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Predictability improvement of Scheduled Flights Departure Time Variation using Supervised Machine Learning

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Cover Page Footnote

We would like to thank Airports Authority of India for providing data for the research.

Air Traffic Flow Management (ATFM) uses Traffic Management Initiatives (TMIs) like Ground Stops (GS) and Ground Delay Programs (GDP) to control the flow of air traffic to capacity constrained-airports. The GDP algorithm depends on the Estimated off Block Time (EOBT) of the filed flight plan and the calculated Estimated Landing Time (ELDT) of the participating flights. Even though ATFM consists of a sequence of preparation processes accompanied by rearranging/rescheduling processes, one of the difficulties is the unpredictable occurrence of delays. The variation of actual values from these estimated values or scheduled values commonly termed as delay and this delay can be positive(early) as well as negative(delay). Airline policies, logistical issues such as glitches with airport infrastructure, baggage handling, ground handling, bad weather conditions, seasonal and holiday demands, pushback limitations, ATC enforced delays, and the accumulation of delays from preceding flights, all these factors contribute to departure delays~~.~~

Strategic and pre-tactical planning stages of ATFM process would be more effective when it can anticipate or predict the possible random variation in departure time, which will affect the entire traffic flow management process. Among the various causes of departure delays, one of the significant factors is the accumulated delay from preceding leg. Most of the domestic flights operate in multileg between different pairs of cities. So, if any delay has occurred in one leg, it most likely will be reflected in succeeding legs. In some cases, airlines use strategies like schedule buffering (adding additional time in flying time and increase turnaround time) to overcome this. But for an Air Navigation Service provider, schedule buffering will introduce reduction in predictability. Hence, in a real-world situation these variations have to be properly traced and predicted.

Due to the amount of data and features involved in this process along with repeatability, an automated process can be devised to detect or predict these delays. Hence, the importance of introducing Machine Learning (ML) to detect and predict the amount of delays using historical flight details. Machine learning is a form of an algorithm that enables to improve accuracy in predicting outcomes without having to be specifically programmed for any specific purpose. Here we propose an ML based departure delay prediction model to improve the predictability and efficiency of air traffic flow management initiatives. We use the prediction technique to evaluate the amount of departure time variation based on various flight information and classify the departure time using classification model.

Problem

The domestic scheduled flight scheduling process is composed of several phases and airlines usually prepare their schedules 4-6 months ahead of time with the approval of the airport operator and regulator. On the day of operation, the airline operators fine tune their operations based on the resource availability and other operational needs. This will make changes in the scheduled operations,which affect strategic ATFM planning. The majority of the scheduled flights in the domestic sector are interconnected and flights are operated in such a manner that the arriving aircraft will be scheduled for the next flight with a minimum turnaround time in the airport. Hence, the scheduled departure time of a directly linked flight have a direct relationship with previous leg departure delay and turnaround time after the previous landing. When comparing Satellite airports (airports that connect to metro city airports) with Hub airports (typically Metro City airports from which airlines operate to satellite airports), the delay risks are higher at hub airports due to a more number of fleet, crew changes, and other operational adjustments. Airport delays may be caused by airline operations, air traffic congestion, weather, air traffic management programmes, and other factors. The majority of the causes are stochastic events that are extremely difficult to segregate and predict in a timely and precise manner. This will lead to inefficient traffic flow management planning, false detection of Traffic Management Initiatives (initiating GDP when the actual number of operations is less than the scheduled number due to delays), underutilization of airport and resources, and even the shift of demand capacity imbalance from predicted duration (if more flights are delayed then the imbalance may even transfer to another hour). As a result, finding an appropriate prediction model for detecting departure delays based on previous leg arrival time and turnaround time is a significant problem in ATFM decision-making (initiating TMIs).

Purpose

The Low-Cost Carriers (LCCs) are the main players in Indian domestic air traffic network, LCCs business strategy is based on achieving a competitive cost advantage through utilising secondary airports, point-to-point networks, or a hub-and-spoke approach from a base location. Therefore, most of the flights are inter-connected, that is, the same aircraft is used with multiple legs with minimal turnaround time. Therefore, if any delay occurs in one leg it will affect another leg of flight if the turnaround time cannot compensate for this delay. This is part of study for improving efficiency and predictability of ATFM Ground Delay program. The statistical evaluation shows that most of the domestic flights that participate in GDP are subject to the effect of these delays. If these delays are predicted properly then the performance and predictability of the GDP can be improved. We assess various attributes in this study to determine these significant attributes that can predict flight departure delays of various airports, as well as the length of delays (difference from scheduled departure time) and classify flights as leaving early, late, or on time based on the preceding leg departure time.

Research Questions

1. Can the Estimated Elapsed Time (EET) filed by airlines can be effectively used for the prediction of landing time and next leg departure time?

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2. How effectively the departure time of scheduled flights can be predicted using machine learning?
3. How effectively the flying time and turnaround time of scheduled flights can be traced with minimal attributes?
4. Using historical data and previous leg flight information, can machine learning effectively classify departure time variance of scheduled flights?

Literature Review

Following the pandemic, the aviation industry is steadily recovering, with airlines gradually increasing the flight schedules as national and regional bans are being lifted. Even if the airline operator organises their new schedules, flight delays are unavoidable and are significant to all stakeholders and passengers. Reliable flight delay estimation remains a challenging task for airlines, airport operators, and air navigation service providers. Many studies have been carried out on the modelling and estimation of flight delays, with many of them attempting to predict the delay by capturing as many features and characteristics as possible.

