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AI Technology Portfolio Framework for Demand Forecasting Management in Aviation Supply Chains

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Abstract. Demand forecasting is of great significance in aviation supply chain management, and its precision affects the inventory level, procurement time, and operating expenses. However, the present forecasting techniques employed in the aviation sector rely on a single method that fails to account for demand variations, seasonal changes, and supply disruptions. From the aspect of technology management, this paper proposes an AI technology portfolio structure for demand forecasting in the aviation supply chain. By analyzing a Bombardier case, the research comprehensively examines the feasibility and management constraints of different AI techniques, such as deep learning, LSTM, and transformers, under various demand conditions. The framework focuses on choosing and organizing proper AI technique combinations based on the data maturity and the organizational and managerial complexities instead of concentrating on the particular algorithms. According to the literature concerning supply chain prediction and AI application, the main factors influencing the technology selection and the performance of its use are recognized. The results provide beneficial advice for the aviation supply chain managers to utilize AI forecasting technology in complex demand situations.

Keywords: demand forecasting, aviation, supply chain management, machine learning

1. Introduction

In the period after the epidemic, the aviation industry encounters two kinds of difficulties, namely significant changes in demand and limited working capital. The advancement of artificial intelligence has introduced the idea of Supply Chain 4.0 management, which stresses the reduction of waste and the optimal distribution of resources through data openness [1]. Nevertheless, the conventional forecasting techniques based on statistical models and the estimation of flight hours are not capable of detecting the nonlinear relationship between the operation intensity and the loss of components, and one kind of algorithm is insufficient to deal with various situations. The enterprises do not have a systematic evaluation method for choosing AI tools, and the data separation among the stakeholders is disadvantageous for companies with low maturity. This paper aims to investigate the way to choose the appropriate AI prediction models to improve the accuracy and decrease the AOG risk under different levels of data maturity and organizational complexity.

Research on aviation spare parts demand forecasting has evolved from traditional statistical methods to machine learning and deep learning. Existing studies point out that the core goal of forecasting is to balance inventory backlog from over-forecasting and downtime risk from under-forecasting [2]. Empirical comparisons show traditional models remain competitive for highly irregular data, while ensemble learning has obvious advantages in capturing nonlinear patterns [3]. The Bootstrap method has verified high flexibility in intermittent demand and has been applied to decision support systems to reduce AOG risk [4]. For deep learning, ANN models with momentum terms can effectively avoid local optimization for block demand of safety-critical parts [5]. LSTM also significantly outperforms linear models such as ARIMA in dealing with demand uncertainty and volatility [6]. Transformer architecture, the latest progress, shows more significant comparative advantages with stronger data sparsity [7]. It also achieves dual improvements in prediction accuracy and computing efficiency in multi-echelon supply chain networks [8]. Besides, an ensemble learning framework with non-overlapping sliding windows can improve prediction accuracy [9].

Existing literature analyzes aviation demand forecasting from the perspective of algorithm accuracy comparison and single model optimization, but there are research gaps in dynamic model selection logic and organizational adaptation conditions for managers. Taking Bombardier's after-sales demand forecast as a case, this paper maps AI models to nine strategic quadrants via a nine-quadrant matrix matching and A/B two-dimensional evaluation. It concludes that no model is universally optimal, and the best choice is always a dynamic fit. Theoretically, this paper introduces matching logic between model requirements and organizational capabilities, incorporating management complexity into technology selection. Practically, it provides operable AI selection tools for aviation enterprises to help improve forecast accuracy, reduce AOG risk, and promote cross-organizational collaboration.

2. Research methodology

2.1. Two-dimensional evaluation system and unified scoring logic

This study aims to build a dynamic selection framework of AI technology portfolio for aviation supply chain demand forecasting management. Its core innovation is establishing a unified evaluation logic, which can determine both the capability quadrant of an enterprise and the condition quadrant required to run an AI model. That is, enterprises and AI models are evaluated under the same dimensional framework, with directly comparable results. This design allows managers to match their scores with AI models' demand profiles after self-assessment to achieve accurate technology selection. Each AI prediction model has inherent and quantifiable requirements for data maturity and organizational and management complexity. The two dimensions are divided into high, medium, and low levels, combined into nine strategic quadrants. Mainstream AI models are mapped to corresponding optimal quadrants to output a matching matrix for managers' technology selection.

This study designs a two-dimensional evaluation system. One is the diagnosis of the current ability of enterprises, and the other is the definition of the operating conditions of the AI model. Dimension A is data maturity, covering five evaluation criteria: data accessibility and integrity, integration standards and interoperability, data quality, governance and security, and Explainability. Dimension B is organizational and management complexity, covering five evaluation criteria: process and change management, strategy and leadership, talent and culture, supplier ecosystem collaboration, compliance and auditing. A. Five criteria in each of the two dimensions of B form a symmetrical evaluation framework to ensure that enterprises and AI models achieve comparable

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evaluation in the same ten-dimensional space. Detailed descriptions of the evaluation criteria are shown in Table 1.

