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Analysis of Aircraft Spare Parts Supply Chain Networks Using Machine Learning for Detecting Delivery Delay Patterns in Repair Processes

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Abstract: The aircraft spare parts supply chain is highly complex and vulnerable to delivery delays that may trigger Aircraft on Ground (AOG) conditions and increase operational costs. This study aims to analyze the characteristics of the aircraft spare parts supply network and to model delivery delay patterns in the repair process using a data-driven machine learning approach. The dataset consists of 4,962 shipment records with variables including delivery status (on-time/delay), ship vendor, origin point, destination point, lead time, and lead time category. Three classification algorithms, namely Decision Tree, Random Forest, and Logistic Regression, are applied to build and compare delay prediction models. The research stages comprise data preprocessing, splitting data into training and testing sets, model development, and performance evaluation using accuracy, precision, recall, and F1-score metrics. The results indicate that operational variables in the supply chain significantly influence delivery status and that the Random Forest model provides the best performance in capturing complex and non-linear delay patterns. These findings offer a basis for developing predictive decision support systems to mitigate delivery risks and enhance the reliability of Maintenance, Repair, and Overhaul (MRO) processes in the aviation industry.

Keyword: Aircraft on Ground, Lead Time, Machine Learning, MRO, Supply Chain

INTRODUCTION

The air transportation industry is a strategic global sector that plays a crucial role in mobility and international logistics distribution. The post-pandemic increase in flight activities has intensified the demand for operational systems that are efficient, reliable, and sustainable. In this context, operational performance is not solely determined by aircraft technology but also by the effectiveness of supporting systems, particularly Maintenance, Repair, and Overhaul (MRO) activities, which heavily depend on the timely availability and distribution of spare parts (Bills, Costello, & Cattani, 2023).

The aircraft spare parts supply chain is highly complex, as it involves cross-organizational and cross-border processes, ranging from procurement and delivery to repair facilities to the return of components to operators. Lead time uncertainty in shipments is a common issue in the air transportation supply chain, influenced by factors such as international logistics processes, customs procedures, and technical repair stages. This variability can result in delivery delays, which may lead to Aircraft on Ground (AOG) conditions, where aircraft are unable to operate due to the unavailability of critical components. Such conditions have direct implications for increased operational costs and disruptions to flight schedules (Rezki & Mansouri, 2024). Furthermore, the characteristics of spare parts—such as unstable demand and high technical complexity—further amplify uncertainty within the supply chain system (Heijenrath & Verhagen, 2023;Shafi et al., 2023).

Numerous studies have explored the application of machine learning in supply chain management to enhance prediction accuracy and decision-making. The complexity of the aircraft spare parts supply chain, which involves multiple operational variables such as origin, destination, component type, material category, and repair duration, results in non-linear relationships that are difficult to analyze using conventional approaches. Therefore, data-driven approaches such as machine learning have become increasingly relevant due to their ability to identify complex patterns and predict operational risks more accurately (Nafiurridha & Choiruddin, 2024).

Algorithms such as Random Forest, Support Vector Machine, and Neural Networks have been proven effective in handling non-linear relationships among variables and delivering superior performance compared to traditional approaches (Polo Triana, Gutierrez, & Leon-Becerra, 2024). Previous studies have also demonstrated that models such as XGBoost are effective in predicting shipment status in general supply chain systems (Damayanti, Ginting, Sudrajat, Md, & Islam, 2025), while Artificial Neural Network-based approaches are capable of addressing demand uncertainty in spare parts with intermittent demand characteristics(Shafi et al., 2023). In addition, the integration of machine learning in supply chains has been shown to improve operational efficiency and risk mitigation (Khedr & Sheeja, 2024;Sattar et al., 2025).

However, most existing studies primarily focus on demand forecasting and inventory management in general supply chain contexts and have not specifically examined the prediction of delivery delays for aircraft spare parts within MRO repair processes. Moreover, the utilization of historical operational data to develop predictive models as decision-support tools in aviation supply chains remains limited.

Based on this research gap, this study proposes a machine learning-based predictive approach to model delivery delays in aircraft spare parts supply chains. The novelty of this study lies in the use of historical MRO operational data and the integration of multiple operational variables, including shipment origin, destination, component type, spare parts category, and lead time, to develop a predictive model within the aerospace supply chain context.

