# A Comparative Study of Deep Learning and Machine Learning Models for Problem Space Reduction in Aircraft Disruption Recovery

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# CERTIFICATE

This is to certify that the project report entitled, "A Comparative Study of Deep Learning and Machine Learning Models for Problem Space Reduction in Aircraft Disruption Recovery submitted by Mrs. "Deepa Raj"(Roll Number: 20IM10006) to Indian Institute of Technology, Kharagpur, India, is a record of bonafide Project work carried out by him under my supervision and guidance and is worthy of consideration for the award of the degree of Bachelor of Technology in Industrial and Systems Engineering of the Institute.

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**Place:** Kharagpur

# Abbreviations

TAIL -Aircraft Name

Tabid – Flight Number

FP- Flight Pair

ASRP- Aircraft Schedule Recovery Problem

ML-Machine Learning

DL- Deep Learning

ANN- Artificial Neural Network

MLP- Multi Layer Perceptron

LSTM- Long ShortTerm Memory

# Abstract

This Research introduces a novel approach for efficient aircraft recovery in airline operations, a vital process in minimizing costs due to disrupted flight schedules. Traditional exact methods, while accurate, are too computationally intensive and impractical for real-time use. Conversely, heuristic approaches, although faster, suffer from inconsistent quality, often resulting in substantial losses. This Research aims to provide solution by employing Supervised Deep Learning Model to expedite the aircraft recovery process. This method refines the optimization problem's solution space by drawing on similarities with past instances during an offline model training phase. In the online phase, it can quickly identify optimal solution components for new problems and integrates them into the optimization model. Hence, enabling the rapid generation of high-quality solutions.

The results show that the DL-based approach significantly surpasses traditional exact methods in computational speed while maintaining a similar level of solution quality. It also outperforms existing heuristic methods by effectively narrowing down solution spaces in a more structured way, thus delivering higher quality outcomes in comparable timeframes. This innovative approach promises to revolutionize the efficiency and reliability of aircraft recovery in airline operations.

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# Chapter 1 Introduction

## 1.1 Organization of Thesis:

Airlines dedicate considerable time, resources, and effort to network planning and scheduling, aiming to maximize the use of their vital assets like aircraft, crew, and ground facilities. Despite these meticulous efforts, unforeseen circumstances and various external factors can disrupt even the most well-crafted plans. Disruptions such as adverse weather, airport shutdowns, mechanical failures, and security holdups can occur unexpectedly. These incidents can drastically compromise previously optimized schedules, sometimes rendering them ineffective or impossible to follow. Such disruptions not only affect an airline's profitability but also inconvenience passengers and have broader economic implications.

Airlines actively monitor their flight operations to manage and lessen the impact of disruptions on their schedules, a process known as disruption management. Given the complexity and magnitude of real-world airline disruption scenarios, these issues are typically broken down and addressed sequentially. This approach involves dividing the larger problem into smaller, more manageable sub-problems to be solved one by one. Due to the need for swift solutions, achieving exact answers for even these smaller issues is often impractical within the limited time available. In addressing these disruptions, airlines usually prioritize the Aircraft Recovery Problem (ARP) before turning their attention to crew and passenger recovery. **During ARP, various strategies are employed, such as swapping aircraft, delaying or cancelling flights, and altering flight routes (Barnhart and Vaze, 2015).** Hence it becomes of key importance to identify key flights that will be affected by a disruption and its schedule that is needed to be managed.

The aviation sector has been at the forefront in adopting and advancing optimization models and algorithms, applying these to complex network optimization challenges. These include the timing of flights, allocating fleets, planning aircraft routes, and scheduling crew. However, the domain of operations recovery presents a significant challenge in the practical application of these optimization-based tools. The necessity for extremely rapid decision-making, often within just a few minutes or ideally seconds, poses a substantial obstacle to their direct use in this context.

Currently, many airlines deploy either fully automated or partially automated decision-support systems for handling operations recovery, which predominantly rely on a range of heuristic methods. These methods vary from simple, localized rules to more advanced, hybrid techniques that might include tackling streamlined optimization sub-problems within limited solution spaces. However, for these systems to be practically useful for airlines, they must deliver viable solutions quickly, typically within a few minutes, as is often required by airline operations controllers (Vink et al. 2020). Existing research in this field seldom meets these time constraints with realistically large problem sets while still offering solutions close to optimal. Our research aims to bridge this gap by introducing a novel data-driven methodology, specifically utilizing supervised Deep learning. This method focuses on effectively narrowing down the solution space for the crucial stages of aircraft routing and flight retiming in airline recovery. The innovative aspect of this approach is the application of supervised Deep learning to refine the solution space for the aircraft recovery optimization problem in a structured, case-specific way, moving beyond the basic pruning rules currently in use.

