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Flight Delay Prediction with Airport Traffic Density Data from an Aviation Risk Management Perspective

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Abstract

Flight delays are significantly important in risk management for the aviation industry, impacting airline operations, passenger satisfaction, and air traffic management. While existing studies primarily focus on weather-related factors in flight delay prediction, this study explores the influence of airport traffic density on delays from an aviation risk management perspective. Using data mining techniques, the study integrates airport traffic and en-route delay datasets from EUROCONTROL to develop predictive models for delay estimation. The methodology follows a structured approach, including data preprocessing, feature engineering, clustering, and predictive modeling using the Random Forest algorithm. The findings indicate that airport traffic density is a critical predictor of delays, alongside seasonal and regional factors. Regression analysis highlights a strong correlation between congestion levels and delay severity, particularly in peak travel periods. The clustering results reveal four distinct delay patterns, reflecting variations in operational disruptions due to equipment failures and adverse weather conditions. The Random Forest model demonstrates high predictive accuracy, with low error rates confirming its robustness for delay estimation. This study contributes to aviation risk management by providing data-driven insights into flight delays and offering strategic decision-making tools for airline and airport operators. The results emphasize the need for proactive delay mitigation strategies, such as improved airspace allocation and enhanced maintenance processes. Future research could extend this approach by incorporating additional delay factors, such as incident-related disruptions, to further enhance predictive capabilities. By integrating operational data and advanced analytics, this study presents a novel framework for improving delay forecasting and optimizing flight operations.

1. Introduction

Flight delays encountered in the aviation sector constitute a significant problem for both airline companies and passengers. Flight delays can cause operational costs to increase for airline companies, passenger satisfaction to decrease, and air traffic service providers to encounter certain complexities in airspace management. In addition, flight delays can cause operational congestion and confusion for airport operators. In the literature, flight delay predictions have been examined by analyzing weather data that directly affects flight timings (Dursun, 2023; Fernandes et al., 2020; Gui et al., 2019). On the other hand, operational factors such as traffic density at an airport can also have a significant impact on delays. Especially in large and busy airports, traffic congestion experienced during the landing and take-off phases of flight operations is considered as one of the crucial factors that prevent flights from taking place on time.

Risk management in the aviation sector is considered a particularly important process to ensure the safety, efficiency, and sustainability of flight operations. Risk management requires proactive measures to minimize the negative effects that operational disruptions, air traffic density, weather variables, and technical failures may cause. Operational risks such as flight delays can cause significant costs and service disruptions for airlines, airport operators and passengers. Therefore, an effective risk management process analyzes the causes of delays, develops preventive strategies, and optimizes operational processes. In addition, the use of advanced analysis techniques such as data mining and artificial intelligence provides important support to decision makers in decision processes by making risk estimation more precise. In this context, the development of risk management applications in aviation is especially important for the development of both sectoral practices and academic research.

The aim of this study is to analyze the relationship between airport traffic density and flight delays in detail using data mining techniques and to perform multi-dimensional evaluations by estimating delays based on this relationship. While flight delays are generally estimated with weather data in the literature (Zhao et al., 2024; Schultz et al., 2021; Qu et al., 2020), this study investigates, the effect of airport traffic density data on delays will be investigated in addition to weather data, and in this context, comprehensive delay models will be created by taking into account factors such as airport landing and take-off traffic, ground handling density and aircraft waiting times.

The study will make significant contributions to both the literature and the managerial practices in the aviation sector. Research investigating the effects of operational factors other than weather conditions on delays are quite limited in the literature, and this study aims to fill the gap in the literature and provide a unique perspective on delay estimation. In addition, the study will provide airline companies and airport managers with opportunities to develop strategies to increase operational efficiency by creating new decision-support tools and mechanisms in air traffic management. Estimating flight delays is a particularly critical issue in terms of optimizing operational processes, reducing costs, and increasing passenger satisfaction. In this regard, the study will enhance both existing literature and practical applications in the sector by introducing a novel approach to flight delay estimation.

In the literature, the topic of delay prediction in the aviation sector has received attention in recent years with numerous studies investigating various data mining and machine learning techniques to increase accuracy and reliability. These studies focus on predictive modeling approaches based on spatiotemporal data features, causal factors, and various aviation applications.

Zhang et al., (2020) and Jiang et al., (2022) analyzed the causes of flight delays with spatiotemporal data mining and graph-based models, and Zhu et al., (2024) and Jiang et al., (2024) developed flight delay predictions model by focusing on air traffic congestion and flight network effects.

While (Fernandes et al., 2020) used the logistic regression method to examine operational inefficiencies that cause flight delays, (Zeng et al., 2021) proposed an optimization model to reduce flight delays by taking operational uncertainties into account. Truong, (2021) evaluated flight delay risks with causal machine learning techniques and determined the underlying causes of flight delays. In addition, Zhao et al., (2024) examined flight delays caused by airspace demand-capacity imbalances, Binias et al., (2020) evaluated the effects of human factors on flight operations by addressing pilots' reaction processes with neurological analyzes.

In addition, flight delays and their consequences have been discussed in the literature with multi-step prediction models. Zhang et al., (2021) and Reitmann & Schultz, (2022) developed multi-step prediction models with spatiotemporal analysis to optimize air traffic management, while Luo et al., (2021) and Zhang et al., (2023) used graph-based techniques (graph convolutional networks (GCN)) to analyze flight delays. In addition, Cai et al., (2022) used time-evolving graph models to predict flight delays in the context of dynamic air traffic.