Accordingly, this research focuses on identifying the factors influencing delivery delays and evaluating the performance of machine learning models in predicting such delays. The objectives of this study are to analyze the characteristics of the aircraft spare parts supply chain, identify key influencing factors, and develop and evaluate predictive models to support decision-making in MRO systems.

METHOD

This study employs a quantitative, data-driven research approach aimed at analyzing and predicting delivery delays of aircraft spare parts within the repair supply chain. This approach utilizes historical shipment data, which are analyzed using machine learning methods to identify relationships among variables and to develop accurate predictive models.

Machine learning methods are selected due to their ability to capture non-linear and complex relationships within logistics data, which are typically difficult to analyze using conventional approaches(Daghistani & Alshammari, 2020) . In this study, several classification algorithms are employed, namely Decision Tree, Random Forest, and Logistic Regression.

Decision Tree is a tree-based method that operates by recursively partitioning the data based on the most informative attributes to generate classification decisions (Quinlan, 1986). The attribute selection process in Decision Tree utilizes the concept of information gain, which is formulated as follows:

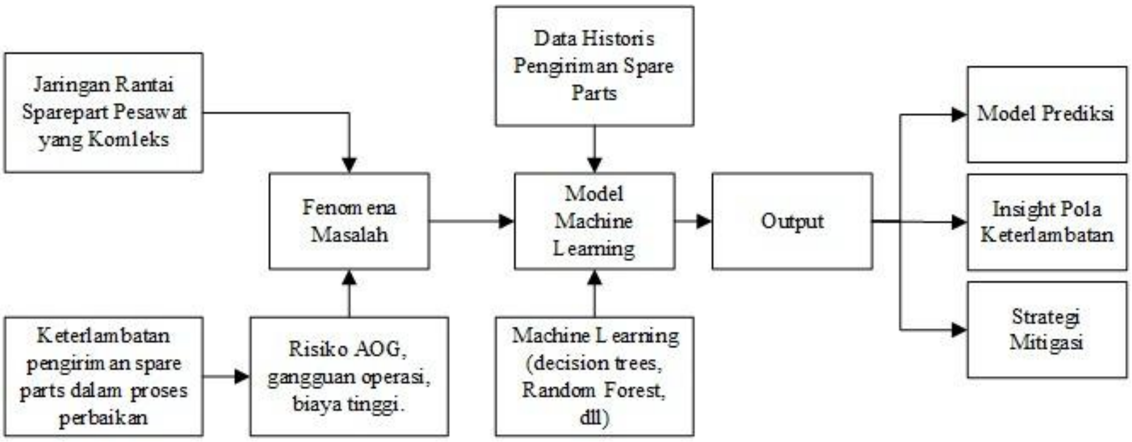
$$Gain\ (S,A) = \sum_{i=1}^{n} pi^{*} \log_2 pi \qquad (1)$$

Random Forest is an extension of the Decision Tree method based on an ensemble approach that combines multiple decision trees to improve accuracy and reduce the risk of overfitting through an aggregation process (Daghistani & Alshammari, 2020). In general, the model can be formulated as follows:

$$RF = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \qquad (2)$$

In addition, Logistic Regression is employed as a baseline model. Although it is a linear model, it remains effective for binary classification and is capable of providing probabilistic interpretation (Vázquez-Veloso et al., 2025). The model can be formulated as follows:

$$P(= 1|X) = \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+\cdots+\beta_n X_n)}} \qquad (3)$$



Source: Research

Figure 1. Research Model

The data used in this study are secondary data in the form of historical shipment records of aircraft spare parts obtained from an operational logistics system, with a total of 4,962 observations. The variables analyzed consist of a dependent variable, namely shipment status (on-time or delayed), and independent variables including ship vendor, origin point, destination point, lead time, and lead time category.

The research process begins with data collection using a documentation method, followed by data preprocessing, which includes data cleaning, handling missing values, transformation of categorical variables, and splitting the dataset into training and testing sets. Subsequently, machine learning models are developed to learn historical shipment patterns and generate delay predictions.

