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Supply-Demand Matching Estimation with Machine Learning in Airline Planning Process

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Abstract

Airline companies operate in a highly competitive and uncertain environment where efficient resource allocation is essential for maximizing economic performance and supporting sustainability objectives. One of the major challenges in airline planning is matching aircraft capacity with uncertain passenger demand while maintaining operational efficiency. This study proposes a machine learning-based decision support framework that integrates demand uncertainty with aircraft tail assignment. Three nonlinear regression models—Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel, Polynomial Regression, and Random Forest Regression—were employed to predict flight-based economic returns using real-world airline operational data, including aircraft type, passenger demand, and cargo volume. In addition, a bounded prediction mechanism incorporating aircraft capacity constraints was introduced to ensure operational feasibility. Model performance was evaluated using R^2, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and cross-validation. At the end of the study, all three regression models achieved a high accuracy rate in representing the data, but the SVR-RBF model performed best. Furthermore, the proposed framework allowed for the determination of demand thresholds for optimal aircraft type selection, contributing to increased economic efficiency and reduced unnecessary capacity utilization. The findings demonstrate that machine learning-based predictive models can effectively support airline planning processes and indirectly contribute to sustainability goals.

Keywords: Aircraft Tail Assignment, Machine Learning, Supply-Demand Matching, SVR, Random Forest, Airline Planning, Sustainability

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1. Introduction

Because passenger demand is unpredictable, one of the fundamental challenges in airline operations is the efficient allocation of resources. To maximize economic returns while taking operational constraints into account, airlines must allocate their limited aircraft resources in a way that ensures optimal returns for scheduled flights. This decision-making process, which is generally addressed during schedule planning and operational control stages, becomes particularly complex under demand uncertainty. In this context, one of the most critical problems is the aircraft fleet and tail assignment problem, which involves matching aircraft types with varying capacities, operating costs, and revenue potentials to fluctuating passenger and cargo demand (Glomb et al., 2024; Moreno et al., 2023).

Mismatches between supply (aircraft capacity) and demand may lead to significant economic losses due to either underutilized capacity or unmet demand. Furthermore, inefficient aircraft assignments may result in unnecessary fuel consumption, thereby negatively affecting environmental sustainability (Glomb et al., 2024; Justin et al., 2022). Since each aircraft has different carrying capacities, flight-based costs and revenues may vary depending on the aircraft type. In other words, a bounded prediction mechanism incorporating aircraft capacity constraints should be applied to ensure operational feasibility; there is a minimum and maximum weight an aircraft could carry, so the predicted income value can not pass this maximum and minimum weights' income value. When there is a significant discrepancy between forecasted and actual demand, airlines may need to reconsider their aircraft assignment planning (Moreno et al., 2023). Because airlines experience economic losses when such optimization is not properly performed, planning according to demand using the appropriate aircraft type and tail assignment is of critical importance.

Traditional approaches to fleet and tail assignment problems have largely relied on deterministic optimization models (Abara, 1989; Barnhart et al., 2002). Later, stochastic and robust optimization methods were developed to incorporate uncertainty into the decision-making process (Kleywegt et al., 2002; Sherali & Zhu, 2008). Although these methods provide strong theoretical foundations, they may encounter computational complexity and scalability problems when applied to large-scale airline networks.

Recent advances in machine learning (ML) have introduced data-driven approaches capable of capturing complex nonlinear relationships in large datasets (Geursen et al., 2023; Paul et al., 2024; Singh et al., 2023; Vos et al., 2023; Yazıcı et al., 2023). ML-based regression models have increasingly been used for demand forecasting and revenue prediction in airline operations. However, studies integrating ML-based predictions with aircraft assignment decision support processes remain limited, especially in terms of comparative analyses of different nonlinear models (An Aircraft Assignment Decision Support is a data-driven algorithmic tool used by airlines to map specific aircraft to scheduled flights,

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maintenance events). It optimizes complex operational variables to ensure safety, minimize costs, and maximize fleet utilization

This study aims to address this gap by proposing a machine learning-based framework for supply-demand matching in airline planning. In this context, three nonlinear regression models—Support Vector Regression (SVR) with an RBF kernel, Polynomial Regression, and Random Forest Regression—are used to forecast flight-based economic returns based on demand parameters. In contrast to conventional methods, the suggested framework incorporates operational constraints into the model via a constrained prediction process, guaranteeing that the model's outputs stay in line with aircraft capacity restrictions.