The effects of weather conditions on flight delays have been discussed in the literature. (Esmaeilzadeh et al., 2020) focused on identifying patterns in historical flight and weather data to increase the prediction accuracy in flight delays, while Schultz et al., (2021) and Ma et al., (2024), which examined the direct and indirect effects of weather conditions on flight delays, focused on reducing flight delays by applying agent-based modeling and simulation methods. In addition, Gui et al., (2019), Wang et al., (2021) and Qu et al., (2020) tried to increase the prediction accuracy in flight delays by combining air traffic and meteorological data.

Studies in the literature show that machine learning and big data analytics play a critical role in flight delay prediction. In addition, the integration of spatial-temporal analytics and operational factors increases efficiency and forecast accuracy in air traffic management.

2. Materials and Methods

The datasets used in this study consist of two main sources, “En-route IFR Flights and ATFM Delays (FIR)” (EUROCONTROL, 2024) and “Airport Traffic” (EUROCONTROL, 2024), published by EUROCONTROL (European Organization for the Safety of Air Navigation), an international organization that coordinates air traffic management (ATM) in Europe and aims to use airspace effectively and efficiently by optimizing air traffic flow. These datasets are considered to be of critical importance in terms of in-depth examination of the relationship between flight delays and airport traffic density.

The “En-route IFR Flights and ATFM Delays (FIR)” (EUROCONTROL, 2024) dataset covers Instrument Flight Rules (IFR) flights and Air Traffic Flow Management (ATFM) delays on specific routes. IFR flights are defined as flights coordinated by air traffic control under adverse weather conditions or when visual references are insufficient. ATFM delays are delays that occur on routes due to reasons such as airspace capacity limitations, disruptions in air traffic management and operational restrictions. The “Airport Traffic” (EUROCONTROL, 2024) dataset includes information on airport-based landing and take-off operations and the traffic density associated with them. Airport traffic is related to airport capacity and is considered the main cause of delays during heavy traffic periods. These two datasets aim to reveal the effect of airport traffic density on delays by analyzing different dimensions of flight delays. These data, provided on a daily basis, provide more meaningful and up-to-date information in terms of short-term planning and operational decisions. Daily forecasts can optimize flight delay management by evaluating the instantaneous effects of factors such as airspace capacity and ground handling. In addition to all this, daily fluctuations in flight traffic and delays are analyzed in detail to predict possible delays.

The data mining process consists of four stages: data understanding, data preparation, modeling, and evaluation (Gui et al., 2021). In the first stage, Data Understanding, delay data and airport traffic density data will be combined with spatial-temporal features. (Zhang et al., 2021) emphasized in their studies that flight delays vary according to time, location, and seasonal factors and stated that spatial-temporal data fusion is a critical step in terms of delay estimation. This method will allow the development of unique models for each airport and route. In the second stage, Data Preparation, the Automated Feature Engineering (AFE) method will be used. (Liu et al., 2024) showed that AFE offers a significant advantage in automatically creating meaningful and interpretable features. Thanks to this method, the data preparation process will be accelerated and the features required for analysis will be created systematically. In the third stage, Modeling, the Random Forest (RF) method was preferred. RF is quite successful in modeling nonlinear relationships and shows effective performance on structured data sets without requiring stationarity. Sarveswararao et al., (2023) stated that RF achieves lower Symmetric Mean Absolute Percentage Error (SMAPE) in time series predictions compared to Long-Short Term Memory (LSTM) models and captures complex data structures better. In the last stage, Evaluation, the performance of the model will be evaluated multidimensionally using cross-validation and various error metrics. Jiang et al., (2020) emphasized that cross-validation helps prevent overfitting in large data sets. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics will be used to measure model performance. These metrics are critical for evaluating the generalization ability and predictive accuracy of the model.

2.1. Data Understanding and Preparation

In the data preparation phase, the "En-route IFR Flights and ATFM Delays (FIR)" and "Airport Traffic" datasets were merged, cleaned, and made suitable for analysis. From the "Airport Traffic" dataset, the "Country Daily Airport Summary Dataset" was created based on flight operational information such as departures (FLT_DEP_1), arrivals (FLT_ARR_1) and total flights (FLT_TOT_1). This dataset includes daily operational flight data for each region. The "En-route IFR Flights and ATFM Delays" dataset provides data classified according to the reasons for the delays on the route (accident/incident, weather, equipment, environmental problems, other, etc.). In the data integration phase, the two datasets were merged based on the variables (FLT_DATE) and (STATE_NAME). This process ensured that the flight operations were consistently matched with the delay criteria. In addition, column names were rearranged to ensure naming standards between data sets and the structure obtained by merging the two datasets was made suitable for analysis and modeling. The missing data problem was considered as a critical issue when evaluated over total flight or delay times. In this study, a zero-input strategy was adopted to process missing data. In line with this strategy, the consistency of the data was preserved by replacing the empty values with zeros and a complete data set was obtained. In the feature engineering phase, a series of derived features were created to better analyze the causes and patterns of flight delays. For temporal analyses, time-based features such as year, month, day, weekday, and week of the year were obtained from the flight date (FLT_DATE). In order to measure the density of the airspace, the traffic density metric was developed and the ratio of total flights to departures (FLT_TOT_1 / FLT_DEP_1) was calculated. In order to evaluate the prevalence of delays, the delay ratio was derived using the ratio of delayed flights to total flights. To reduce the skewness in the distribution of the data, logarithmic transformation was applied to the total delay time (DLY_ERT_1) and a log-transformed total delay feature was created. In addition, the average delay per flight was calculated to develop the average delay metric and obtain an intuitive measure of the delay severity. As a result of all these steps, an enriched dataset containing the original and derived features was created. The final dataset was saved as "Merged_Country_Daily_Data_Optimized.csv" to be used in the modeling phase. This file provides a strong basis for developing forecasting models by providing comprehensive features regarding flight operations and delays.