Flight delays are caused by irregularities in airline activities caused by a wide variety of factors(Mueller & Chatterji, 2002). Some studies have indicated that air traffic control restrictions caused by inadequate airport/airspace capacity to satisfy the demand of air travel may also cause flight delays (Abdel-Aty et al., Takeichi et al., 2017), and bad weather can also be a significant factor in causing system delays (Belcastro et al., 2016; Janić, 2005; Wu et al., 20180). Owing to the presence of several agencies, flight delays can be caused by a variety of causes, also any disturbance in the air traffic system induced by these factors can result in further delays for flights affecting several airports and airlines (Abdelghany et al., 2004; Bubalo & Gaggero, 2021; Deshpande & Arikan, 2012; Wong & Tsai, 2012).

In general, there are two types of existing research approaches for delay prediction: (1) methods that are focused on delay propagation and (2) data-driven methods. Methods based on delay propagation that study the phenomenon of flight delay propagation within air transport networks and attempt to predict delays using the network's underlying mechanism (Churchill et al., 2010; Kafle & Zou, 2016; Schaefer & Millner, n.d.). Liu and Ma (2008) proposed a Bayesian network-based (BN) flight delay and delay propagation model, which employs Expectation-Maximization (EM) arithmetic to investigate the effects of arrival-delay and flight-cancellation on departure-delay in different states. Waltenberger et al. (2018) conducted an analysis to look at the gaps in on-time efficiency, turnaround scheduling, turnaround performance, and block time setting between low-cost and non-low-cost carriers on an operational level. The findings demonstrate that performance is dependent on a combination of quick turn around of aircraft and having adequate time on the ground to absorb delays. Dinler and Rankin (2020) used a hierarchical regression analysis to find a statistically significant link between airport performance and capacity indicators and on-time arrival rates at U.S. airports.

Data-driven analyses, rather than analysing delay propagation processes, have become very popular methods for flight delay prediction in recent years, owing to its ability to directly apply data mining, statistical inference, and/or machine learning techniques (Ding, 2017; Qu et al., 2020; Sahadevan et al., 2020; Yu et al., 2019). The random forest algorithm, Multiple Linear Regression (MLR), logit probability, artificial neural network, and deep learning are some of the prominent data-driven approaches that have been used to predict flight delays. The main goal of these approaches is to extract significant influential variables from real-world systems, in order to build prediction models that are accurate, reliable, and highly efficient. Rebollo and Balarishnan (2014) proposed air traffic delay prediction models focused on networks that use random forest algorithms to forecast departure delays by considering both spatial and temporal delay states as explanatory variables. Both local and network delay variables, which characterise the arrival or departure delay states of the most influential airports and links (origin–destination pairs), are included. Belcastro et al. (2016) proposed a method for predicting the arrival delay of a scheduled flight due to weather factors that consider all flight information (origin airport, destination airport, scheduled departure, and arrival time) as well as weather conditions at the origin and destination airports according to the flight schedule. Kim (2016) proposed the Long Short-Term Memory Recurrent Neural Networks (RNN) architecture to model day-to-day sequences of departure and arrival flight delays at a single airport. They mostly use delay states from previous days' flights to predict subsequent days' flight delays. However, schedules and traffic patterns often differ on different days.

In recent years, there has been a lot of research into determining the root cause of delays and developing models to detect and predict future delays, along with the causes for them, as well as the time, place, magnitude, and likelihood of them happening (Carvalho et al., 2020; Zhang et al., 2019). However, considering the aforementioned stochasticity in the airspace and air traffic condition, predicting potential delays is a challenging task. Most of the delay perdition can be broadly classified into Arrival Time prediction and Departure time prediction (Thiagarajan et al., 2017) and the Delay propagation term interconnects these two. Since most of the arrival and corresponding departure flights directly linked departure time variation prediction becomes complex comparing to arrival time variation.

Guleria et al. (2019) proposed a multi-agent method for estimating reactionary delay based on the classification of flights as delayed or non-delayed in terms of departure. With a delay classification threshold of 15 minutes, the classification results indicate an overall accuracy of 80.7%. Euro control conducted a case study (Dalmau Codina et al., 2019) for the Maastricht upper area control centre area to improve the predictability of take-off times using Machine Learning.

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The predictions made by a Gradient Boosted Decision Trees (GBDT) and an Artificial Neural Network (ANN) were based on three years of historical flight and weather data, and the MAE for take-off time prediction was 7 minutes.

Ye et al. (2020) investigated supervised learning methods to propose a framework for predicting aggregate flight departure delays in airports, and analysed individual flight data and meteorological information to obtain four types of airport-related aggregate characteristics for prediction modelling. According to their findings, the Light GBM model has the best results for a 1-hour prediction horizon, with an accuracy of 0.8655 and a mean absolute error of 6.65 minutes, which is 1.83 minutes less than previous study results.

Nevertheless, the majority of previous research (Demir & Demir, 2017; Esmaeilzadeh & Mokhtarimousavi, 2020; Kim & Bae, 2021) has focused on predicting expected departure delays from an airline and airport perspective using as many attributes as possible, including time and weather-related factors. Hardly any of the studies have considered early departures (departing earlier than scheduled) as a possible result of airline schedule time padding, which could cause subsequent leg departures to depart earlier than planned. When considering the realistic scenario case, some aggregate features influencing flight schedules and airport delays have yet to be thoroughly investigated, as well as a limitation in the availability of exact future weather information, the risk of overfitting, and excess computational cost due to a greater number of attributes not addressed in the previous works.