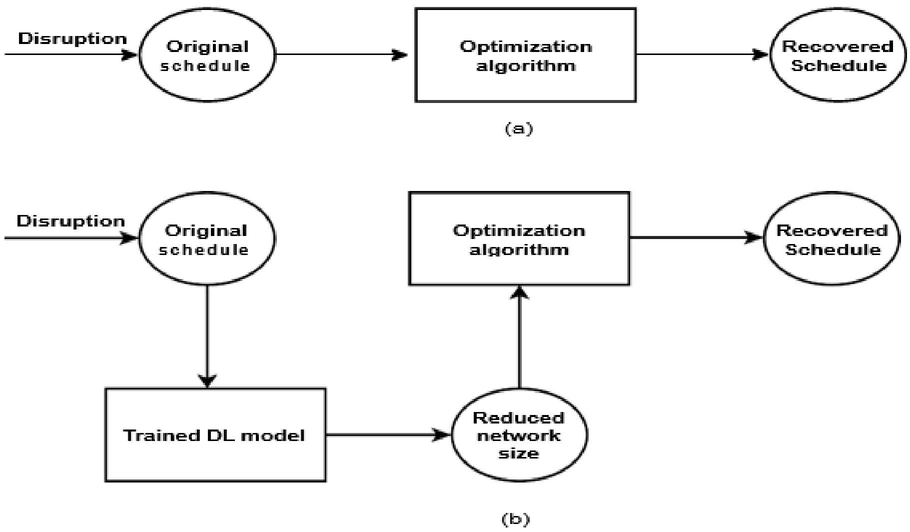



*Figure 1: Optimization (a) without DL (b) with DL*

The above mentioned discussion highlights the criticality of selecting efficient methods that can swiftly address real-world challenges when disruptions unfold during the day. It's crucial to explore how deep learning can hasten the optimization steps in Advanced Schedule Recovery Processes (ASRP), where it is applied before optimization begins. Disruptions lead to a domino effect across the airline's network.

To rectify a disturbed schedule, a set of aircraft, termed 'key aircraft,' undergo rescheduling, which includes delays and flight cancellations. Meanwhile, 'non-key aircraft' continue to follow their original schedules. Deep learning is tasked with forecasting a streamlined subset of the network by excluding non-key aircraft. This subset is then integrated into the optimization algorithm, diminishing the time needed for computation while maintaining the integrity of the solution. In contrast, optimization processes that do not utilize deep learning have to process the full fleet, leading to prolonged computational times. Deep learning harnesses data from previously rectified schedules to train models in an offline setting. Although preparing the training dataset is labor-intensive, it is an investment that promises to significantly cut down the time required by the optimization algorithm to adjust future schedules in light of disruptions.

### 1.2 Objective:
To prune the problem space by identifying subnetwork of aircrafts (key aircrafts) using deep learning models and compare with machine learning models.

# 2. Related Work:

## 2.1 Literature Review
Since the deregulation of markets, airlines have prioritized developing optimal flight schedules with little room for error to accommodate deviations from the ideal plan. Disruptions due to weather, technical issues, and crew sickness necessitate airline disruption management techniques. These techniques aim to provide a comprehensive overview of disruption management, describe planning processes, and report on experiences from a development project on disruption management at a major airline's operations control centre (Rodovia and Sao 2023). Airline disruption management has seen an upsurge in research, particularly in integrated resource recovery.

Since over half of the studies have been published post-2010, this paper critically reviews literature from 2009 to 2018 on airline disruption management. It includes integrated recovery of aircraft, crew, and passengers, discusses the gap between actual airline operations control canters and theory, and suggests future research directions (Hans, Bruno and Thomas 2015). Disruptions to airline schedules are a common occurrence with significant operational and financial implications. The aircraft recovery problem (ARP) deals with restoring disrupted flight schedules by determining new departure times, flight cancellations, and route revisions. This study systematically reviews ARP literature, focusing on the realism of the problem, optimization objectives, practical constraints, and the methodologies used for solution. It identifies gaps in the literature and avenues for future research, noting the increasing complexity and sophistication of ARP studies over the years.

The journal by L.K. Hassan, B.F. Santos and J. Vink (2021) presents a dynamic modelling framework to the aircraft schedule recovery problem (ASRP), a response to irregular operations that disrupt flight and aircraft schedules. Unlike prior static approaches, this dynamic Disruption Set Solver (DSS) handles the problem as disruptions occur, using parallel time-space networks for tracking individual aircraft. It aims to minimize operational, delay, and cancellation costs through an efficient aircraft selection algorithm and linear-programming model. The paper concludes that static approaches may be unreliable and the dynamic DSS can provide real-time solutions.