2.2. Data Exploration

During the data exploration phase, various analyses were performed to understand the temporal patterns of flight delays and to improve model performance. In this context, temporal feature engineering was applied and the trends of delays in certain periods were evaluated. Within the scope of temporal feature engineering, temporal variables such as year, month, weekday, and season were derived from the flight date. These features enabled the analysis of seasonal and monthly trends in delays and allowed the model to capture short- and long-term temporal changes. For example, it was observed that flight delays peaked in the summer months due to increased traffic density and in the winter months due to adverse weather conditions. This analysis also paved the way for the development of category-specific delay estimates. Regression analysis results are shown in Table 1.

Table 1. Regression Analysis Results

Delay Category	Adjusted R^2	Significant Predictors	Coefficient t (β)	P-value
DLY_ERT_A_1	0.78	Traffic Density	2.01	<0.01
		Log-Transformed Total Delay	1.56	<0.01
		Season (Summer Indicator)	0.43	0.02
DLY_ERT_E_1	0.82	Traffic Density	2.13	<0.001
		Log-Transformed Total Delay	1.74	<0.001
		Average Delay	0.87	0.003
		Season (Winter Indicator)	0.51	0.015
DLY_ERT_W_1	0.78	Traffic Density	1.90	<0.01
		Log-Delay (DLY_ERT_W_1)	1.84	<0.001
		Temporal Feature (Month Indicator)	0.41	0.002

Regression analyses allowed the determination of the effect of traffic density on delays and category-specific models. It was found that traffic density had a strong effect on all types of delays. In peak periods, inadequate capacity of air traffic management causes delays to increase. In category-specific analyses, factors such as accidents and incidents (DLY_ERT_A_1), equipment failures (DLY_ERT_E_1) and weather conditions (DLY_ERT_W_1) were examined. It was observed that delays due to accidents and incidents (DLY_ERT_A_1) increased during the summer months when traffic was heavy. However, the absence of specific accident records in the data set in this category prevented further analysis. This category was excluded from the study due to the lack of details such as the frequency, severity, and operational impact of the accidents. To provide a comprehensive and reliable analysis, only categories with sufficient data were focused on. Accordingly, (DLY_ERT_E_1) (delays due to equipment failures) and (DLY_ERT_W_1) (delays due to weather conditions) categories were selected. This selection was supported by the strong statistical significance and high adjusted R-squared values obtained as a result of regression analyses. It was observed that delays due to equipment failures increased especially in winter months; this situation was associated with adverse weather conditions, increasing equipment fragility or complicating maintenance processes.

Delays due to weather conditions reached their peak levels in winter months when visibility was low and adverse weather effects were intense.

2.3. Clustering

In this study, the aim is to create strategic solutions for delay management by separating delay models into homogeneous groups. Cluster analysis process includes data pre-processing, feature selection, scaling, determination of optimum number of clusters and visualization of results. In the Data Preprocessing stage, temporal indicators and delay measures were used. Temporal indicators were formed from variables such as weekday, weekend indicators, month, and season. In addition, criteria such as delay rates and log-transformed delay values belonging to (DLY_ERT_E_1) and (DLY_ERT_W_1) categories were included in the clustering process. In the Feature Selection and Scaling step, temporal indicators and delay measures were evaluated together. These features were scaled using the Standard Scaler method and thus the differences between numerical data and binary indicators were balanced. Elbow Method and Silhouette Scores were used to determine the optimum number of clusters. As shown in Figure 1, the Elbow Method plot shows that the within-cluster sum of squares (WCSS) decreases significantly at k = 4. This point represents the critical threshold above which additional clusters provide limited improvement on compactness.

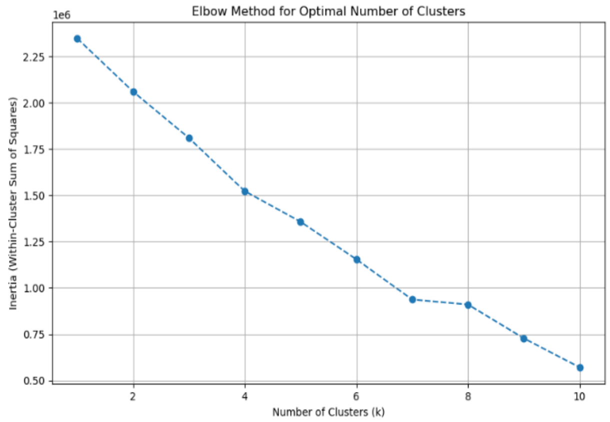


Figure 1. Elbow Method for optimal number of clusters

The analysis results regarding the silhouette scores are presented in Figure 2. Although the silhouette score has the highest value for k = 2, this poses a risk of oversimplification. While the score drops significantly with k = 3, it is seen that the scores stabilize, and the clustering quality improves after k = 4. As a result of these analyses, it was determined that k = 4 clusters are the optimum number of clusters.