However, delays to flights (demand-capacity imbalance is to impose ground delay) are dependent on expected departure time and flight plan details from the perspective of an Air Navigation Service Provider's Air Traffic Flow Management (ATFM). Aircraft operators normally have a buffer period in their schedules to prepare for expected delays and increase on-time efficiency. Aircraft operators often have a buffer interval in their schedules to account for anticipated delays and improve on-time performance(Sahadevan et al., 2020). The current method of allocating ATFM delays ignores whether flights have any residual schedule buffer to absorb ATFM delays and prevent delay transmission to subsequent flights (Ivanov et al., 2017).

The aim of this paper is to propose a methodology for predicting linked scheduled flights departure delays of airports using supervised learning methods that take into account aggregate flight data as well as other factors.

Methodology

For this research, the authors used an exploratory and applied approach.

Data Collection

Scheduled flights to and from Mumbai International Airport (ICAO: VABB), Delhi International Airport (ICAO: VIDP) and Bangalore International Airport (ICAO: VOBL) , India, were the study cases in this research. A database of

accurate data for individual flights as well as airport information was compiled from September to November 2020. Each flight's data consists of date of flying, flight number, type of aircraft, departure, destination, scheduled /actual time of departure and scheduled /actual time of arrival. The departure delays for each flight are measured as the difference between the actual departure time and the expected(filed) departure time.
The actual time of arrival and departure variation from scheduled flights are classified into three categories.

Table 1
Schedule Variation Categories

Departure / Arrival Time	**Category**
Actual -Scheduled < **-5 Minutes**	**Early**
-5Minutes<= Actual -Scheduled<=**10 Minutes**	**On Time**
Actual -Scheduled>**10Minutes**	**Delay**

Initial Observations from data

Figure 1 shows scheduled flight actual departure time departing from VABB, VIDP, and Bangalore, consists of overall (all the three airports) 8876 (15%) flights with Early departures, 32819 (57%) flights departed On Time, 15861 (28%) flights delayed. Similarly, for Arrival, consists of overall (all the three airports) 13571 (23%) flights with Early Arrivals, 29189 (51%) flights arrived On Time, 14796 (26%) flights delayed. The statistics indicate that on-time performance of scheduled flights is around 50%.

Figure 1
Scheduled Flight Departure Time Variation

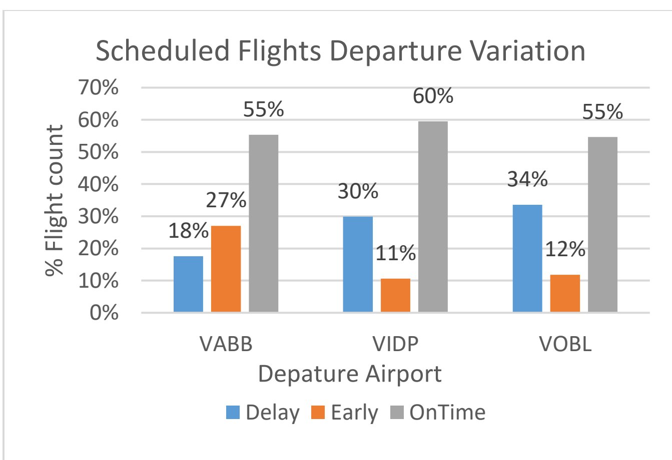

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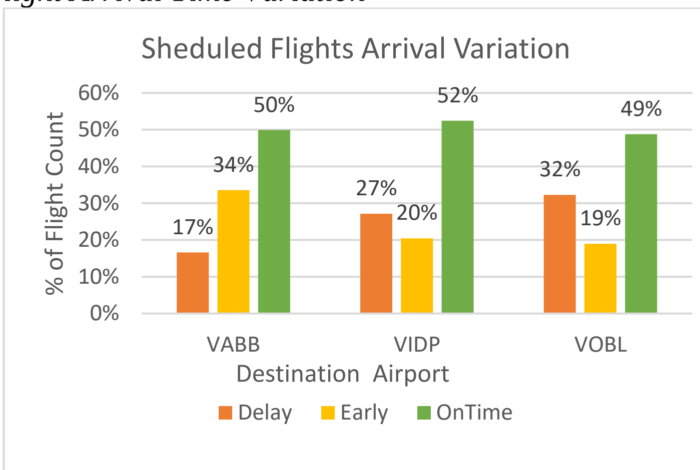
Figure 2
Scheduled Flight Arrival Time Variation