In the Rashedi 2023 paper, a novel approach to aircraft recovery in airline operations is presented, addressing the limitations of traditional computationally intensive methods and inconsistent heuristics. The paper proposes a supervised machine learning technique to streamline the aircraft recovery process by pruning the optimization problem's solution space, significantly enhancing solution quality and computational efficiency. This approach is

particularly relevant in scenarios involving large-scale airline operations with extensive daily schedules. The study also delves into the complexities of modelling aircraft routing decisions, disruption characterization, delay propagation, and recovery costs and constraints, offering a comprehensive framework for tackling the Aircraft Recovery Problem (ARP) in a more efficient and practical manner. This innovative method combines machine learning with optimization, showcasing its potential in improving rapid decision-making in airline operations recovery.
A novel approach that harnesses machine learning for column selection during column generation was introduced by Morabit et al. (2021), leading to a marked decrease in computational time. In tackling the crew-pairing problem, Tahir et al. (2021) utilized a deep neural network within a supervised learning framework to predict flight connection probabilities, demonstrating the strength of integrating machine learning with traditional optimization methods.

Further, Alston et al. (2022) demonstrated the utility of decision trees for classification and regression by proposing mixed integer linear optimization formulations to design optimal binary classification trees. The convergence of optimization and machine learning has been the subject of various scholarly reviews, which bridge the gap between the two domains. These include Bennett and Parrado-Hernández (2006) on machine learning models as continuous optimization problems, Olafsson et al. (2008) and Corne et al. (2012) on the intersection of operations research and data mining, and discussions on methodological advances in machine learning optimization problems by Curtis and Scheinberg (2017), Bottou et al. (2018), and Wright (2018).

The contributions by Lodi and Zarpellon (2017) explore machine learning's advancements in mathematical programming, while the interactions between optimization and machine learning are further examined by Song et al. (2019) and Sun et al. (2019). Recent progress in applying machine learning to combinatorial optimization problems has been documented by Bengio et al. (2021), and the articulation of machine learning problems within the framework of optimization models has been critically analyzed from a mathematical perspective by Gambella et al. (2021). Additionally, the application of reinforcement learning to tackle complex combinatorial issues has been explored by Mazyavkina et al. (2021). For those seeking in-depth understanding, these reviews provide comprehensive insights into machine learning's application in resolving optimization problems.

**Research Gap:** Most of the Researchers have tried Machine Learning approaches to solve the ASRP very few or none have tried Deep Learning Approach as it requires a huge amount of dataset and is usually complex and hard to explain how and why it gives better results. Deep learning has capabilities to predict better and hence give accurate results that will prune the solution space for optimization and then compare it with other machine learning models to get a qualitative idea which is a better approach and has more scope for research.

# Chapter 3 Dataset Description:

## 3.1 Dataset :

In the study, raw data representing a week's flight schedule during the winter season is obtained from an airline company. The assumption is that this schedule repeats weekly, meaning that a specific day's schedule, such as that of Monday, remains the same throughout the winter. The analysis concentrates on delays experienced by a single aircraft across various time periods, labeled as 'Ti'. For training purposes, the value of 'i' is set to 5, but it's noted that different values can be selected based on the researcher's preference, affecting only the size of the training dataset. To ensure a comprehensive representation of disruption, the duration of each aircraft's disruption is evenly divided into five intervals. Disruption times are randomly generated from these intervals to prevent any bias in the dataset. Hence one data point is a schedule and we have total 2000 schedules .(approx. 50 aircrafts each day of the week and 5 disruption for each.)

## 3.2 Analysis

Data analysis and preprocessing are crucial stages in any data-driven project, including those in Deep learning, statistics, and general data analysis. It improves data quality by cleaning and transforming raw data into a higher quality format. This includes handling missing values, removing duplicates, correcting errors, and dealing with outliers. High-quality data is fundamental for accurate and reliable analysis. Without proper preprocessing, data analysis can be significantly skewed or misleading. Data often comes from multiple sources and can be in various formats. Preprocessing standardizes this data, ensuring consistency across the dataset. This standardization is crucial for comparative analysis and for feeding data into machine learning models, as these models often require data in a specific format to function correctly.

## 3.3 Data selection and preprocessing

In the realm of neural network modelling, particularly when dealing with categorical data such as aircraft names, the transformation of these names into a machine-understandable format is not just beneficial but essential. This transformation is adeptly accomplished through the process of one-hot encoding. One-hot encoding is a pivotal method in data preprocessing, especially for neural network models, as it converts categorical variables into a binary matrix representation. This method is instrumental in handling the challenge that neural networks face when interpreting text-based categories, as they inherently process numerical data more efficiently. The importance of one-hot encoding lies in its ability to distinctly represent each aircraft name as a unique combination of zeros and ones, where each aircraft is assigned a unique 'hot' (1) against a backdrop of 'cold' (0) values. This format is particularly advantageous for neural network models, as it removes any hierarchical or ordinal misconceptions that might arise from purely numerical representations. By employing one-hot encoding, the model can clearly differentiate between different aircraft without falsely attributing any form of numeric relationship or order between them. Furthermore, this transformation facilitates the feeding of categorical data into neural networks, enabling these advanced models to comprehend and utilize this data effectively. In the context of flight schedule optimization and other aviation-related analyses, the accurate categorization and recognition of different aircraft types are crucial for predictive accuracy. One-hot encoding thus ensures that each aircraft's unique characteristics and operational parameters are properly accounted for in the model's analysis, leading to more accurate, reliable, and insightful outcomes.