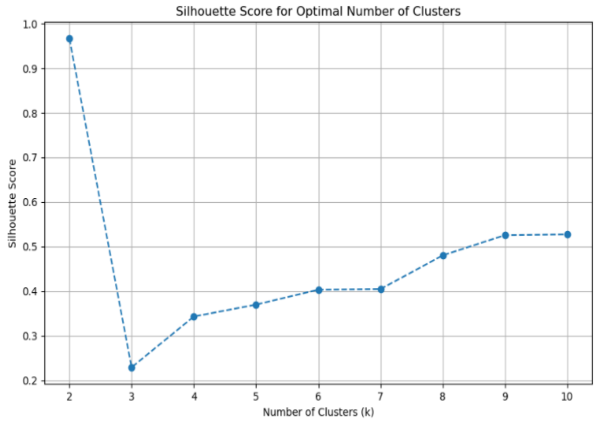


Figure 2. Silhouette Score for optimal number of clusters

The clustering process was performed using the k-Means algorithm and the data was divided into four clusters. Cluster labels were added to the data set as a new column. Principal Component Analysis (PCA) was applied to visualize the clustering results in two dimensions and the results are shown in Figure 3. In the PCA plot, Cluster 0 and Cluster 3 show a clear separation, while partial overlaps are observed between Cluster 1 and Cluster 2. This shows that there are some common features among the delay models.

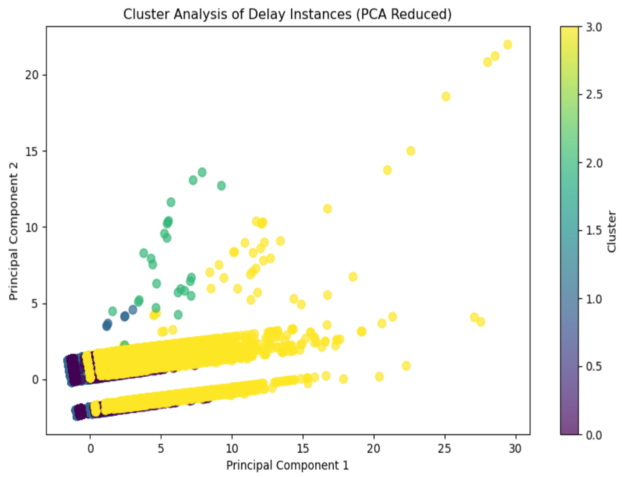


Figure 3. Analysis of Delay Instances

In the Figure 4, a heat map is created showing the average values of each cluster within the scope of Cluster Feature Analysis. Cluster 0 represents efficient operations with low delay rates. Cluster 1 stands out with serious delays due to equipment failures, where delays (DLY_ERT_E_1) are effective. Cluster 2 reflects the winter months, where delays due to weather conditions are high. Cluster 3 is characterized by high delays observed in the summer months due to increased air traffic.

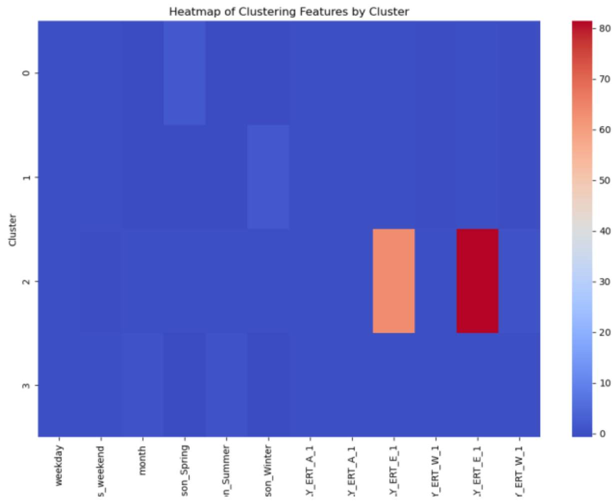


Figure 4. Heatmap of Clustering Features by Cluster

2.4. Train-Test Splitting and Homogeneity Testing

In the training and test set splitting process, it was aimed to represent clusters and geographic regions proportionally. In the Feature Preparation stage, temporal features (weekday, weekend, month, and seasonal indicators) and category-specific features (DLY_ERT_E_1) and (DLY_ERT_W_1) log-transformed lag values) obtained from the previous clustering analysis were reused. In addition, cluster labels were included in the data set as additional features. In the Data Stratification step, a new column named "stratify_col" was created by combining the variables STATE_NAME (geographic region) and Cluster (lag category segmentation). This stratification provided a balance of both geographic and cluster distributions in the training and test sets. The data set was split into training and test sets in a ratio of 80/20. Figure 5 and Figure 6 show the cluster distributions in the training and test sets for the categories (DLY_ERT_W_1) and (DLY_ERT_E_1), respectively. The graphs confirm that both delay categories are proportionally represented in the training and test sets.