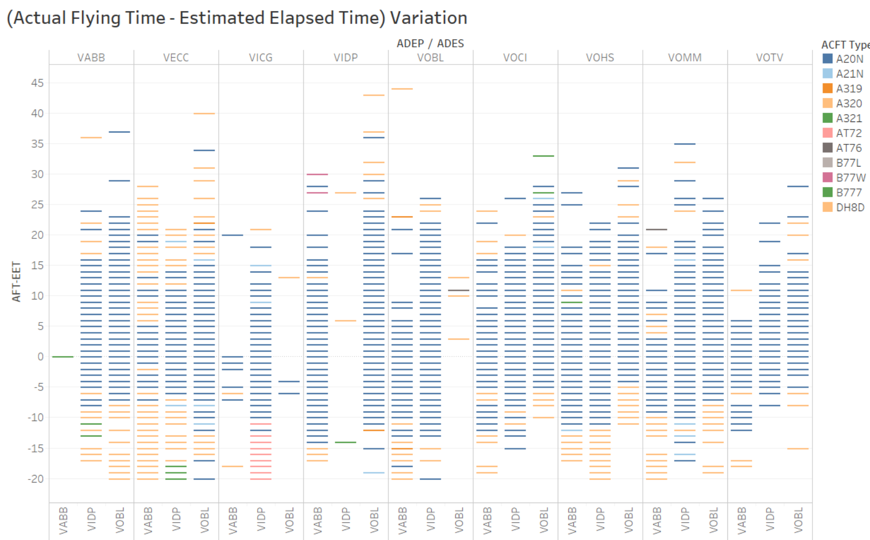
The Actual Flying Time (AFT) and Estimated Elapsed Time Filed (EET) by the Airline for each flight are evaluated. It is observed that the EET filed by the airlines and AFT varies in a large window (-20 Minutes to +45 Minutes) due to many factors and even for same departure destination with same aircraft type. The maximum number of variations is observed between -15 Minutes to +30 Minutes. Figure shows the Arrivals to VABB, VIDP and VOBL from different departure stations and variation of flying time (AFT-EET). If these random variations can be traced properly using available historical information and along with the EET filed by Airline, they can be used for predicting landing time and Next leg departure time. Our objective is to predict the schedule departure variation using machine learning technique for Air Traffic Flow Management decision making.

Characterization of Airport Departure Delay

The scope of this study is limited to the prediction of departure delays based on the assumption that normal weather prevailing at the airport for normal operations. The study explores the possibility of improving the predictability of departure time for multileg flight operations using machine learning technique. The aggregate of flight delay statics indicates that multileg operations of domestic flights cause the propagation delays to successive segments. By proper identification of connected flights (same aircraft used for next segment) these propagation delays can be traced.

Figure 3

AFT-EET Variation for Different Departure Destination



If the delay affected flights unable to recover its delay using turnaround time, the affected flight delay will induce delay in successive legs. These flights can be treated as delay infected flights. During the evaluation of Traffic Management Initiatives (TMIs), i.e., GDP and GSPs, these delay infected flights degrade the efficiency and predictability. As a general practice, the Airline operator normally updates the delays if more than 45 minutes due to the requirement of air defence clearance. So, tracing the factors for the previous leg delays accurately predicting these delays improves the performance of the ATFM system along with effective utilisation of airports and airline operators' resources. The prediction of departure time also helps to provide more accurate gate information and departure flight status to passengers.

Initial data analysis indicates that variations in flying time and turnaround time, as compared to taxi time, are significant contributor to multileg flight departure time variations. Based on previous leg departure time and schedule variance, we propose a supervised machine learning based method for improving departure time prediction of directly linked flights.

Proposed Model

In existing practice, the ATFM and ATM system treat and process each flight plan individually and the delay in one flight plan do not link to other flight plans automatically. This makes it difficult for the system to identify or predict network delay or even congestion at an airport due to multisegmented delays. Here we propose the linking of flight plan based on registration and frequent trailing flight based on history, to identify the arrival and corresponding departures of each airport. This first step of linking the flights based on the registration can be used for predicting inbound arrival delays and corresponding departure time variation of connected flights. As the landing time varies due to the terminal congestion, apron movements and boarding delay departure time varies based on airline, hours of the day and due to various other factors departure time also can vary. Here we attempt to trace and predict this departure time using the previous leg flight departure time of the same flight, which is 2 to 3 hours before the departure of the next leg. The following characteristics are used for the prediction.

Table 3
Aggregate Characteristics

Attribute Characteristic	Details
Time characteristics	Hour of the day and Day of the week
Flight plan-based characteristics	Filed Estimated Elapsed Time (EET), Airline, Departure station (Previous Leg) Route and Distance (Previous Leg) Aircraft Registration Scheduled and Actual Departure time (both leg)
Derived Delay characteristics	Exponential Moving Average(window=3) 1. Flying time of the same type of Aircraft and same departure station 2.Turn Around Time for the same airline for the same type of aircraft. 3.Difference of EET and Actual Flying time
Airport Characteristics	Runway The number of departures and arrivals for the hour.

The estimated delay time for departure aircraft is set as a target and variables are determined and labelled using the raw data. As a result, the problem addressed in this study can be considered a conventional supervised learning process. Unlike previous work that used all available attributes to predict the Landing Time and Departure Time, we use the historic error or random variation of flying time, that is the difference between the Estimated Elapsed Time (t_{EE}) filed by each flight and

Actual Flying Time (t_{AF}) , used to predict future variation. The Actual Flying time is calculated from Actual departure (t_{AT}) and Actual Landing time (t_{AL}).