Another feature that was selected was the disruption time. The data available was of optimal schedules and the time, airport and aircraft of disruption had to be extracted from the schedule. Moreover the optimal schedule time and original schedule time was not in the same format and hence was 1st converted to same format after extraction of time and then subtraction of original schedule time and optimal schedule time of the disrupted aircraft was done to obtain the disruption duration column.

## 3.4 Feature Engineering and Label Creation

Since the features were not enough and data was sparse with labels unknown we needed to create features and labels that was of releavance. Also all the flights were Repeated every week the dataset was taken of 7 weeks then each of the airplanes disrupted 5 times total no. of flights approx. 150 each day hence total datapoints is 2000(approx.).Due to small amount of dataset big models like transformers, encoder, decoder ,CNN and other deep learning techniques can't be used. To create more data new labels and featureds were created to make datapoints from existing data , it was done by first extracting the arrival airport, destination airport and the time of departure of each flight these were concatenated to make a unique flight identifier . Label as a single presentation was difficult and had to be created such that it forms a binary vector where 0 shows no disruption and 1 showed disruption of the aircraft Hence, each of the flights of the original schedule had a unique Id (Unique flight Identifer) These were then stored as Target variables and were converted to numeric form to feed the neural network. These variables were generated for each flight of the optimal schedule and was compared with the original schedule hence giving us the target variable binary vector of 0's and 1's for our training data.

Discretization is a critical process in data preprocessing, particularly when dealing with time-based data. The discretization of time, plays a vital role in standardizing and simplifying time data. This function rounds time values to the nearest half-hour, making the data more manageable and consistent for analysis. The importance of this process lies in its ability to reduce the complexity of time-related data, which can often be highly granular and varied. By discretizing time into uniform intervals, it becomes easier to compare, aggregate, and analyze time-related patterns in the dataset. For instance, in the context of flight schedules, discretization helps in aligning departure times to a standardized scale, facilitating more straightforward comparisons and pattern recognition across different flights. This standardization is crucial for machine learning models that perform better with data structured in a consistent and simplified manner. Discretization thus enhances the accuracy and efficiency of subsequent analyses, such as optimization algorithms or predictive models, by providing a cleaner, more uniform dataset.

# Chapter 4 Methodologies

## 4.1 Data Splitting

In the process of training and evaluating deep learning models for the Aircraft Schedule Recovery Problem (ASRP), a critical step involves splitting the dataset into training and testing subsets. This is typically done following an 80:20 ratio, where 80% of the data is used for training the model, and the remaining 20% is reserved for testing its performance. This division is a widely adopted practice in machine learning, balancing the need for sufficient training data with the necessity of having an adequate separate dataset to evaluate the model's generalization capabilities. The larger portion for training ensures that the model has access to a comprehensive range of data, encompassing various scenarios and nuances of flight schedule disruptions. This extensive training helps the model in learning and adapting to the complexities inherent in the data. Conversely, the smaller testing subset, drawn from the same distribution but not used in training, provides an unbiased evaluation of the model's effectiveness. It tests the model's ability to apply its learned patterns to new, unseen data, thus assessing its real-world applicability. This 80:20 split is a strategic choice that helps in achieving a balance between overfitting and underfitting, ensuring the developed models are both accurate and robust.

### 4.2 MLP Classifier

In the intricate task of solving the Aircraft Schedule Recovery Problem (ASRP), a sophisticated method was devised, involving the creation of 136 distinct labels. These labels represent a binary classification system for flight status, with '0' denoting flights that were not disrupted and '1' for those that were. The enormity and diversity of these target variables necessitated a robust approach beyond traditional singular models. To address this, individual Multi-Layer Perceptron (MLP) classifiers were trained for each target variable. This method ensures a high degree of precision in predictions, as each classifier is specifically tuned to the unique patterns and characteristics of each flight's disruption likelihood. The choice of MLP classifiers stems from their ability to effectively model complex, non-linear relationships within data, which is quintessential in capturing the intricate dynamics of flight schedules and their susceptibility to disruptions.