This study's primary contributions can be summed up as follows: (i) comparison of nonlinear machine learning models for economic return prediction in airline operations; (ii) incorporation of a capacity-constrained prediction approach into an ML-based decision support system; and (iii) contribution to sustainability and economic efficiency by identifying demand thresholds for the best choice of aircraft type.

The rest of this paper is structured as follows: The pertinent literature is reviewed in Section 2, the technique is presented in Section 3, the results are discussed in Section 4, and conclusions and future study suggestions are given in Section 5.

2. Literature Review

The best use of airlines' resources is critical to their ability to gain a competitive advantage. Assigning aircraft—an airline's most critical resource—to flights involves a forecasting-based planning process. Aircraft allocation decisions are typically determined not only based on operational performance metrics but also on passenger and cargo demand forecasts (Glomb et al., 2024; Moreno et al., 2023). However, airline demand is inherently volatile due to various external factors such as economic fluctuations, pandemics, and geopolitical developments. This variability can sometimes lead to significant discrepancies between the demand forecasted at the flight base and actual demand. It causes mismatches between supply (aircraft capacity) and demand, leading to complex optimization problems and negatively impacting airline performance (Glomb et al., 2024; Moreno et al., 2023; Justin et al., 2022).

Sustainability has become a key element of airline operations, covering economic, environmental and social aspects. The correct aircraft type for each flight is important for optimizing the economic return and for reducing the fuel consumption and the carbon emissions (Kiracı et al., 2026**;** Martín-Domingo et al, 2025; Yildiz et al., 2026). Inaccurate demand forecasts lead to suboptimal aircraft assignment decisions, which can result in excess fuel consumption and increased emissions. Thus, the difference between the demand and the capacity of aircraft directly affects the achievement of sustainability goals in airline operations (Martín-Domingo et al, 2025; Yildiz et al., 2026; Karanki et al., 2026).

To address demand uncertainty, machine learning (ML) methods have increasingly been utilized in airline planning processes. ML models can learn complex patterns from historical data and generate accurate demand forecasts, which can subsequently be integrated into aircraft assignment decision processes (Geursen et al., 2023). Unlike traditional statistical approaches, machine learning techniques can model nonlinear relationships and interactions among variables. Due to these capabilities, ML approaches provide more effective results in dynamic and uncertain environments. Among the commonly used ML algorithms for regression problems are Support Vector Regression (SVR), Polynomial Regression, and Random Forest, which is one of the ensemble learning methods.

Support Vector Machines (SVM) are widely used supervised learning models that are applicable to both classification and regression problems. In regression applications, SVM is called Support Vector Regression (SVR) and it tries to find the optimal hyperplane that minimizes the prediction error and maximizes the margin. SVR can model nonlinear relationships by using kernel functions to map data to higher dimensional spaces. Among these, the Radial Basis Function (RBF) kernel is one of the most widely used due to its flexibility in capturing complex patterns (Smola et al., 2004; Dezsö et al., 2023; Omrani et al., 2024; Zheng et al. 2024).

Polynomial regression is an approach that incorporates polynomial terms into the regression function to model nonlinear relationships between dependent and independent variables. This method increases model flexibility and enables better representation of curvilinear data structures compared to linear models (Arslankaya & Toprak, 2021; Wu et al. 2025). Also, Random Forest is an ensemble learning method that uses a set of decision trees and is very good at handling high dimensional data and complex interactions. It also reduces overfitting problems by aggregating the outputs of individual trees (Ghattas & Manzon 2023; Maduranga, 2024; Vinod et al. 2024).

The aircraft assignment (fleet assignment) problem has been extensively addressed in literature since early studies such as Abara (Abara, 1989). Initial studies mainly focused on deterministic optimization models based on fixed demand assumptions. However, because these models fail to adequately represent real-world uncertainty, they may generate suboptimal solutions under operational conditions (Abara, 1989; Barnhart et al., 2002; Lohatepanont & Barnhart 2004). To overcome this limitation, stochastic and robust optimization approaches were developed. Two-stage stochastic programming models have been widely utilized. In these models, aircraft assignments are made in the first stage, while assignments are optimized in the second stage according to different demand scenarios. Although these models improve decision quality, they suffer from rapidly increasing computational complexity as the flight network grows (Glomb et al., 2024; Moreno et al., 2023; Kenan et al., 2017; Liu et al., 2023).