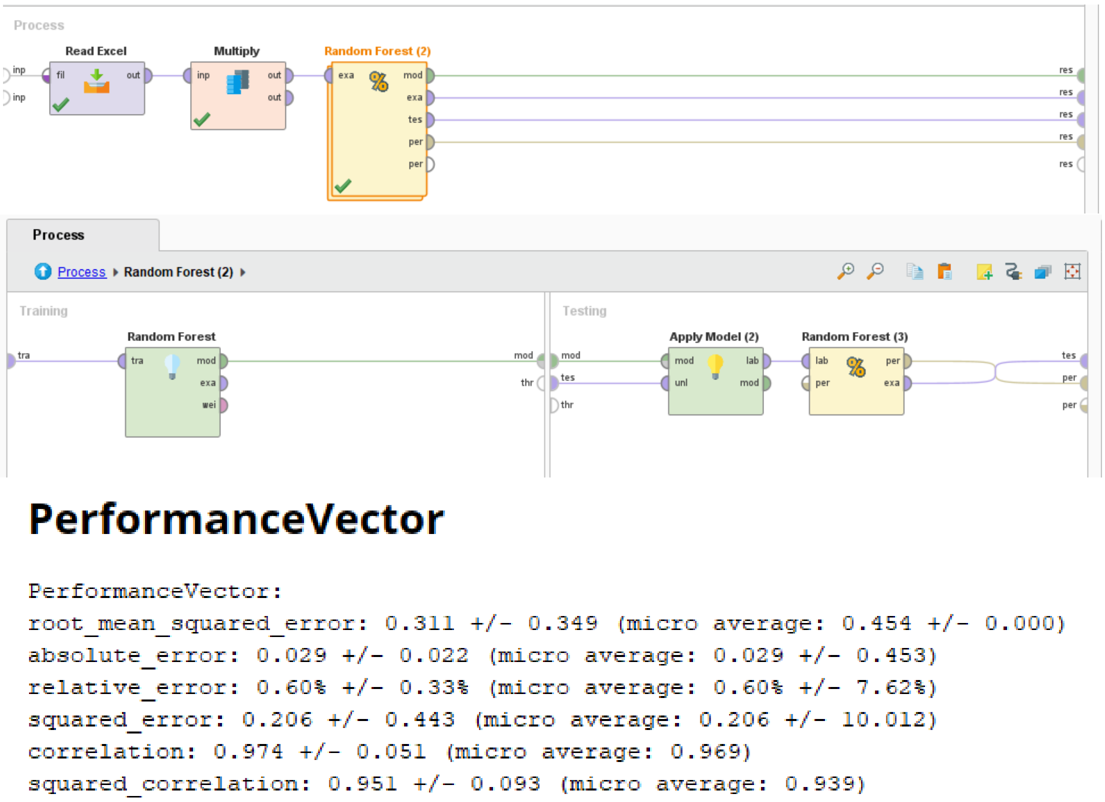
To provide a clearer understanding of the research flow, the methodological framework is presented in Figure 1, illustrating the stages from problem identification, historical data processing, and application of machine learning models, to the generation of outputs in the form of predictive models, delay pattern insights, and mitigation strategies.

Model evaluation is conducted using classification performance metrics, namely accuracy, precision, recall, and F1-score, to determine the best-performing model. The analysis results are not only used for prediction but also to identify delay patterns that can serve as a basis for developing mitigation strategies in supply chain management (Soellaart, 2019;Monoarfa, Hariyanto, & Rasyid, 2021).

RESULTS AND DISCUSSION

The results of this study were obtained through the analysis of historical shipment data of aircraft spare parts using a machine learning approach to identify delay patterns and develop predictive models. The analyzed data include information on shipment origin, destination, component category, and lead time, which are used to model delay status in the repair process. This study applies three classification algorithms—Random Forest, Decision Tree, and Logistic Regression—to compare the performance of each model in predicting delivery delays of spare parts.

Random Forest Modeling Results



```
PerformanceVector:
root_mean_squared_error: 0.311 +/- 0.349 (micro average: 0.454 +/- 0.000)
absolute_error: 0.029 +/- 0.022 (micro average: 0.029 +/- 0.453)
relative_error: 0.60% +/- 0.33% (micro average: 0.60% +/- 7.62%)
squared_error: 0.206 +/- 0.443 (micro average: 0.206 +/- 10.012)
correlation: 0.974 +/- 0.051 (micro average: 0.969)
squared_correlation: 0.951 +/- 0.093 (micro average: 0.939)
```