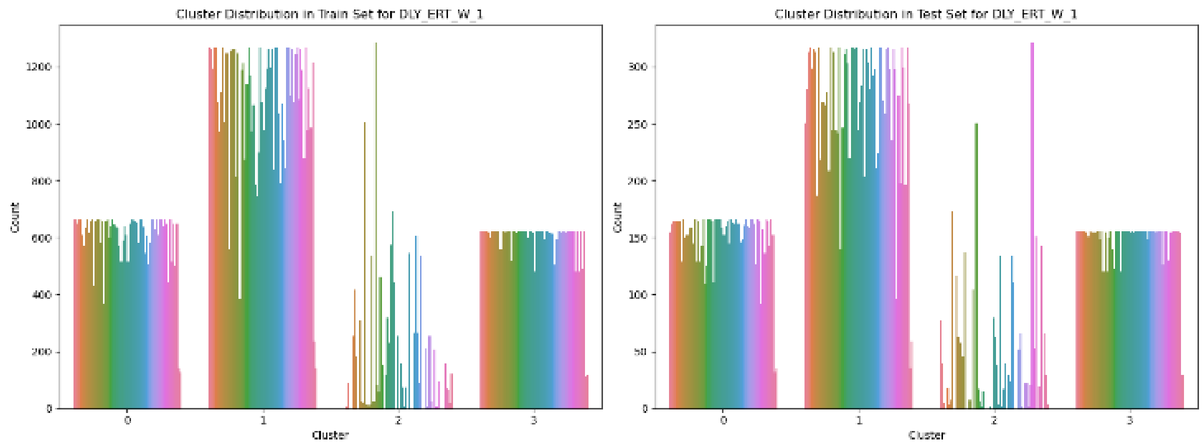


Figure 5. Distributions of training and test set clusters for DLY_ERT_W_1

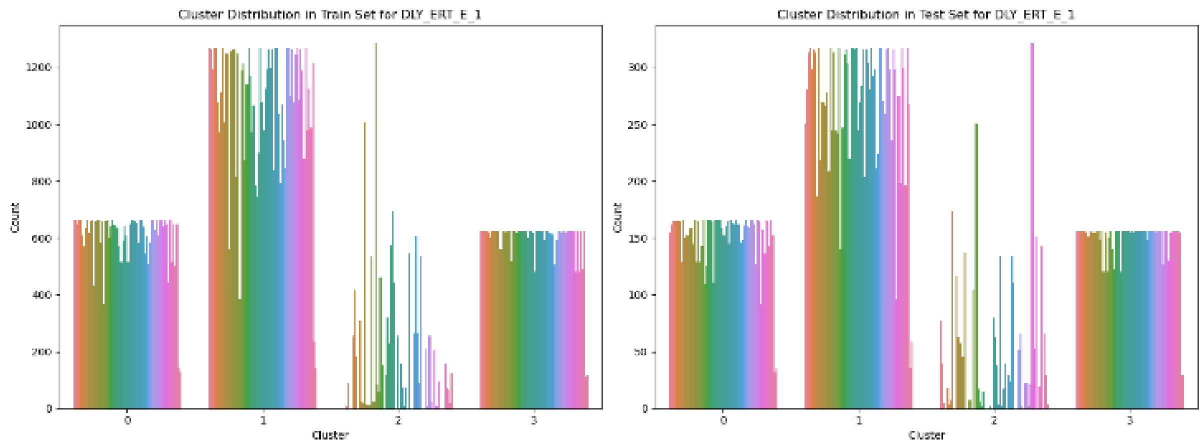


Figure 6. Distributions of training and test set clusters for DLY_ERT_E_1

Homogeneity tests were performed to verify the statistical homogeneity of the training and test sets. For the distribution comparison, the distributions of the Cluster and STATE_NAME variables in the training and test data sets were visualized with bar graphs. Figure 7 and Figure 8 show the distributions for (DLY_ERT_W_1), and Figure 9 and Figure 10 show the distributions for (DLY_ERT_E_1). It is seen in the graphs that both clusters and geographical regions are distributed equally in the training and test sets.