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In recent years, the number of studies integrating machine learning models for demand forecasting with aircraft assignment optimization under uncertainty has increased rapidly (Geursen et al., 2023; Paul et al., 2024; Vos et al., 2023) However, the existing literature generally addresses either demand forecasting or optimization problems separately, while studies integrating these two components remain limited. Furthermore, comparative analyses of SVR (RBF kernel), Polynomial Regression, and Random Forest algorithms in the context of aircraft assignment and sustainability are still scarce.

Research Gap and Contribution

The literature reveals limited studies that: (i) address demand uncertainty using machine learning models, (ii) integrate these predictions into aircraft assignment decisions, and (iii) evaluate the outcomes from a sustainability perspective.

In particular, the comparative performance of SVR (RBF kernel), Polynomial Regression, and Random Forest algorithms within such an integrated framework has not been sufficiently examined.

Accordingly, this study aims to fill this gap by proposing a model that integrates demand forecasting and aircraft assignment problems using three different machine learning algorithms. The proposed approach not only improves supply-demand matching but also contributes to sustainability objectives by reducing fuel consumption and carbon emissions. In this respect, the study may provide both methodological and practical contributions to the airline operations management literature.

3. Methodology

3.1 Problem Definition

The aircraft assignment problem with uncertain demand is to find the best aircraft type for a particular flight to maximize the economic return, while meeting the operational constraints. Passenger demand is stochastic in nature and affected by various external factors such as economic conditions, seasonality and market dynamics. This uncertainty makes it difficult to find a balance between aircraft capacity and actual demand.

In this study, the problem is posed as a supervised regression problem. The goal is to predict the economic return of a flight based on demand-related features. Based on these estimations, a decision support mechanism is developed for the determination of the most appropriate aircraft type for various demand levels.

3.2 Dataset Description and Preprocessing

The dataset used in this study is based on a real airline operation. It contains the observations of flights of a specific route during the period of 2021–2022. Each observation contains:

- Aircraft type
- Number of business class passengers
- Number of economy class passengers
- Cargo quantity (kg)
- Economic return (USD)
- Feature Representation

Unlike the original formulation, aircraft type is treated as a categorical variable and encoded using one-hot encoding to avoid introducing artificial ordinal relationships.

Data Cleaning

Domain specific filtering rules were used to remove outliers and inconsistent observations (e.g. flights with high demand but negative returns). There were no missing values in the dataset.

Feature Scaling

All numerical features were standardized using z-score normalization:
$x' = (x - \mu) / \sigma$
x: data
μ: mean
σ: standard deviation

This makes sure that all features contribute equally to the learning process, especially for distance-based models such as SVR.

3.3 Model Framework

To model the complex relationship between demand variables and economic returns, three non-linear regression models were employed:

Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel, Polynomial Regression, Random Forest Regression.

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3.3.1 Support Vector Regression (SVR)

SVR aims to find a function f(x) that deviates by at most ϵ (epsilon) by considering data points located at a certain distance from each other by creating a hyperplane.

SVR Estimator Function

$f(x)= \sum_{i=1}^{n} (\alpha i-\alpha i^*) \,.\, K(xi \,,\, xj)+b$
αi,αi*: Lagrange multipliers obtained from training.
b: the bias term
K(xi,xj): kernel function
xi , xj : data points

RBF Kernel Fonksiyonu:

$K(xi,xj)=\exp(-\gamma\|xi-xj\|2)$
γ (gamma): a hyperparameter that controls the width of the RBF kernel

3.3.2 Polynomial Regression

Polynomial regression models nonlinear relationships by expanding the feature space:

$$y = \beta 0 + \beta 1\ x + \beta 2\ x2 + \beta 3\ x3 + ... + \beta n\ xn + \varepsilon$$

The degree of the polynomial is selected based on validation performance.

3.3.3 Random Forest Regression

It is an ML algorithm that combines the prediction values of two or more decision trees to prevent overfitting;

$$\hat{y}(x) = \frac{1}{T} \sum_{t=1}^{T} ht(x)$$

where (T) is the number of trees and (ht(x)) represents the prediction of each tree.

3.4 Hyperparameter Optimization

To ensure fair comparison and optimal performance, hyperparameters of all models were tuned using Grid Search with 5-fold cross-validation:

SVR: (C, γ , ϵ)

Random Forest: number of trees, max depth, min samples split Polynomial Regression: polynomial degree The best parameter combination was selected based on cross-validation RMSE.