Source: Altair Studio

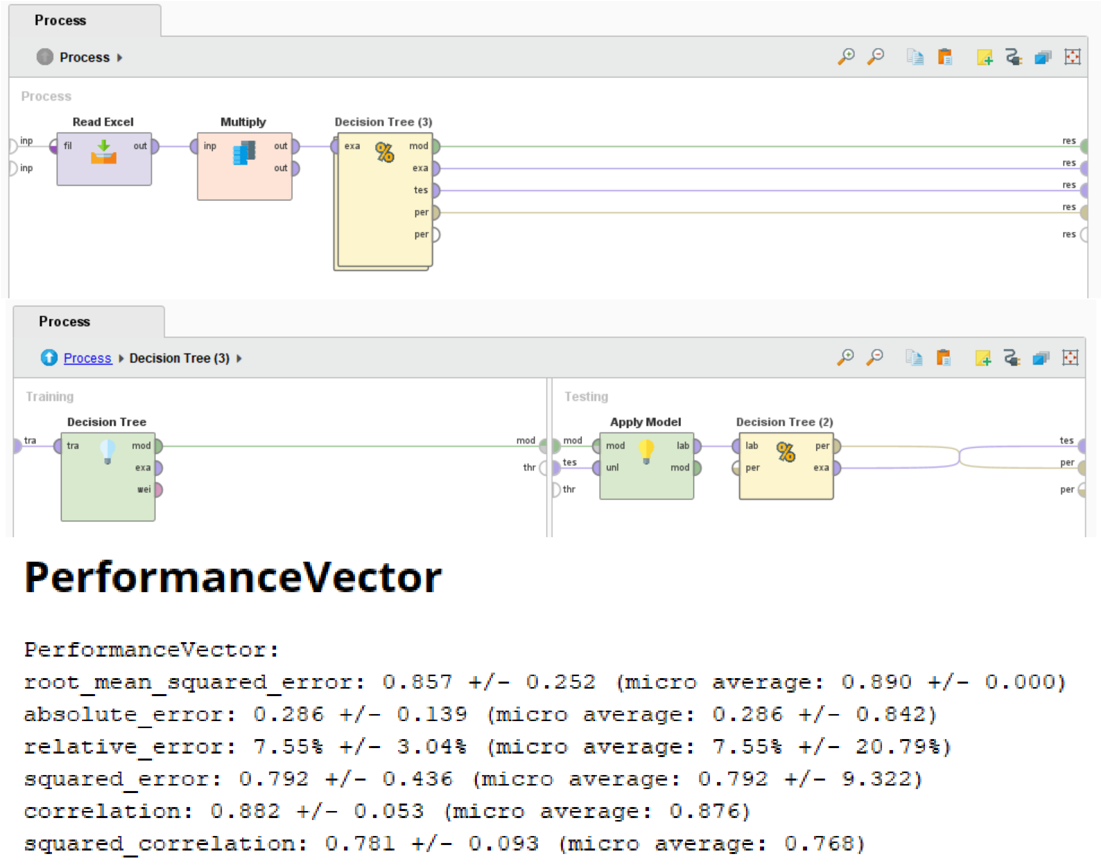
Figure 2. Random Forest Modeling Result

The very low root mean squared error (RMSE) value of 0.311 indicates that the model produces minimal prediction errors in shipment status, demonstrating a high level of precision in predicting delivery delays and on-time performance. Furthermore, the low absolute error and relative error values suggest that the model is efficient in estimating the difference between predicted and actual values, both in absolute terms and proportionally to the observed shipment status.

The very high correlation value of 0.974, along with a squared correlation of 0.951, indicates a strong relationship between the input variables—such as origin, destination, goods, and lead time—and the output variable, namely shipment status. This finding confirms that the model is capable of effectively capturing the complex patterns inherent in the aircraft spare parts delivery process.

The model’s high predictive accuracy in identifying delivery delays enables its application as an early warning system in Maintenance, Repair, and Overhaul (MRO) management. This capability can support various stakeholders, including airlines, MRO providers, and export–import operators, in implementing timely and effective risk mitigation strategies. For instance, it can facilitate adjustments in purchase order (PO) processes, strategic allocation of spare parts, and dynamic logistics planning based on model predictions. The implementation of this model in real-world operations is expected to enhance supply chain efficiency and reduce the risk of Aircraft on Ground (AOG) situations caused by delivery delays.