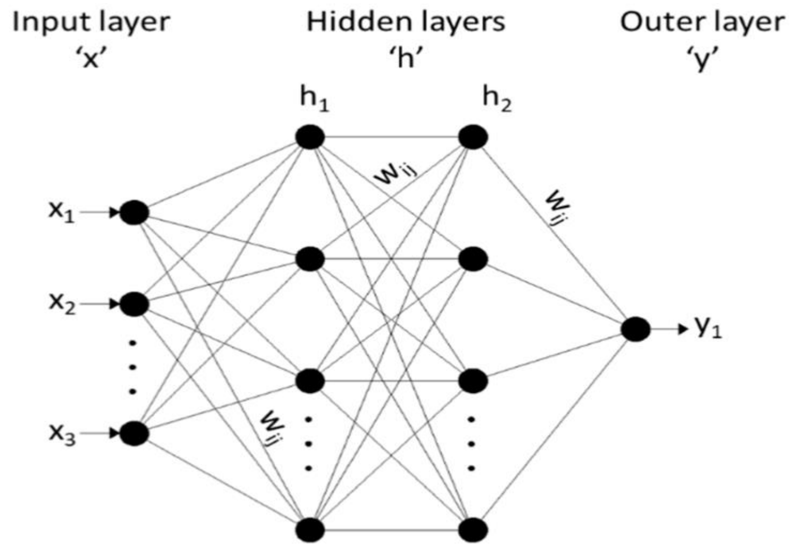
The adoption of multiple MLP classifiers in this study is pivotal. It caters to the heterogeneous nature of flight schedules, where each flight potentially has different factors influencing its disruption status. By assigning a dedicated MLP classifier to each target variable, the approach allows for an in-depth, nuanced analysis, tailoring the predictive model to the unique attributes of each flight. This granularity in modeling is crucial in a domain as variable as airline operations, where factors such as weather, technical issues, and airspace congestion can differently impact each flight. Furthermore, this approach significantly enhances the overall accuracy and reliability of the system, providing a comprehensive and detailed predictive framework capable of handling the multifaceted aspects of ASRP.

Customizing prediction models for each of the 136 labels in ASRP is not just a methodological choice but a strategic necessity. The airline industry deals with a plethora of variables that can disrupt flight schedules, making it imperative to have a prediction model that can adapt to a wide range of scenarios. Individual MLP classifiers offer this adaptability and specificity. Each classifier becomes an expert in predicting the disruption status for a particular flight, considering the unique operational, environmental, and logistical factors that affect it. This specificity ensures that the predictive analysis is not just a broad stroke across the entire schedule but a series of detailed, insightful assessments tailored to each flight’s context.

### 4.3 MLP Classifiers’ Architecture for Enhanced Predictive Performance

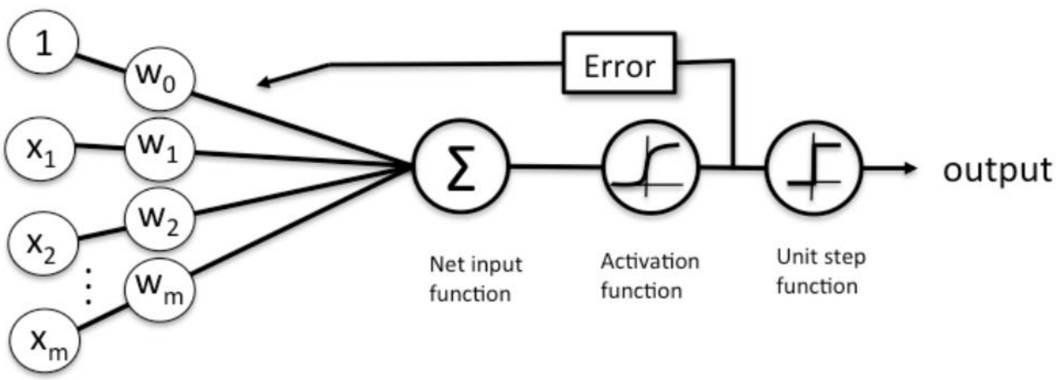
The architecture of the MLP classifiers used in this study is meticulously designed to match the complexity of the ASRP. Each classifier consists of two hidden layers, with the first layer housing 124 neurons and the second 64 neurons with relu activation function. This configuration allows the classifiers to delve into different levels of data abstraction, capturing both broad and intricate patterns in flight disruptions. The first layer, with its higher neuron count, is designed to identify general trends and signals in the data, while the second layer refines these into more detailed insights. The 1000 iterations for each classifier ensure that these layers have sufficient opportunity to learn and adapt to the data, optimizing the model's predictive capabilities. This depth and breadth in architecture are critical for understanding the myriad factors influencing flight disruptions.

The choice of 1000 iterations in training each MLP classifier is a deliberate one, balancing the need for thorough learning with computational efficiency. These iterations allow the classifiers to progressively refine their weights and biases in response to the training data, a process crucial for capturing the nuanced relationships within the data. It's a balancing act – too few iterations might leave the models under-trained and unable to capture the complexity of the data, while too many could lead to overfitting, where the models become too tailored to the training data and lose their ability to generalize. Thus, 1000 iterations represent a sweet spot, giving each model ample scope to learn and adapt, while safeguarding against the pitfalls of overfitting.



The architecture of the MLP classifiers, with their dual-layered structure and specific neuron allocation, is a strategic decision aimed at optimizing the neural network for the ASRP’s unique demands. This structure enables the classifiers to handle various data types and relationships – from linear correlations to complex, non-linear interactions that are characteristic of flight schedule data. The first layer's broader neuron base casts a wide net to capture a range of data signals, while the second layer, more focused in its neuron count, hones in on these signals, refining and interpreting them in the context of flight disruptions. Such a carefully calibrated architecture ensures that the classifiers are not just processing data, but deriving meaningful, actionable insights, crucial for effective disruption management in airline operations.