3.5 Capacity-Constrained Prediction

To ensure that predictions remain consistent with real operational constraints, a bounded prediction function is introduced:

$\hat{Y}_i^{bounded} = \min(\max(\hat{y}i, L(xi)), U(xi))$
Where:

(L(x)): minimum feasible economic return
(U(x)): maximum achievable economic return based on aircraft capacity

These bounds are derived from historical observations for each aircraft type and reflect capacity limitations.

3.6 Model Evaluation

For model evaluation, data was divided into 80% training and 20% testing. Additionally, a 5-fold cross-validation test was applied to improve model robustness. Model performance was determined using the following tools (Setiadi et al., 2023; Akıl et al., 2024; Gao, 2023; Rajawat, 2022).

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

3.7 Decision Support Mechanism

Based on the predicted economic returns, the optimal aircraft type for a given demand scenario is selected as follows:

$\text{Aircraft}^* = \text{argmax}_k \ \hat{y}_k(x)$
where k is the different types of aircraft.

Such an approach allows identifying the demand thresholds at which switching between different aircraft types would result in higher economic returns and provides actionable decision-support insights for airline planners.

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4. Results and Discussion

4.1 Model Performance Comparison

The predictive performance of the three machine learning models—SVR with RBF kernel, Polynomial Regression, and Random Forest Regression—was evaluated using both hold-out test data (80:20 split) and 5-fold cross-validation. The results for the A–B and B–A routes are presented in Tables 1 and 2.

Table 1 Scale values for the 80%-20% training-test ratio for the A-B flight route

	MSE	RMSE	MAE	R^2
SVR RBF KERNEL	0.0247	0.1572	0.0864	0.9754
POLYNOMIAL REGRESSION	0.0573	0.2394	0.1412	0.9430
RANDOM FOREST REGRESSION	1.0385	1.0190	0.6446	0.9699

Source: Authors' calculations

Table 2 Scale values for the 80%-20% training-test ratio for the B-A flight route

	MSE	RMSE	MAE	R^2
SVR RBF KERNEL	0.0218	0.1476	0.0881	0.9759
POLYNOMIAL REGRESSION	0.0530	0.2303	0.1696	0.9415
RANDOM FOREST REGRESSION	0.2634	0.5132	0.1122	0.9709

Source: Authors' calculations

Across both routes, all models demonstrate strong predictive capability, as indicated by high (R^2) values (above 0.94). This indicates that the nonlinear machine learning models can learn the complex relation between demand variables and economic return.

The best of the evaluated models is the SVR with the RBF kernel, which always outperforms the others with the lowest error metrics (MSE, RMSE, MAE) and the highest (R^2) values. The performance was due to the ability of the RBF kernel to capture highly nonlinear relationships by projecting the input space into a higher dimensional feature space. Polynomial regression also performs competitive but slightly less accurate with SVR. This might be because its global functional form does not account for local non-linearities in demand-revenue relationships. Random Forest Regression has higher error metrics but relatively high (R^2) values. This might be due to its sensitivity to data distribution and the tendency of overfitting in some parts of the feature space despite its ensemble structure.

4.2 Robustness and Generalization

The consistent performance of training and testing indicates that all the models can generalize well on unseen data. The robustness of the models is further confirmed using cross-validation and reduced risk of overfitting. Especially, SVR has a good generalization ability because of its structural risk minimization principle. This makes the method particularly suitable for airline demand modeling where data can be noisy and highly variable.

4.3 Impact of Capacity-Constrained Prediction

In particular, the bounded prediction function is critical to bring the model outputs in accordance with the operational limits of the real-world system. Without this constraint, machine learning models could generate unrealistic estimates of economic returns beyond the bonds of aircraft capacity. The model has lower and upper bounds from historical data to ensure that predictions are operationally feasible. This greatly enhances the practical value of the proposed framework for real-world airline planning applications.

4.4 Demand Threshold Analysis and Aircraft Switching

Demand thresholds for aircraft type switching were identified using the best performing SVR model. The results (Tables 3 and 4) suggest that the aircraft assignment decision is not only driven by the capacity level but also by the marginal economic return of the various demand segments.

For example, the switch from narrow-body to wide-body aircrafts only happens when passenger increases are large enough to generate sufficiently higher economic returns. This result shows that capacity expansion does not always ensure profitability and can lead to inefficient use of resources if demand is not matched properly.