Decision Tree Modeling Results



```
PerformanceVector:
root_mean_squared_error: 0.857 +/- 0.252 (micro average: 0.890 +/- 0.000)
absolute_error: 0.286 +/- 0.139 (micro average: 0.286 +/- 0.842)
relative_error: 7.55% +/- 3.04% (micro average: 7.55% +/- 20.79%)
squared_error: 0.792 +/- 0.436 (micro average: 0.792 +/- 9.322)
correlation: 0.882 +/- 0.053 (micro average: 0.876)
squared_correlation: 0.781 +/- 0.093 (micro average: 0.768)
```

Source: Altair Studio

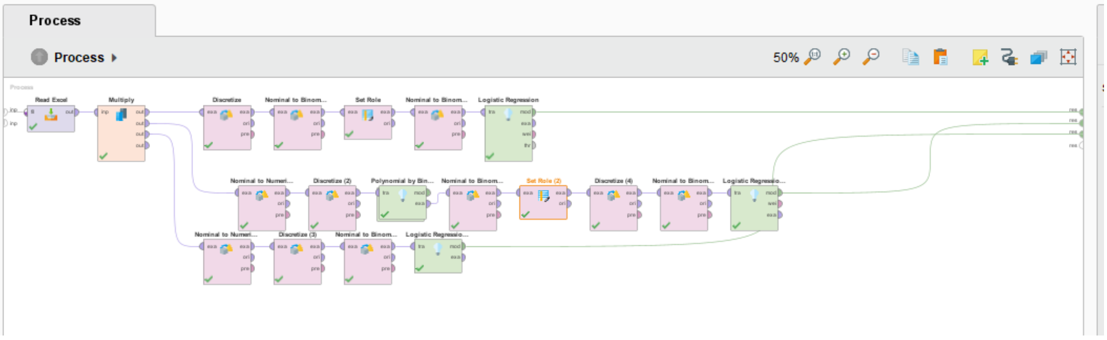
Figure 3. Decision Tree Modeling Results

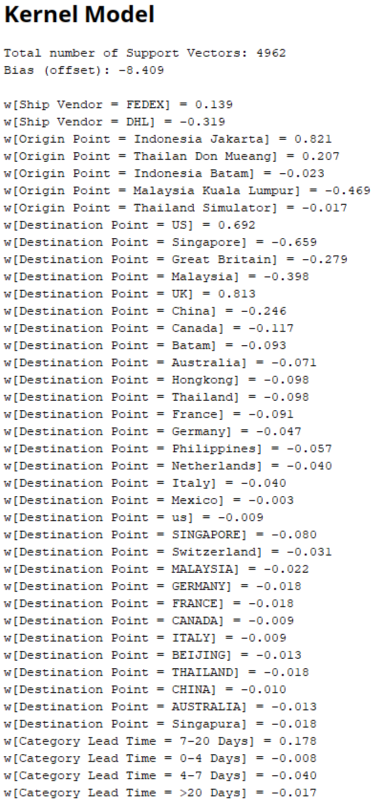
The performance vector results of the Decision Tree model show a root mean squared error (RMSE) of 0.857 with a standard deviation of 0.252, and a micro average of 0.890. The absolute error is 0.286 ± 0.139 with a micro average of 0.286, while the relative error is recorded at 7.55% ± 3.04%. The squared error is 0.792 ± 0.436, with a relatively high micro average of 0.792. The correlation between input and output variables is 0.882 ± 0.053, with a squared correlation of 0.781 ± 0.093, indicating a fairly strong relationship among the model variables, although not as strong as the Random Forest model.

These results indicate that the higher RMSE and absolute error values, compared to the Random Forest model, reflect a relatively significant level of prediction error in shipment status. The relative error of 7.55% further suggests that the Decision Tree model is not yet optimal in minimizing the gap between predicted and actual outcomes. Nevertheless, the correlation value of 0.882 demonstrates that the model is still capable of capturing general patterns in the relationships between input variables—such as origin, destination, goods category, and lead time—and the shipment status.

In terms of implications, the Decision Tree model can be utilized as a baseline model for predicting delivery delays; however, it is not sufficiently accurate for early warning systems or operational mitigation without further feature engineering and data enhancement. The moderate level of predictive accuracy necessitates additional validation before full implementation in aircraft spare parts supply chain management processes.