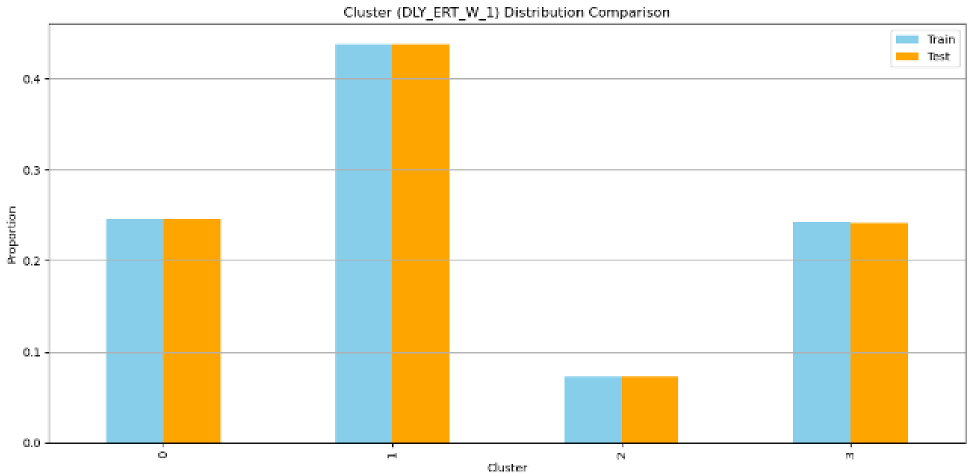


Figure 7. Cluster distributions for DLY_ERT_W_1

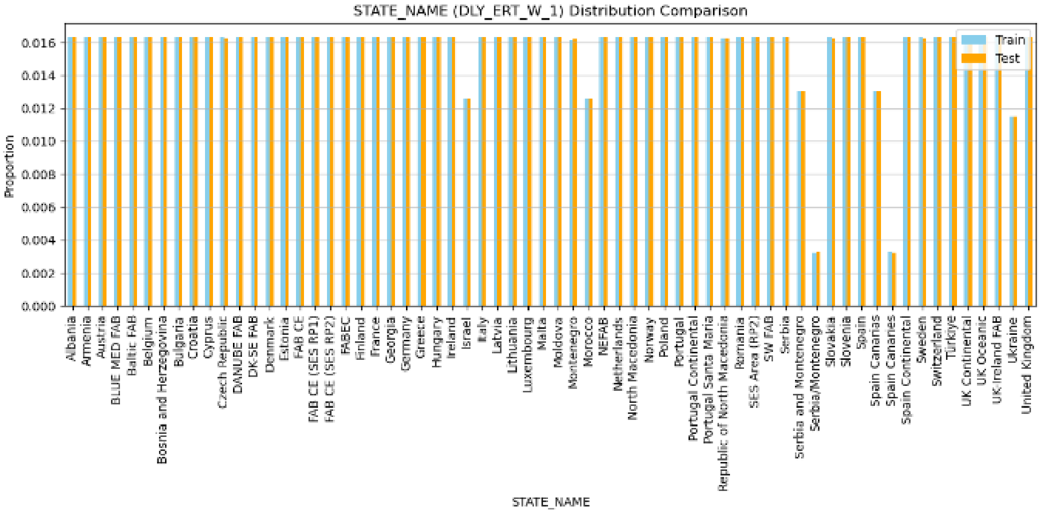


Figure 8. "STATE_NAME" cluster distributions for DLY_ERT_W_1

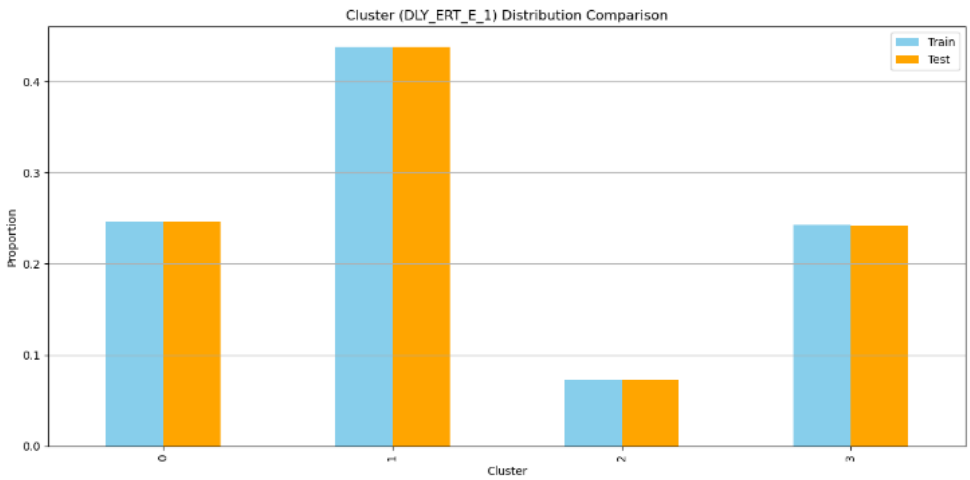


Figure 9. Cluster distributions for DLY_ERT_E_1

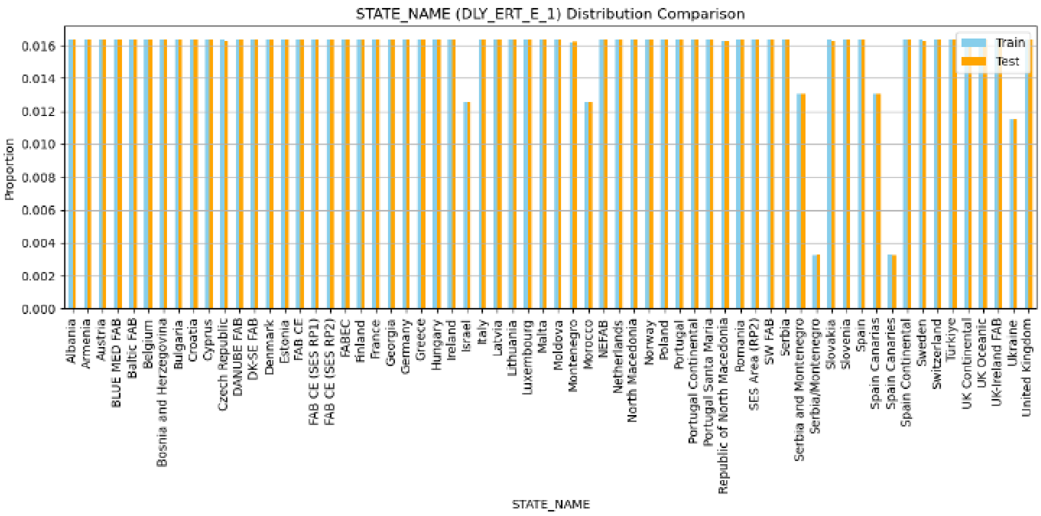


Figure 10. "STATE_NAME" cluster distributions for DLY_ERT_E_1

Statistical test was performed to compare Cluster and STATE_NAME distributions between two datasets. In H_0 Hypothesis, it was assumed that there was no significant difference between training and testing distributions.

Table 2. Chi Square Test and Results

Test	Chi-Square value	p-value	Degrees of Freedom	Result
Cluster (DLY_ERT_E_1)	0.02	0.9994	3	There is no significant difference between the distributions.
STATE_NAME (DLY_ERT_E_1)	0.04	1.0000	63	There is no significant difference between the distributions.
Cluster (DLY_ERT_W_1)	0.02	0.9994	3	There is no significant difference between the distributions.
STATE_NAME (DLY_ERT_W_1)	0.04	1.0000	63	There is no significant difference between the distributions.

The Chi-Square statistics and p-values confirm that the Cluster and STATE_NAME variables are distributed proportionally in the training and test sets. For example, the p-value for the Cluster variable is 0.9994, indicating that the clusters are represented evenly in both data sets. Similarly, the p-value for the STATE_NAME variable is 1.0000, indicating that the regional features are distributed equally in the training and test sets.