$$t_{AF} = t_{AL} - t_{AT} \qquad (1)$$

We assume that the difference in (t_{EE}) and (t_{AF}) includes all the random variation of flying time under normal weather and airport conditions. The random variation of flying time for the nth flight ($t_{e(n)}$) can be calculated by

$$t_{e(n)} = t_{AF(n)} - t_{EE(n)} \qquad (2)$$

Prediction of random variation in flying time is a challenging task since this variation depends on various contributing factors, and segregation of contributing factors is a tedious task. Most of the previous studies used all the attributes as input for predicting the estimated time of arrival, but in practical scenarios, this is not the case. The random variation may due to individual components, maybe the partial effect, nonlinear, and may be due to collective contribution. Quantifying and segregating each attribute's contribution are challenging tasks until a mechanism is devised to quantify the contribution of individual components in each movement. Even if they are segregated, each contribution's prediction makes calculation very complicated due to the involvement of wind, weather, and human factors, which is highly random and time-varying. In a detailed analysis, we observed that most of these variations are temporal, and the moving average is one of the solutions to trace the temporal variation. There are different methods, including deep learning, available for time series forecasting. We evaluated the extent of improvement in prediction accuracy by incorporating the Exponential Moving Average (EMA) of random variation (error) previous flights as input attributes to the regression model. Based on weighted observations, moving averages strive to smooth short-term irregularities in the data set (Deepudev et al., 2021; Sahadevan et al., 2020). If the data is reasonably consistent over a period of time, the exponential moving averages effectively traverse the variation.

The Exponential Moving Average (EMA) of the previous random variation denoted $\mathrm{EMAe}_{n,s}$ where `n' denotes the flight number and `s' denotes the span over which the exponential moving averages are taken. Here we use the grouping same category of aircraft and same departure station for EMAe. Here we used the exponential moving average of the last three movement random variation $t_{e(n)}$.

Hence, $\mathrm{EMAe}_{n,s}$ can be rewritten as

$$\mathrm{EMAe}_{n,s} = \propto t_{e(n-1)} + (1-\propto) t_{e(n-2)} + (1-\propto)^2 t_{e(n-3)} \qquad (3)$$

$t_{e(n-1)}, t_{e(n-2)}, t_{e(n-3)}$ are random variation occurred for $(n-1), (n-2), (n-3)$ flights respectively, $\propto$ refers to a smoothing factor, which is calculated as follows; $\propto = 2/(s+1)$ where ‘s’ represents the number of periods the EMA uses.

Similarly, the turnaround time variance can be tracked using the EMA of the last three flights of the same type of aircraft and airline.

$$\mathrm{EMATA}_{n,s} = \propto t_{ta(n-1)} + (1-\propto) t_{ta(n-2)} + (1-\propto)^2 t_{ta(n-3)} \qquad (4)$$

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$t_{ta(n-1)}, t_{ta(n-2)}, t_{ta(n-2)}$ denotes turnaround time of n-1, n-2, and n-3 flights. These two attributes improve the predictability of departure time using machine learning models. Therefore, finally the departure time variation of n^{th} flight is calculated by

$$t_{ATe(n)} = t_{AT(n)} - t_{ET(n)} \qquad (5)$$

He we propose the $t_{ATe(n+1)}$ of can be predicted using machine learning, that is $\hat{t}_{ATe(n)} = f\{\mathrm{EMAe}_{\mathrm{n,s}}, \mathrm{EMATA}_{\mathrm{n,s}}, RWY, ACFT, t_{ATL1}\}$ (6)
Where is f is a function, which can be modelled using supervised machine learning techniques. Once random variation $\hat{t}_{ATe(n)}$ predicted the actual take-off time $\hat{t}_{AT(n)}$ can be predicted using

$$\hat{t}_{AT(n)} = t_{ST} + \hat{t}_{ATe(n)} \qquad (7)$$

Therefore, once random variation ($\hat{t}_{ATe(n)}$) is predicted, the take-off time of next leg can be predicted easily using scheduled departure time t_{ST}.

Several supervised learning methods have been tested with the available attributes for predicting $\hat{t}_{ATe(n)}$, of which the M5P regression tree and Multi-layer Perceptron (MLP) have given the best results compared to other methods. Since the prediction results of the aforesaid models have been much superior to the regression models of multiple linear regression (MLR) and random forest (RF), the outcome of MLR and RF models is not included in this article.

M5P Regression Tree

A decision tree learner, M5 tree, was introduced by Quinlan (1992), for regression problems. It assigns terminal node linear regression functions and suits each subspace with a multivariate linear regression model by categorising or splitting the whole data space into several subspaces. The M5P is a non-linear regression model based on Quinlan's M5 algorithm (Wang et al., 1996), which is a hybrid of a conventional decision tree with linear regression capability at each node. To maximise the expected error reduction, the tree nodes are chosen as a function of the output parameter's standard deviation.

Multi-layer Perceptron (MLP):

MLP is a supervised learning algorithm that maps multi-layer feed-forward neural networks in a nonlinear manner (Gupta et al., 2004). MLP is made up of three basic layers: an input layer, a hidden layer, and an output layer, with each node being fully connected to the nodes in the subsequent layer with appropriate weights. Because of the benefits of a single hidden layer MLP, only one hidden layer is included in the proposed work. It's likely that MLP has a non-linear activation mechanism not seen in other neural networks because it uses a backpropagation method for training.