Table 3. Demand Threshold Levels from Point A to Point B

TYPE	BUSINESS CLASS	ECONOMY CLASS	CARGO QUANTITY
TYPE 3 (NARROW)	16	135	0
TYPE 4 (NARROW)	16	152	0
WIDE BODY	16	218	0

Source: Authors' calculations

Tablo 4 Demand Threshold Levels from Point B to Point A

TYPE	BUSINESS CLASS	ECONOMY CLASS	CARGO QUANTITY
TYPE 3 (NARROW)	16	135	0
TYPE 4 (NARROW)	16	149	0
WIDE BODY	20	215	0

Source: Authors' calculations

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4.5 Managerial Implications

The proposed framework has several important implications for the airline decision makers:

- It enables flight-level, data-driven aircraft assignment decisions in the face of uncertain demand.
- It reduces the risk of over-capacity deployment and thus improves cost efficiency.
- It enables decision making in real time or near to real time especially during the phases of operational planning.
- It improves revenue optimization by finding economically optimal demand-capacity matches.

4.6 Sustainability Implications

The model is mainly oriented to economic return but its indirect contribution to sustainability is remarkable. The model prevents unnecessary capacity increases and therefore, excess fuel consumption and related carbon emissions. This fits well with the increasing focus on sustainable aviation activities, where operational efficiency is a key factor in reducing environmental impact. Future extensions of the model could include explicit emission calculations to further strengthen this contribution.

4.7 Comparison with Existing Literature

The results of this study are in line with the recent literature emphasizing the effectiveness of machine learning applications in airline operations. In contrast to many previous studies that focus only on demand forecasting or optimization, this study integrates prediction and decision support.

The proposed approach has higher computational efficiency and flexibility than the traditional deterministic and stochastic optimization models and is thus more suitable for real-time applications. In addition, a bounded prediction mechanism incorporating aircraft capacity constraints was applied to ensure operational feasibility; there is a minimum and maximum weight an aircraft could carry, so in the study the predicted income value was limited to this maximum and minimum weights' income value. Reinforcement learning and deep learning approaches provide more dynamic decision-making capabilities but require larger datasets and more computational costs.

5. Conclusions and Future Studies

This paper proposes a machine learning based framework for supply–demand matching in airline planning by considering demand uncertainty in aircraft assignment decisions. Unlike traditional optimization-based methods, the proposed method estimates flight-level economic returns using nonlinear regression models and supports decision-making through a prediction-driven mechanism.

Three machine learning algorithms namely Support Vector Regression (SVR) with RBF kernel, Polynomial Regression and Random Forest Regression have been evaluated using real world airline data. The results show that all models generate high prediction accuracy which confirms the effectiveness of machine learning techniques to deal with complex nonlinear relationships between demand variables and economic performance.

The RBF kernel SVR model was always better than the other models in terms of prediction accuracy and generalization ability. This suggests that kernel-based methods are especially well-suited for modeling the nonlinear dynamics of airline demand and revenue structures. One of the key contributions of this paper is the development of a prediction approach for capacity constraints that guarantees that the model outputs are consistent with real operational constraints. The model's constraint feature prevents unrealistic predictions from being generated, thereby providing a practical decision-support framework.

Furthermore, this study demonstrates that the decision to change the aircraft type assigned to a flight is not solely dependent on the aircraft's load factor but also requires an assessment of the marginal economic return. The identification of demand thresholds for aircraft type changes in the model provides practical, actionable data, thereby enabling optimal resource allocation. In addition to the economic considerations, the proposed framework contributes indirectly to the sustainability agenda. The model improves fuel efficiency by preventing capacity increases that do not yield economic benefits. This, in turn, contributes to sustainability goals by reducing carbon emissions.

In addition to its strengths, the model also has limitations. The data covers a single flight pair and a specific time. Furthermore, the study does not account for variables such as pricing strategies, competition, and macroeconomic conditions. Additionally, the impact on sustainability has been assessed only indirectly. Future research could take this study further. First, the generalizability of the study could be increased with more data and flight pairs. Second, studies integrating machine learning models with other optimization approaches could provide a more comprehensive decision support framework. Thirdly, determining and incorporating fuel consumption and carbon emissions into the model would strengthen the sustainability aspect. Finally, the research framework can be expanded to include dynamic planning, disruption management, weather uncertainty, or real-time operational optimization.

In conclusion, this study demonstrates that machine learning-based forecasting models can contribute to planning processes by improving airlines' supply-demand matching decisions. The proposed framework offers an easy-to-implement, scalable, and data-driven approach that has the potential to enhance the economic efficiency and operational sustainability of the airline industry.

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