3. Result and Discussion

In this study, the Random Forest algorithm is used for delay estimation for (DLY_ERT_W_1) (delays due to weather conditions) and (DLY_ERT_E_1) (delays due to equipment failures). The modeling process includes preparation of data features, hyperparameter optimization, calculation of model evaluation metrics and feature importance analysis.

Target variables are determined as weather-related delays (DLY_ERT_W_1) and equipment failure-related delays (DLY_ERT_E_1). Numerical variables such as traffic density, delay rate, and log-transformed delay measurements are used in these models. In order to capture the effect of regional variations, categorical variables such as STATE_NAME are included in the model with a one-hot encoding method. In addition, temporal and operational characteristics (such as seasonal indicators, weekdays, and weekends) are used as important predictor variables in delay analysis.

The hyperparameter tuning process was performed for the optimization of model parameters. Overfitting and underfitting analyses were performed (see Appendix), and the performance of different hyperparameter combinations was evaluated. During hyperparameter tuning, Root Mean Square Error (RMSE) was calculated to measure performance and recommended ranges were determined. According to the results of underfitting and overfitting analyses performed for (DLY_ERT_W_1) and (DLY_ERT_E_1), recommended ranges for hyperparameter tuning are shown in Table 3.

Table 3. Recommended ranges for hyperparameter tuning

	DLY_ERT_W_1	DLY_ERT_E_1
n_estimators (number of trees)	[150,200,250]	[100, 150,200]
max_depth (tree depth)	[20,25,30]	[20,25,30]
min_samples_split (minimum number of samples to split a node)	[3,5,6]	[2, 3,5]
min_samples_leaf (minimum number of samples in a leaf node)	[1, 2]	[1, 2]
max_features (maximum number of features to use for splitting)	['sqrt']	['sqrt']

According to the analysis results, the optimum hyperparameters were obtained by the Grid Search method and 5-fold cross-validation (5-fold CV). The final hyperparameter values were optimized for both delay categories as presented in Table 4.

Table 4. Chi Square Test and Results

DLY_ERT_W_1		DLY_ERT_E_1	
n_estimators	250	n_estimators	100
max_depth	30	max_depth	30
min_samples_split	3	min_samples_split	3
min_samples_leaf	1	min_samples_leaf	1
max_features	'sqrt'	max_features	'sqrt'

Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics on both cross-validation (CV) and test set. As shown in Table X, RMSE value for (DLY_ERT_W_1) was calculated as “700.98” in cross-validation stage and “416.16” in test set. Similarly, RMSE value for (DLY_ERT_E_1) was obtained as “2.19” in cross-validation stage and “0.91” in test set. Low MAE and RMSE values in both models revealed that the models have high prediction accuracy and exhibit robust performance. The consistency between cross-validation and test metrics confirms that the models do not have overfitting problems and have strong generalization ability.

Table 5. Evaluation Criteria Results for DLY_ERT_W_1 and DLY_ERT_E_1

	DLY_ERT_W_1	DLY_ERT_E_1
MAE (CV)	48.88	0.03
RMSE (CV)	700.98	2.19
MAE (Test)	39.93	0.01
RMSE (Test)	416.16	0.91

According to the feature importance analysis, traffic density is determined as the most critical variable predicting delays for both models. This situation emphasizes the impact of airspace congestion on delays and the importance of effective air traffic management. Especially in weather-related delays (DLY_ERT_W_1), the cascading effect of past delays stands out as a remarkable finding. In equipment failure-related delays (DLY_ERT_E_1), regional and seasonal variables have a strong effect, which reveals the importance of preventive maintenance activities.

Using separate Random Forest models for different delay categories provided significant advantages in the modeling process. While analyzing all delay types in a single model created difficulties in understanding varied factors, using separate models captured the specific factors of each delay type better. This approach increased the prediction accuracy and provided a simpler, more optimized structure for the models.

As a result, the Random Forest algorithm performed well in predicting delays due to both weather conditions and equipment failures. Traffic density and past delays were the strongest predictors of the models, while regional and temporal variations also had an impact on delay analysis.

4. Conclusion

This study presents a comprehensive data mining and modeling process to provide a deeper understanding of the relationship between airport traffic density and flight delays and to evaluate the effectiveness of prediction models in this context. Delays due to weather conditions and equipment failures were determined as two important disruption points of flight operations and the Random Forest algorithm was used for delay prediction in these categories. The analyses conducted within the scope of the study clearly revealed the effects of traffic density, past delays, regional and temporal factors on flight delays. The low error rates, high prediction accuracy and generalization capacity of the Random Forest algorithm support the usability of this method in operational decision support systems.