The backpropagation algorithm, which stands for "backward propagation of errors," aims to minimise network error by changing the weights at each node based on the gradient of the loss function with respect to the corresponding weight (Stulp

& Sigaud, 2015). The error $\boldsymbol{\varepsilon}_{j}(n)$ at the j^th output node in the n^{th} data point can be determined using the actual output value $y_{j(n)}$ and predicted output value $\hat{y}_{j(n)}$,

$$\varepsilon_{j(n)} = y_{j(n)} - \hat{y}_{j(n)} \tag{8}$$

The minimization of error by weight correction using backpropagation is given in the equation below:

$$\sigma(n) = \frac{1}{2}\sum_{j} |\varepsilon^{2}(n)| \tag{9}$$

$$\Delta W_{ji}(n) = -\alpha \frac{\partial \sigma(n)}{\partial_{j(n)}} \hat{y}_{i(n)} \tag{10}$$

Where $y_i(n)$ is the previous node output where and α is the learning rate. The iterative process is repeated till the error is fixed. To make the prediction, the network uses a basic MLP with 8 input neurons, 256 hidden neurons with Relu activation, and 1 output neuron with Linear activation. The network is trained for 5 epochs with a batch size of 15 and has a total of 2665 trainable parameters.

Classification of Schedule Departure Time Variation Using Multinomial Logistic Regression

The predictability of actual flight departure times variation with respect to scheduled times is one of the primary concerns for the ATFM, Airport Operators, and Airline Operators. The accuracy of departure time predictions has a significant impact on resource and bay allocation, which also has a substantial impact on AFTM strategic planning (GDP/GS). Based on variation in actual departure time of the previous leg (Early, On time, and Delay) and predicted landing time($\hat{t}_{AL}$), we propose a multinomial logistic regression model to predict the on-time performance (Early, On time, and Delay) of scheduled flights departure time.

Multinomial logistic regression (Bohning, 1992) is a binary logistic regression extension that models discrete multi-criteria choice, allowing classification of more than two categories. Multinomial logistic regression is a common classification machine learning algorithm that works well with continuous data and multiclass variables, as with this analysis. This model's premises are much simpler than those used in other approaches, such as discriminant function analysis (Kwak & Clayton-Matthews, 2002). The fundamental principle is that the probability of a choice is determined by the number of users who select that option, implying that the choices are not mutually exclusive. Since each flight schedule is independent, this is nearly true in our case. The multinomial logistic regression model can be expressed in the following way:

$$logit(p) = log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 * A_1 + \beta_2 * A_2 + \beta 3 * A_3 \ldots \tag{11}$$

$p(\mathrm{Y} = 1)$ denotes probability, and Y is the response variable, i.e., the category of variation from the scheduled departure time ($t_{AT} - t_{EO}$). The odds logarithm is denoted by logit (lot), which has a linear approximation relationship. Three types of qualitative responses are included in the qualitative answer component: Early, Delay, and On Time schedule. The explanatory variables departure ($t_{AO1} - t_{SO1}$)

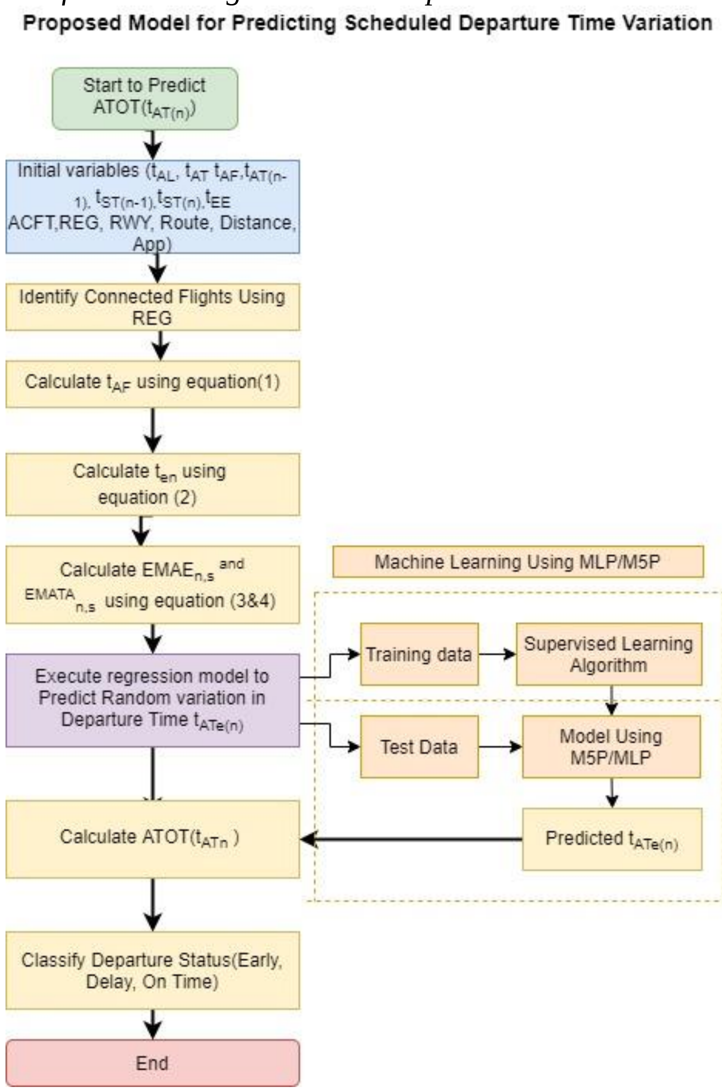
as per table 1, the exponential moving average of flying time and turnaround time, Runway, Aircraft Type denoted by $A_{1,}\, A_{2,}\, A_{3,}$ .... are the attributes used for prediction. The explanatory variable impact on the log odds, that is Y =1 is indicated by $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ ... . The data was divided into two sets: a training set (75%) and a test set (25%).