Table 1. Detailed descriptions of the evaluation criteria

Criterion	Description	AHP weight	Key assessment points
A1	Data Accessibility and Integrity	0.28	Historical data depth, coverage scope, component heterogeneity, and asset utilization records
A2	Integration Standards and Interoperability	0.20	Unified data protocols and the capacity to bridge legacy systems
A3	Data Quality	0.20	Accuracy of data entry, structural integrity, and timeliness of ingestion
A4	Governance and Security	0.12	Cross-enterprise privacy control, IP protection, and secure data sharing
A5	Explainability	0.20	Deployment of verifiable and auditable supervised learning frameworks
B1	Process and Change Management	0.22	Structural alignment of existing workflows with AI decisions and organizational inertia
B2	Strategy and Leadership	0.20	Executive-level consensus on digital transformation and formal technology roadmaps
B3	Talent and Culture	0.24	Workforce analytical literacy, change readiness, and cross-departmental communication
B4	Supplier Ecosystem Collaboration	0.18	Incentive design for external suppliers and cross-stakeholder asset visibility
B5	Compliance and Auditing	0.16	Algorithmic auditing mechanisms, fairness controls, and supply chain safety compliance

The criteria are scored on a five-point scale, based on the analytic hierarchy process to decompose complex problems into hierarchical structures, construct judgment matrices, calculate weight vectors, and ensure rationality via consistency tests. Four experts from Airbus Singapore and Nanyang Technological University formed the evaluation team for weight determination. A comprehensive score ≥ 4.0 is judged as high grade, 2.5–3.9 as medium grade, and below 2.5 as low grade. For enterprise evaluation, the team calculates weighted scores based on actual situations to determine their A/B level combination. For AI models, the panel rates each criterion based on technical features. For example, LSTM scores 5 on data accessibility and integrity, while linear regression scores 2. Each model calculates its A/B score via the same formula and falls into the corresponding demand quadrant.

2.2. AI model matching matrix

Based on the above unified A/B scoring logic, this study systematically evaluated each type of model to obtain a nine-quadrant matching matrix, as shown in Table 2. The high data maturity quadrant recommends deep sequence models, the medium data maturity quadrant recommends integrated learning models, and the low data maturity quadrant recommends lightweight interpretable models or simulation tools. This step-by-step matching relationship shows that the technical complexity of the model should evolve synchronously with the database and organizational capabilities of the enterprise. In practical applications, substitute the item-by-item

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score to calculate the comprehensive score. After determining its own quadrant, refer to the matching matrix to obtain the recommendation model, and finally fine-tune it in combination with specific business objectives.

Table 2. Nine-quadrant matching matrix

Enterprise quadrant	Recommended AI models	Matching logic
High A - High B	Transformer, LSTM, etc.	Complete data foundation and strong organizational coordination support computationally intensive models requiring cross-functional collaboration.
High A - Medium B	Attention mechanisms, deep learning, etc.	Sufficient data with moderate coordination; models can automatically extract features with limited human intervention.
High A - Low B	EBM, hybrid rule-deep learning, etc.	Mature data with flat organization, requires high explainability for fast independent decision-making.
Medium A - High B	Supervised learning with SHAP, XGBoost with enhanced explainability, etc.	Medium data with organizational momentum, requires explainable outputs to build managerial trust.
Medium A - Medium B	Random Forest, LightGBM, etc.	Medium data and organization, robust and fault-tolerant models
Medium A - Low B	Simplified ensemble learning, lightweight GBDT, etc.	Medium data and simple management, pursues rapid deployment and low maintenance cost.
Low A - High B	Simple linear/logistic regression, rule engines, etc.	Fragmented data with strategic commitment; models must be highly transparent to compensate for data limitations.
Low A - Medium B	Few-shot learning, transfer learning, etc.	Limited data with some organizational support, can leverage external pre-trained knowledge.
Low A - Low B	Croston method, SBA, Bootstrap, AnyLogistix simulation, etc.	Highly fragmented data and early-stage organization, prioritizes statistical baseline methods and process optimization over complex algorithms.