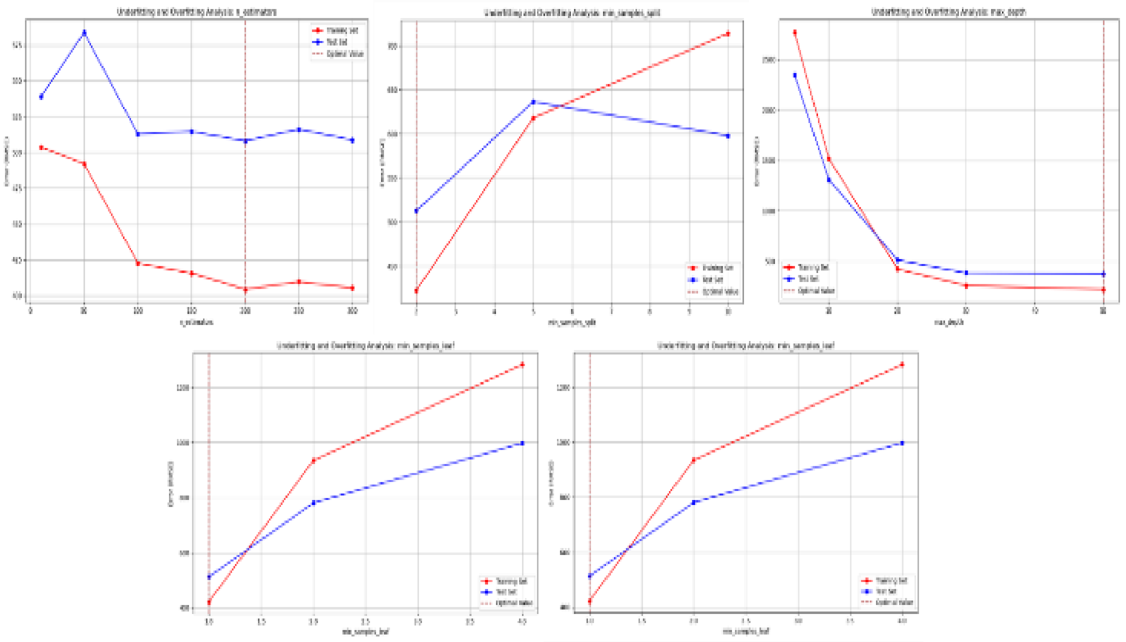
Risk management in the aviation sector is a principal element that aims to increase flight safety and minimize delay-related disruptions by ensuring effective management of operational processes. In this context, the current study presents important findings in terms of risk management in the aviation sector by providing data-driven analyses for predicting flight delays. Proactive evaluation of airport traffic density data allows for the prediction of potential delays and the development of preventive strategies. The predictive models applied in the study offer new and effective approaches that can be used in aviation risk management processes and contribute to the making of strategic decisions to increase operational efficiency in the aviation sector.

The findings have prepared the ground for strategic policy recommendations for managers for operational efficiency and minimizing flight delays. It has been observed that efficient and dynamic airspace allocation and alternative routing strategies should be implemented to control traffic congestion, especially during periods of high traffic density such as summer and winter. In addition, considering that past delays have gradually led to systemic disruptions, it is recommended to develop proactive maintenance processes and rapid intervention mechanisms. In this context, it is evaluated that optimizing operational processes and disseminating predictive analytical methods in the sector will contribute to both reducing costs and increasing passenger satisfaction.

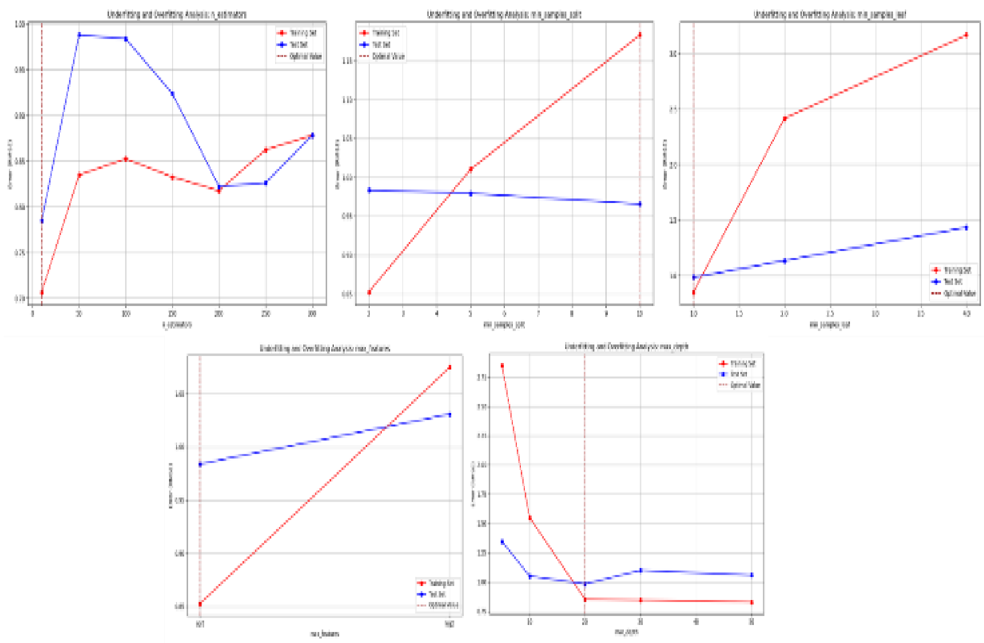
The study also highlights the importance of predictive analytical approaches for managing delays in the aviation sector and provides a valuable contribution to academic literature. This comprehensive approach, especially considering operational and environmental factors together, fills the gaps in the literature and offers a new perspective for predicting flight delays. However, the inclusion of missing data categories such as accidents and incident-related delays in the analysis scope stands out as an important research area for future studies. In addition, the use of alternative modeling approaches and wider data sets will increase the validity of the findings and strengthen their applicability in different scenarios.

As a result, this study has examined the critical relationships between airport traffic density and flight delays in detail and has suggested innovative decision support mechanisms for both academic and sectoral applications in the light of the findings. In addition to all, the study provides a guide for managerial practices in the aviation sector in terms of increasing operational efficiency, reducing costs and ensuring customer satisfaction.

Appendix



Hyperparameter results for (DLY_ERT_W_1)



Hyperparameter results for DLY_ERT_E_1

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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