Proposed Model for Predicting Scheduled Departure Time Variation

The Figure 4 summarise the steps involved in the proposed model for predicting departure time ($\hat{t}_{AT(n)}$).

Figure 4

Proposed Model for Predicting Scheduled Departure Time



Performance Measures

For comparing the prediction results of different models, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are chosen as performance measures. The square root of the mean of the square sum of all deviations (errors) between the predicted and actual values is the RMSE. MAE is the mean absolute error, which calculates the absolute difference between the expected and actual value and more accurately represents the actual situation of predicted value error. The estimated model is close to the real value if these parameters have a small value. MAE and RMSE are calculated using Equations (12) and (13), respectively.

$$MAE = \frac{1}{n}\sum_{i-1}^{n} |t_i - \hat{t_i}| \qquad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(t_i - \hat{t_i})^2} \qquad (13)$$

Where t_i denotes the actual data, $\hat{t_i}$ denotes predicted data and 'i' denotes the number of prediction samples.

Results and Discussion

The analysis was carried out for prediction accuracy of different segments of multileg flights. Initially, we analysed the prediction capability of the proposed method for predicting the landing time of the first leg using historical variation in Estimated Elapsed time filed by the airline and Actual Flying time. The performance measurements for various supervised learning models for predicting first leg landing time are shown in Table 4. The Landing time of various scheduled flights to Mumbai International is predicted using the proposed model with M5P and Multilayer perception.

Table 4

Landing Time Prediction Performance

Parameter	**M5P**	**Multilayer Perception**	**%Improvement with Previous work** (Deepudev et al., 2021)
Correlation coefficient	0.874	0.865	
MAE	1.998	2.175	43%
RMSE	2.924	3.042	38%

The results of both nonlinear models are comparable and M5P regression models give better prediction accuracy than Multilayer Perception Model. The last column denotes a comparison prediction error with previous work (Deepudev et al., 2021), where the prediction accuracy was MAE of 3.5 and RMSE of 4.8.

Prediction of Actual Take-off Time of Scheduled Flights

Table 5 compares the proposed supervised learning models to previous work in terms of performance measures. The different categories of flights operated to/from different airports to Mumbai International Airport were validated with both the models. The proposed model's RMSE ranges from 4.8 min to 5.4 min, implying that the M5P model provided the best performance and compared to previous work, around 50% increase in prediction accuracy. In previous work using a greater number of attributes such as Ye et al. (2020), the departure time performance was with maximum RMSE and MAE of 9.67 and 6.64 respectively. Here the departure time variation from -30 minutes to 60 minutes of the scheduled departure time was considered in both training and test data. Even though the departure time varies in a large window, the model is able to capture variations based on previous leg departure time and previous flight information with an accuracy of 4.84 Minutes. The result obtained is as follows:

Table 5

Scheduled Departure Time Variation Prediction Performance

	Proposed Method		**Previous Work**(Ye et al., 2020)		**%Improvement**
Parameter	**M5P**	**Multilayer Perception**	**SVM**	**Light GBM**	
Cor coef.	0.938	0.927			
MAE	3.436	3.982	6.69	6.64	48%
RMSE	4.846	5.406	9.87	9.67	50%

In order to analyse the robustness of the model, analysis was carried out for the perdition accuracy of various types of aircraft with different departure stations. The results obtained for Bangalore International Airport are given in Table 6. It is observed that, depending upon the airline and type of aircraft, the prediction accuracy varies slightly. This is mostly due to the variation in turnaround time and sometimes due to arrival delay. The M5P model performs better than Multilayer perception in most cases. Figure 5 shows the Actual Departure Time variation of test data vs Residual and Predicted values. The residual distribution is concentrated around zero. From the figure it can be inferred that residual varies more from the zero values as the extreme ends (-30Minutes and 60 Minutes of variation), that is for large variation prediction accuracy reduces. The nonlinear regression model is able to capture random variation.