Logistic Regression Modeling Results





Kernel Model

```
Total number of Support Vectors: 4962
Bias (offset): -8.409

w[Ship Vendor = FEDEX] = 0.139
w[Ship Vendor = DHL] = -0.319
w[Origin Point = Indonesia Jakarta] = 0.821
w[Origin Point = Thailan Don Mueang] = 0.207
w[Origin Point = Indonesia Batam] = -0.023
w[Origin Point = Malaysia Kuala Lumpur] = -0.469
w[Origin Point = Thailand Simulator] = -0.017
w[Destination Point = US] = 0.692
w[Destination Point = Singapore] = -0.659
w[Destination Point = Great Britain] = -0.279
w[Destination Point = Malaysia] = -0.398
w[Destination Point = UK] = 0.813
w[Destination Point = China] = -0.246
w[Destination Point = Canada] = -0.117
w[Destination Point = Batam] = -0.093
w[Destination Point = Australia] = -0.071
w[Destination Point = Hongkong] = -0.098
w[Destination Point = Thailand] = -0.098
w[Destination Point = France] = -0.091
w[Destination Point = Germany] = -0.047
w[Destination Point = Philippines] = -0.057
w[Destination Point = Netherlands] = -0.040
w[Destination Point = Italy] = -0.040
w[Destination Point = Mexico] = -0.003
w[Destination Point = us] = -0.009
w[Destination Point = SINGAPORE] = -0.080
w[Destination Point = Switzerland] = -0.031
w[Destination Point = MALAYSIA] = -0.022
w[Destination Point = GERMANY] = -0.018
w[Destination Point = FRANCE] = -0.018
w[Destination Point = CANADA] = -0.009
w[Destination Point = ITALY] = -0.009
w[Destination Point = BEIJING] = -0.013
w[Destination Point = THAILAND] = -0.018
w[Destination Point = CHINA] = -0.010
w[Destination Point = AUSTRALIA] = -0.013
w[Destination Point = Singapura] = -0.018
w[Category Lead Time = 7-20 Days] = 0.178
w[Category Lead Time = 0-4 Days] = -0.008
w[Category Lead Time = 4-7 Days] = -0.040
w[Category Lead Time = >20 Days] = -0.017
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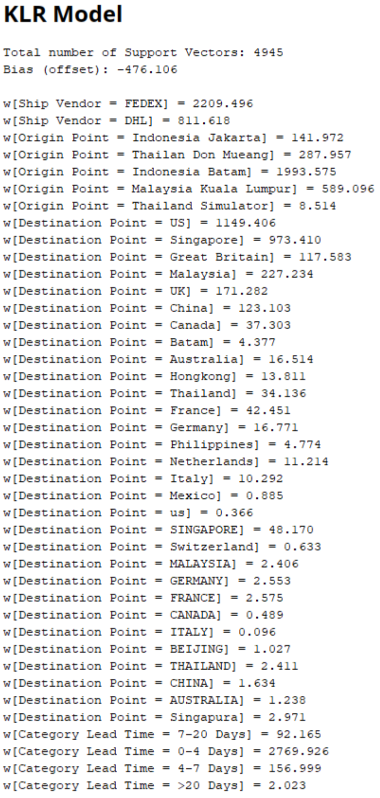
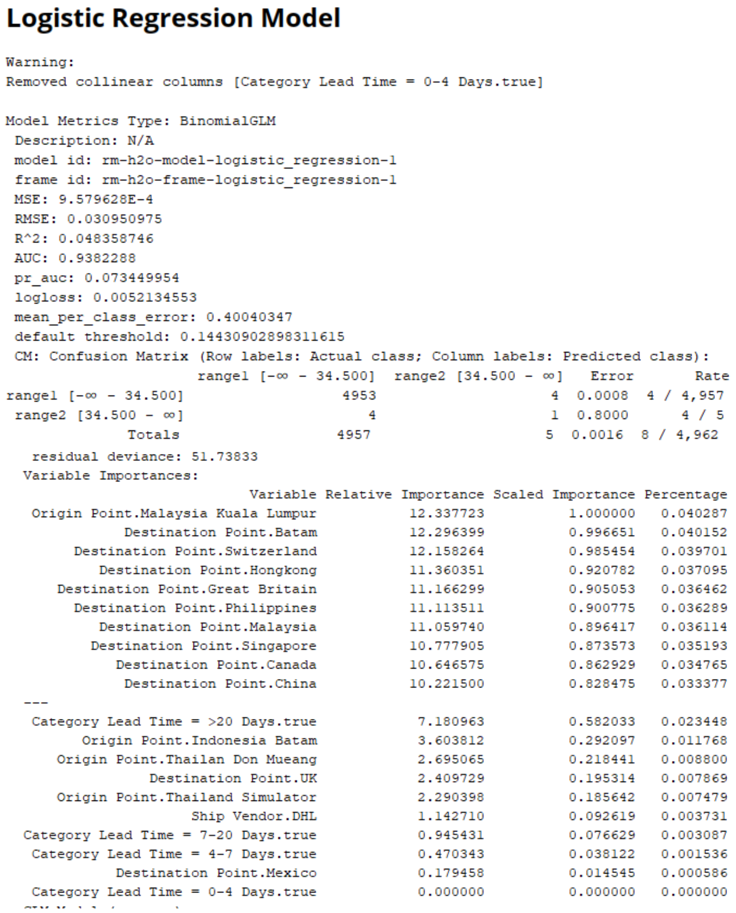


KLR Model