3. Bombardier aftermarket demand forecasting

3.1. Case study design

To verify the nine-quadrant matching matrix, Bombardier was selected as an in-depth single case. Bombardier is the world's leading manufacturer of commercial aircraft, with more than 4800 active aircraft and more than 70000 spare parts in more than 15 locations around the world. Its after-sales department serves corporate flight departments, partial ownership plans, and charter operators. Until 2020, Bombardier relied on traditional Croston-based forecasting software that required frequent manual adjustments and produced inconsistent results. In September 2020, Bombardier worked with IVADO Lab to develop a machine learning-based forecasting system, which was deployed in February 2021 [10]. After weighted calculation using the ten criteria and their AHP weights, Bombardier's scores are obtained as shown in Table 3. Thus, Bombardier is positioned in the High A – Medium B quadrant.

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Table 3. Bombardier A/B diagnostic results

Dimension	Assessment	Score	Final level
Data Maturity	Historical transaction data, flight data integrated, unified ERP/MRO, some regional data fragmentation	4.2/5.0	High A
Organizational and Management Complexity	Cross-functional coordination across planning, maintenance, and IT, global operations, high explainability demand	3.8/5.0	Medium B

3.2. Recommended AI models and alignment

According to the matching matrix, a deep learning or attention-enhanced ensemble is recommended for High A – Medium B quadrants, which utilizes rich data while matching moderate organizational abilities. Bombardier's solution is an LGBM ensemble with a rotatable elastic mesh and a Croston-style decomposition for consumables, which falls into this category. Two constraints calibrate its complexity to Medium B rather than High B. Firstly, the team needs a high degree of interpretability to gain the support of planners. Tree-based integration provides clear functional importance, while black-box deep models lack an approved XAI workflow. Secondly, the project schedule for 2020-2021 is earlier than the mature MLOps of industrial deep learning, resulting in excessively high maintenance costs. Therefore, Bombardier's selection confirms the high A-to-B alignment, which means that with abundant data, the model complexity should fit the management readiness, indicating that the best AI option relies on the compatibility between data maturity and organizational limitations.

3.3. Forecast performance comparison

By using time series cross-validation, Bombardier evaluated its ML-based systems against the old software, as indicated in Table 4. The ML-based system shortened the runtime from about 30 hours to 8 hours, which is a 73% decrease. These results indicate that the ensemble portfolio suggested by the High - High quadrant brings significant operational advantages compared to the traditional methods.

Table 4. Accuracy results

Metric	Legacy software	RML ensemble	Improvement
Rotable Parts, RML Framework			
RMSSE (error)	0.55	0.51	-7.3%
Unbiased NFB (% within threshold)	72.4%	77.5%	+7.0%
Overforecast reduction	-	-	-49.5%
Expendable Parts, IML Framework			
RMSSE (error)	0.55	0.49	-10.9%
Unbiased NFB (% within threshold)	69.2%	74.2%	+7.2%
Overforecast reduction	-	-	-32.4%

In May 2026, this study carried out face-to-face interviews with two independent experts in Singapore, namely a senior Airbus supply chain manager for APAC spare parts planning and an NTU professor specializing in AI-based supply chains. The interviews reveal three main points. Firstly, the true obstacle is not the availability of algorithms but the lack of trust in the predictions

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made by black-box models by the front-line planners. Secondly, the wrong choice of model results in very high expenses, because deep learning may increase the maintenance burden by five times and be discarded easily. Lastly, the general idea of using only one static model is detrimental, and the best method should fit the data, personnel, and processes of each firm. The professor also mentioned that the academic comparisons on public datasets do not consider the actual business situations, which supports the framework from various aspects.

4. Conclusion

This paper presents a dynamic AI technology portfolio framework for aviation supply chain demand forecasting. The main point is that there is no one suitable artificial intelligence model for all cases. Depending on the data maturity and the organizational and management complexity of the enterprise, an appropriate model should be chosen. A 9xN matching matrix is used as a selection tool for the enterprise. The Bombardier case confirms this framework: their tree-based combination, due to the interpretability and technical limitations from 2020 to 2021, reduces the RMSSE by 7-11%, increases the unbiased prediction by 5-7%, and shortens the running time by 73% compared to the conventional methods. These results show that the preparation of management and the implementation restrictions have a greater effect on the application of artificial intelligence models than the algorithm accuracy itself, thus giving useful advice for the aviation supply chain managers.

This research eliminates the main difference between the algorithm effectiveness in the AI prediction literature and the actual implementation by companies. It regards management complexity as an independent factor, puts forward the matching theory between the demand side and the supply side of the model, and improves the accuracy compared with that of a single algorithm. In fact, it decreases the trial-and-error expenses for large companies and offers a simple entry-level method for the digital transformation of immature suppliers. From the environment standpoint, the enhanced accuracy can reduce the number of emergency airlifts and obsolete waste. Further studies should expand the structure to include real-time dynamic quadrant changes, confirm its validity in other industries with intermittent demands, and incorporate the matching matrices into the aviation ERP/MRO systems for direct application.

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