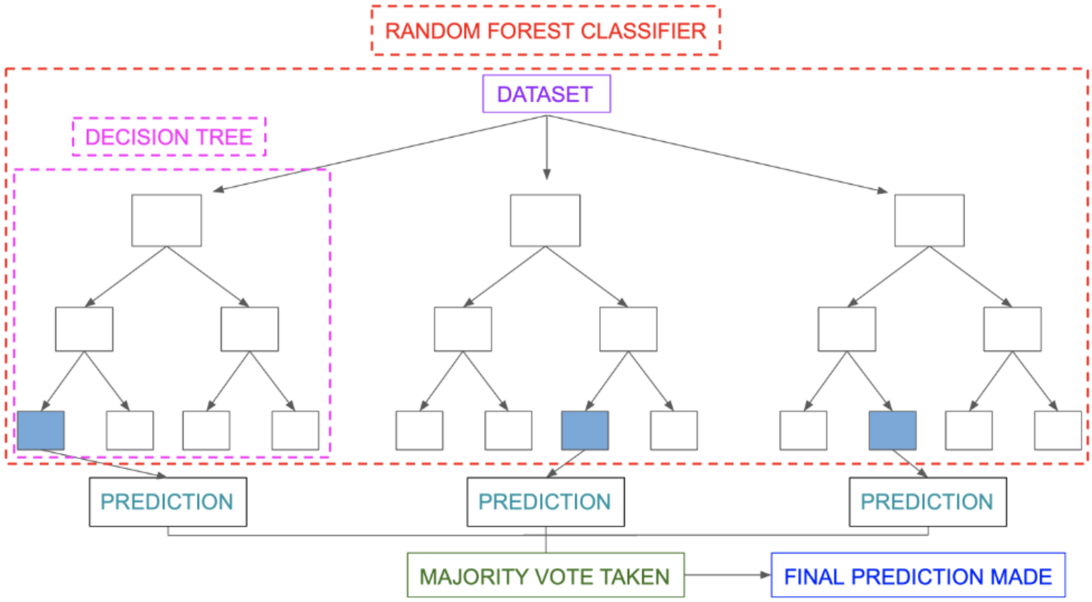
### 4.4 Logistic Regression for ASRP




**Schematic of a logistic regression classifier.**

In the context of the Aircraft Schedule Recovery Problem (ASRP), employing Logistic Regression presents a straightforward yet effective approach to classification tasks. Logistic Regression, fundamentally a linear classifier, excels in predicting binary outcomes – in this case, determining whether a flight will be disrupted ('1') or not ('0'). Its application in ASRP is particularly apt for scenarios where the decision boundary between disrupted and non-disrupted flights can be approximated linearly. The model estimates the probability of disruption based on various input features, such as flight timings, aircraft type, and historical delay data. The strength of Logistic Regression lies in its simplicity and interpretability: it not only provides a clear probabilistic outcome but also allows for an understanding of how different factors weigh in the prediction. This feature is invaluable in ASRP, where logistical and operational decisions are made based on model insights. The model's coefficients can be analyzed to understand the influence of different variables, aiding in strategic decision-making for flight schedule adjustments and optimization.