```
Total number of Support Vectors: 4945
Bias (offset): -476.106

w[Ship Vendor = FEDEX] = 2209.496
w[Ship Vendor = DHL] = 811.618
w[Origin Point = Indonesia Jakarta] = 141.972
w[Origin Point = Thailan Don Mueang] = 287.957
w[Origin Point = Indonesia Batam] = 1993.575
w[Origin Point = Malaysia Kuala Lumpur] = 589.096
w[Origin Point = Thailand Simulator] = 8.514
w[Destination Point = US] = 1149.406
w[Destination Point = Singapore] = 973.410
w[Destination Point = Great Britain] = 117.583
w[Destination Point = Malaysia] = 227.234
w[Destination Point = UK] = 171.282
w[Destination Point = China] = 123.103
w[Destination Point = Canada] = 37.303
w[Destination Point = Batam] = 4.377
w[Destination Point = Australia] = 16.514
w[Destination Point = Hongkong] = 13.811
w[Destination Point = Thailand] = 34.136
w[Destination Point = France] = 42.451
w[Destination Point = Germany] = 16.771
w[Destination Point = Philippines] = 4.774
w[Destination Point = Netherlands] = 11.214
w[Destination Point = Italy] = 10.292
w[Destination Point = Mexico] = 0.885
w[Destination Point = us] = 0.366
w[Destination Point = SINGAPORE] = 48.170
w[Destination Point = Switzerland] = 0.633
w[Destination Point = MALAYSIA] = 2.406
w[Destination Point = GERMANY] = 2.553
w[Destination Point = FRANCE] = 2.575
w[Destination Point = CANADA] = 0.489
w[Destination Point = ITALY] = 0.096
w[Destination Point = BEIJING] = 1.027
w[Destination Point = THAILAND] = 2.411
w[Destination Point = CHINA] = 1.634
w[Destination Point = AUSTRALIA] = 1.238
w[Destination Point = Singapura] = 2.971
w[Category Lead Time = 7-20 Days] = 92.165
w[Category Lead Time = 0-4 Days] = 2769.926
w[Category Lead Time = 4-7 Days] = 156.999
w[Category Lead Time = >20 Days] = 2.023
```



Logistic Regression Model

```
Warning:
Removed collinear columns [Category Lead Time = 0-4 Days.true]

