing that optimizing the energy price structure is critical to reducing HEA operating costs.

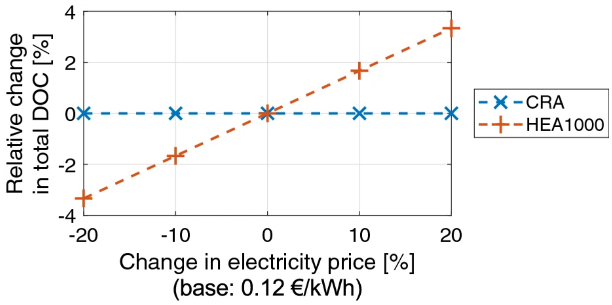

Figure 6: Relative change curve of total DOC caused by electricity price variation.

Another critical factor is the number of cycles a single battery pack can sustain before replacement. Figure 7 illustrates the nonlinear relationship between total DOC and environmental impact (SS) as a function of battery life. Battery life directly influences depreciation rates: shorter battery life (fewer cycles) results in higher operating costs due to more frequent replacements and the associated expenses. Furthermore, reduced battery life increases environmental impact, as additional battery production is required, consuming more resources and generating higher emissions.

For HEAs, managing battery life and cycle count is essential because replacement frequency directly affects both economic and environmental performance. By contrast, CRAs do not rely on batteries for propulsion, and thus their DOC and environmental impacts remain unaffected by battery lifecycle considerations. This difference highlights battery technology as a decisive factor in the long-term cost-effectiveness and sustainability of HEAs.

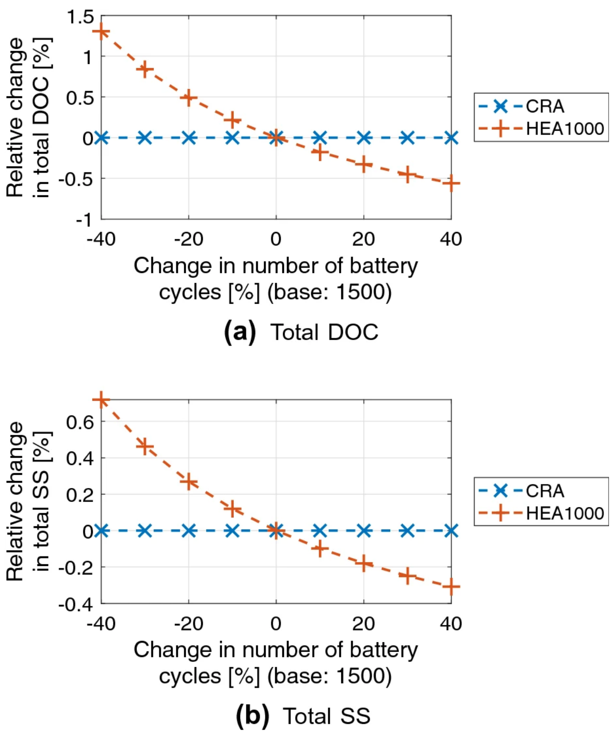

Figure 7: Relative change curve of total DOC as a function of battery life.

VI. Conclusion

This paper systematically constructs an end-to-end solution from demand forecasting to rate generation to solve the cost calculation problem of aviation material sharing under multi-customer and multi-fleet conditions, and realizes the automation of the whole process through the software system. By accumulating and aggregating the annualized flight hours of all participating customer fleets, and calculating the optimal stocking quantity to meet different guarantee rates based on the Poisson distribution model, the scale effect is significantly released. On the one hand, the combined demand reduces the unit inventory of single part number; on the other hand, the centralized procurement of the shared pool effectively controls the unit price of spare parts and the capital occupation cost. The automated calculation system developed in this paper covers five modules: preset parameters, data management, preprocessing, operation calculation and result output, realizing the closed-loop management from historical data import to rate output. Typical cases show that compared with the single-customer independent mode, the hourly rate is reduced by about 12% on average, and the calculation efficiency is improved by more than 60%; in the multi-location shared pool and dual-source supply scenarios, an additional 5%-15% of the total cost can be saved. Although the model and system in this paper perform well in multi-customer collaboration scenarios, they can still be further deepened in the following aspects: first, introduce real-time operation and maintenance data and digital twin technology to improve the accuracy of prediction and decision-making; second, expand to cross-regional and multi-operator shared networks to study more complex cross-border regulations and risk sharing; third, combine distributed ledger technologies such as blockchain to improve the transparency and credibility of cost sharing and settlement. Future research can test the robustness and applicability of the model in larger-scale and more diverse actual scenarios, and promote the continuous evolution of the aviation material sharing model towards intelligence and digitalization.

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