### 4.5 Random Forest For ASRP

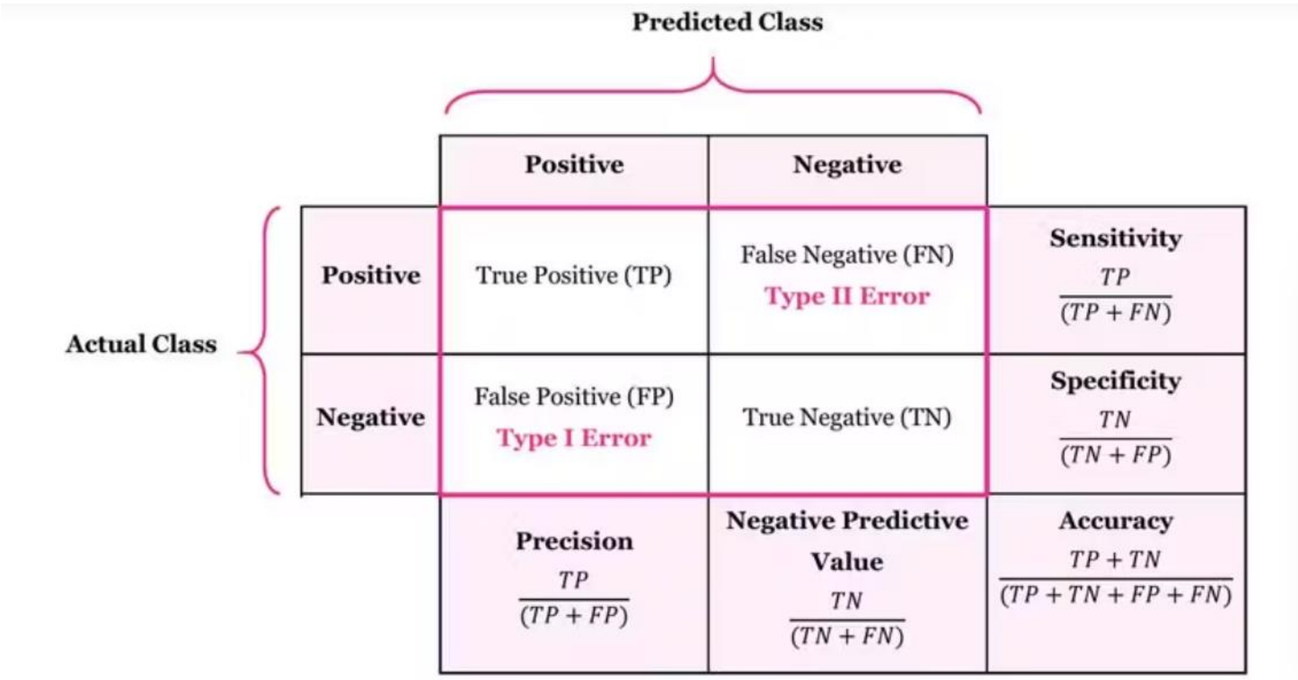



Random Forest, a versatile and robust ensemble learning method, offers a significant advantage when applied to the Aircraft Schedule Recovery Problem (ASRP). This method operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (disrupted or not disrupted) of the individual trees. This ensemble approach is particularly beneficial for ASRP, where the complexity and variability of factors influencing flight disruptions are high. Random Forest effectively captures these complexities through its multiple trees, each considering different aspects and combinations of features. This leads to a model that is not only comprehensive in its analysis but also less prone to overfitting compared to individual decision trees. By aggregating predictions from various trees, Random

Forest ensures a more balanced and reliable outcome, crucial for accurately predicting flight disruptions.

Hence, in addressing the Aircraft Schedule Recovery Problem (ASRP), three distinct deep and machine learning techniques are employed, each with its unique strengths. The Multi-Layer Perceptron (MLP) Classifier is adept at modeling complex, non-linear data relationships, with a deep architecture tailored to each of the 136 target variables. This specificity ensures detailed and nuanced predictions for each flight's disruption status. The Random Forest algorithm, with its ensemble of decision trees, excels in handling the diverse and variable factors influencing flight disruptions, effectively reducing overfitting and enhancing predictive reliability. Lastly, Logistic Regression offers a simpler yet effective approach, ideal for situations where the decision boundary is approximately linear, providing clear probabilistic outcomes and interpretable insights into the influence of different variables on flight disruptions. Together, these methods offer a comprehensive and multi-faceted approach to predicting and managing flight schedule disruptions.

# Chapter 5 Results and Discussion:




*Confusion Matrix*

The results from applying Logistic Regression, Random Forest, and Multi-Layer Perceptron (MLP) classifiers to the Aircraft Schedule Recovery Problem (ASRP) offer intriguing insights into the efficacy of these models in a complex, real-world scenario. Logistic Regression exhibits a commendable precision of 0.92, indicating its strong ability to correctly identify disrupted flights. This high level of precision suggests that Logistic Regression, despite its relative simplicity, is quite adept at handling linear relationships within the dataset. However, it's important to note that the model's linear nature might limit its ability to capture more complex, nonlinear patterns that could be prevalent in the ASRP data. This could potentially lead to limitations in scenarios where the disruption factors are not linearly separable.

| Day | LR | | RF | | MLP Classifier | |
|---|---|---|---|---|---|---|
| | Precision | Recall | Precision | Recall | Precision | Recall |
| Mon | 0.92 | 0.86 | 0.98 | 0.93 | 0.908 | 0.91 |
| Tue | 0.91 | 0.89 | 0.96 | 0.94 | 0.88 | 0.85 |
| Wed | . | . | . | . | . | . |
| Thu | . | . | . | . | . | . |
| Fri | . | . | . | . | . | . |
| Sat | . | , | . | | . | . |
| Sun | 0.87 | 0.85 | 0.97 | 0.981 | 0.89 | 0.83 |

In contrast, the Random Forest classifier achieves an even higher precision of 0.98, underscoring its superiority in handling the intricacies of the ASRP. The ensemble nature of Random Forest, which aggregates predictions from multiple decision trees, contributes to its robust performance. This methodology effectively captures the diverse and variable factors influencing flight disruptions, leading to more accurate predictions. The high precision indicates that Random Forest is particularly effective in minimizing false positives, a crucial aspect in airline disruption management where incorrectly predicting a flight disruption can lead to significant logistical and financial repercussions.