Model Metrics Type: BinomialGLM
 Description: N/A
 model id: rm-h2o-model-logistic_regression-1
 frame id: rm-h2o-frame-logistic_regression-1
 MSE: 9.579628E-4
 RMSE: 0.030950975
 R^2: 0.048358746
 AUC: 0.9382288
 pr_auc: 0.073449954
 logloss: 0.0052134553
 mean_per_class_error: 0.40040347
 default threshold: 0.14430902898311615
 CM: Confusion Matrix (Row labels: Actual class; Column labels: Predicted class):
                      range1 [-∞ - 34.500]  range2 [34.500 - ∞]   Error       Rate
range1 [-∞ - 34.500]                  4953                    4  0.0008  4 / 4,957
 range2 [34.500 - ∞]                     4                    1  0.8000      4 / 5
            Totals                    4957                    5  0.0016  8 / 4,962
  residual deviance: 51.73833
 Variable Importances:
                            Variable Relative Importance Scaled Importance Percentage
  Origin Point.Malaysia Kuala Lumpur           12.337723          1.000000   0.040287
              Destination Point.Batam          12.296399          0.996651   0.040152
        Destination Point.Switzerland          12.158264          0.985454   0.039701
           Destination Point.Hongkong          11.360351          0.920782   0.037095
      Destination Point.Great Britain          11.166299          0.905053   0.036462
        Destination Point.Philippines          11.113511          0.900775   0.036289
           Destination Point.Malaysia          11.059740          0.896417   0.036114
          Destination Point.Singapore          10.777905          0.873573   0.035193
             Destination Point.Canada          10.646575          0.862929   0.034765
              Destination Point.China          10.221500          0.828475   0.033377
 ---
  Category Lead Time = >20 Days.true            7.180963          0.582033   0.023448
        Origin Point.Indonesia Batam            3.603812          0.292097   0.011768
     Origin Point.Thailan Don Mueang            2.695065          0.218441   0.008800
                 Destination Point.UK           2.409729          0.195314   0.007869
     Origin Point.Thailand Simulator            2.290398          0.185642   0.007479
                     Ship Vendor.DHL            1.142710          0.092619   0.003731
 Category Lead Time = 7-20 Days.true            0.945431          0.076629   0.003087
  Category Lead Time = 4-7 Days.true            0.470343          0.038122   0.001536
             Destination Point.Mexico           0.179458          0.014545   0.000586
  Category Lead Time = 0-4 Days.true            0.000000          0.000000   0.000000
```

Source: Altair Studio

Figure 4. Logistic Regression Modeling Result

The Logistic Regression model results obtained from Altair Studio present several key evaluation metrics. The mean squared error (MSE) is recorded at 0.579, with a root mean squared error (RMSE) of approximately 0.303. The correlation between predicted and actual values is 0.048, while the model achieves an area under the curve (AUC) of 0.938, indicating excellent classification performance. The confusion matrix further shows that the model is able to classify the data with a very low error rate (below 0.002 for both output classes), along with high average precision and recall for each label.

These results indicate that Logistic Regression is sufficiently effective in capturing patterns related to delivery delays and on-time performance of aircraft spare parts. The low RMSE and near-perfect AUC value suggest that the model performs well in detecting shipment status with a satisfactory level of accuracy. Moreover, the variable importance results—such as shipment origin and destination (e.g., Malaysia, Batam, Switzerland, Hong Kong), as well as lead time categories—confirm that these variables play a significant role in enhancing the model's predictive performance.

From a practical perspective, Logistic Regression can be utilized as a baseline model to support decision-making in spare parts supply chain management. For example, it can assist in identifying critical routes or components that are more prone to delays, thereby enabling targeted logistics interventions and improved operational planning.

CONCLUSION

The Based on the analysis of historical shipment data of aircraft spare parts and the application of machine learning methods to predict delivery delays in the repair process, the following conclusions can be drawn:

1. Supply chain network factors influence delivery delays of aircraft spare parts.

Operational variables such as origin point, destination point, ship vendor, and lead time are proven to contribute to determining shipment timeliness. The complexity of the distribution network, which involves multiple locations and logistics stakeholders, increases variability in delivery time and consequently raises the risk of delays.

2. Historical shipment data can be utilized to systematically identify delay patterns.

Through the analysis of operational data, this study finds that delivery delays do not occur randomly but follow specific patterns related to route characteristics and distribution duration. This demonstrates that historical data can provide deeper insights into the performance of the aircraft spare parts supply chain.

3. Machine learning methods are capable of developing accurate predictive models for delivery delays.

Among the evaluated algorithms, the Random Forest model demonstrates the best performance in predicting delays, as it effectively captures complex and non-linear relationships among supply chain variables. This model can be utilized as a predictive analytics tool to estimate delay risks before they occur.

4. The modeling results provide operational insights to support logistics decision-making.

The developed predictive model enables organizations to identify potential distribution bottlenecks, manage lead time more effectively, and improve spare parts delivery planning to reduce the risk of Aircraft on Ground (AOG) conditions and operational disruptions.

5. A data-driven and machine learning-based approach enhances supply chain management effectiveness in the aviation industry.

This study shows that integrating historical data analysis with machine learning methods can transform supply chain management from a reactive approach into a predictive one, allowing organizations to implement more proactive delay mitigation strategies.

Overall, this study successfully addresses the research problem by demonstrating that delivery delays of aircraft spare parts can be analyzed and predicted using a machine learning approach based on historical data, while also providing a strategic foundation for improving distribution performance in repair processes.

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