The MLP Classifier, with an average precision and recall of 0.908, showcases its capability to model complex, non-linear relationships in the ASRP data. The highest precision recorded at 0.9998 demonstrates the MLP's potential to achieve near-perfect accuracy under certain conditions. However, the lowest precision of 0.67 reflects variability in its performance, likely due to the diverse and complex nature of the data and the model's sensitivity to different data distributions and features. The variability between the highest and lowest precision also points to the potential overfitting in specific scenarios or the need for further tuning of the model’s parameters to achieve consistent results across various aspects of the data.

The insights gleaned from the MLP (Multi-Layer Perceptron) classifier's performance in the Aircraft Schedule Recovery Problem (ASRP) are particularly noteworthy when examining the data points where the precision was lowest. The approach of training 150 different classifiers, as opposed to a singular model for all data points, played a crucial role in this analysis. Each individual MLP classifier was finely tuned to specific aspects of the dataset, allowing for a detailed examination of how different variables and scenarios influenced the model's predictions. This granularity in the modeling approach meant that each classifier could effectively 'specialize' in its subset of the data, providing insights into particular patterns and anomalies that might be missed by a more generalized model.

Crucially, this approach enabled the identification of data points where the precision was lowest. By analyzing the performance of each classifier separately, it was possible to pinpoint specific scenarios or flight profiles where the model struggled to make accurate predictions. This level of detail is invaluable in understanding the limitations and strengths of the MLP approach in ASRP. It provides a roadmap for further refinement of the models, whether through additional feature engineering, data preprocessing, or adjusting the network architecture. Furthermore, this insight into the weakest points of the model's predictions is instrumental in guiding further data collection and analysis, ensuring future iterations of the model are more robust and accurate across the entire range of potential flight disruption scenarios.

# Chapter 6 Future Scope and Improvement Opportunities in ASRP Research

**Enhancing Data Quality and Volume**: Future research in ASRP can significantly benefit from the incorporation of more diverse and extensive datasets. This includes gathering data under a broader range of conditions and scenarios, such as varying weather patterns, diverse geographical locations, and different aircraft types. Enhanced data quality, with more detailed attributes, can provide deeper insights and strengthen the model's predictive accuracy. Additionally, integrating real-time data could enable models to adapt to current conditions, improving their applicability in dynamic operational environments.

**Advanced Feature Engineering**: There is substantial scope for advanced feature engineering to improve model performance. Exploring more sophisticated methods of extracting, selecting, and transforming features can help in uncovering subtle patterns and relationships within the data. Techniques like deep learning-based feature extraction, especially for unstructured data (e.g., text from pilot reports, weather forecasts), can be explored to enhance the models' understanding of complex scenarios.

**Experimenting with Hybrid Models**: Combining different machine learning approaches into hybrid models could yield better results. For instance, integrating the strengths of MLP classifiers with the robustness of Random Forest or the interpretability of Logistic Regression could create a more powerful predictive tool. Ensemble methods that blend predictions from multiple models or stacking techniques could also be explored to leverage the complementary strengths of different algorithms.

**Utilization of Deep Learning and Neural Networks**: Exploring more complex neural network architectures like Convolutional Neural Networks (CNNs) for image-based data (e.g., satellite imagery for weather patterns) or Recurrent Neural Networks (RNNs) for time-series data (e.g., historical flight schedules) could offer significant improvements. The use of Autoencoders for dimensionality reduction or Generative Adversarial Networks (GANs) for data augmentation are other promising areas.

**Improving Real-Time Predictive Capabilities**: Enhancing the models to function effectively in real-time is a crucial area for future research. This includes developing models that can rapidly adjust to new data, providing immediate insights for dynamic decision-making. The ability to predict disruptions in real-time could significantly enhance operational efficiency and response strategies.

**Robustness to Data Anomalies and External Factors**: Future models need to be more robust against data anomalies and external factors like sudden policy changes, global events, or unexpected operational challenges. This might involve incorporating more adaptive learning algorithms or developing models that can factor in a wider range of external influences.

**User-Friendly Implementation and Integration with Existing Systems**: Ensuring that the models are not just accurate but also user-friendly and easily integrable with existing airline operation systems is essential. This includes developing intuitive interfaces for model outputs and ensuring compatibility with various airline software systems for seamless implementation.

**Ethical and Environmental Considerations**: Incorporating ethical and environmental considerations into the models, such as reducing the carbon footprint of flight schedules, can be a significant area of development. Models that optimize for both operational efficiency and environmental sustainability could be highly valuable in the current global context.

In summary, the future of ASRP research lies in enhancing data handling capabilities, experimenting with advanced modeling techniques, and focusing on real-time applicability and integration. These advancements not only promise improved accuracy and efficiency in disruption prediction and management but also align with broader objectives like sustainability and ethical decision-making in the airline industry.

**Code links for the Models trained:**

https://www.kaggle.com/code/deepa77/arp-most-latest/edit

https://www.kaggle.com/code/deepa77/asrp-part3/edit

# 7. References: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