Figure 5

Departure Time Variation- Actual vs Residual and Predicted

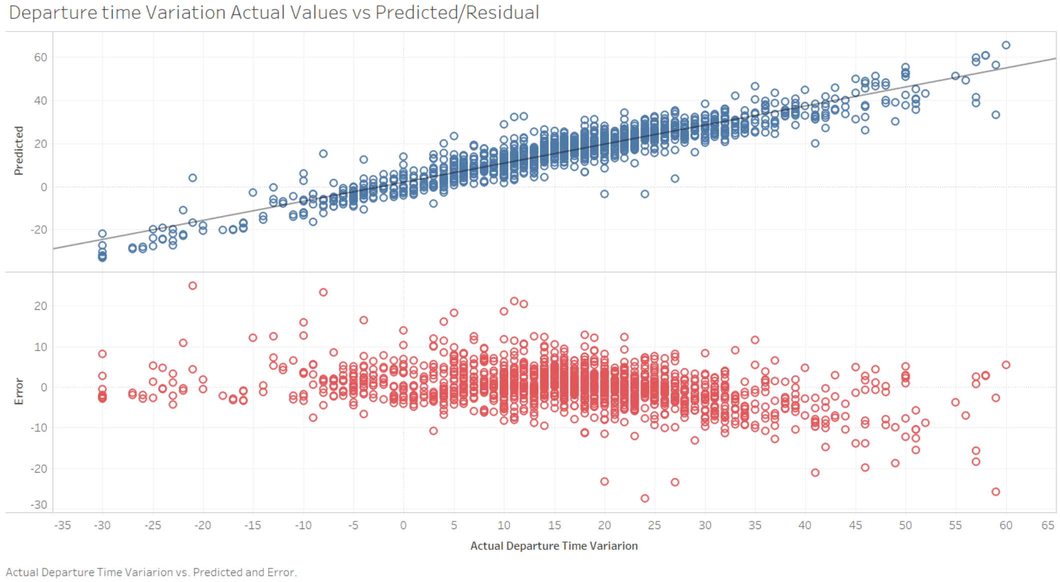


Table 6

Scheduled Departure Time Variation Prediction Performance

	Chennai International Airport (VOMM)		New Delhi International Airport (VIDP)	
Parameter	**M5P**	**Multilayer Perception**	**M5P**	**Multilayer Perception**
Cor coef.	0.9222	0.8606	0.9069	.8702
MAE	3.5312	4.2805	4.4484	5.1819
RMSE	4.4368	5.5855	5.3149	6.1256

Here we can observe that the predictability of departure time of a flight which arrives from Delhi international airport is less compared to Chennai. The flying time of Delhi to Bangalore is more comparing Chennai to Bangalore and therefore more variation in actual flying time and turnaround time for these flights are slightly more and it varies very randomly. But the overall prediction accuracy is very good and the model gives significant improvement compared to previous works. For various departure destinations and aircraft categories, the model demonstrates its robustness.

Prediction of Scheduled Departure Time Variation Using Logistic Regression

The proposed method correctly classified 1765 of 1954 test instances with an accuracy of 90.33%, according to the test results. The confusion matrix is used to evaluate classification performance and is given in Table 7.

Table 7

Confusion Matrix for Departure Time Variation

Actual \ Predicted	Early	On Time	Delay
Early	**105**	**29**	**1**
On Time	**14**	**228**	**101**
Delay	**1**	**43**	**1432**

Each category's classification precision, i.e. Early, Ontime, and Delay, is 0.875,0.760, and 0.934, respectively. Previous methods proposed by Thiagarajan et al. (2017) and Guleria et al. (2019) were used to compare classification results (Table 8). The proposed model provides much better prediction results with minimal attributes, minimal complexity and thereby minimal computational cost.

Table 8

Classification Performance Comparison

	Proposed Model	**Thiagarajan et al (Thiagarajan et al., 2017)**	**Guleria et al. (Guleria et al., 2019)**
Classification	Multinomial Classification (Early, On Time, Delay)	Binary Classification of 0 or 1 (15minutes from the scheduled time)	Binary classification with Delay >15 Minutes or Not
Accuracy	**90.33%**	**86.48%**	**80.7%**

The results of the proposed method allow for early detection of departure time variations (Early, On Time, and Delay), allowing airlines and airport operators to better allocate resources and avoid unnecessary gate changes. ATFM would benefit greatly, especially in the case of ground delay programs, as accurate departure delay prediction removes delayed flights from the program, increasing GDP predictability and efficiency (Etani, 2019). The proposed model gives very good results for multileg operations. Using the proposed models above, the ATFM can detect schedule conformance of participating flights in GDP. This will increase the efficiency and predictability of the Ground Delay Programs.

Conclusions

Flight schedule changes are inevitable in an air transportation network for a variety of reasons, including the fact that these delays are detrimental to the system. This paper proposes a hybrid form of machine learning with an exponential moving average to reliably predict reactionary departure delays in an airport network. Rather than predicting the departure time directly, the proposed model predicts the deviation/error from real values using historical variations. This research predicts reactionary departure delays in an aircraft's itinerary, which occur as a result of the turnaround period and arrival delays faced by flights following the departure of their previous flight legs. The proposed model employs the exponential moving average of various flight segments to efficiently trace temporal stochastic variations. Such predictions would help in improved scheduled flight preparation and resource utilization by prior knowledge of possible delays on various flight legs. This also improves ATFM TMI’s efficiency and predictability.

In contrast to previous studies, the proposed model is able to predict landing time with an RMSE of 2.94 and a minimal number of attributes, which is a significant accomplishment. In terms of predicting departure time, the M5P model does marginally better than the MLP model, with MAE and RMSE of 3.43 and 4.84, respectively. The findings on classifying scheduled departure deviation flights as Early, Ontime and Delayed had an overall accuracy of 90.3%, which was significantly higher than previous literature on delay propagation prediction. The model's robustness is shown by the model validation findings for various departure destination pairs and diverse types of aircraft. Future research will continue to expand the framework to include other complex airport-based characteristics such as equipment outages, runway changes, wind speed and delay propagation, and investigate their effects on departure delay.

Recommendations

In order to increase the predictability of Ground Delay Programs, the research recommends that the interconnected flight and its schedule variance (positive and negative delays) be included in the ATFM strategic planning phase. The temporal variation in scheduled flight flying time and turnaround time can be better traced by using an exponential moving average of historical flight data. Nonlinear supervised machine learning (M5P and MLP) models provide greater departure time predictability. By using logistic regression, the departure schedule variation (early, on time, and delay) can be classified very accurately. The predictability of landing and departure times of scheduled flights can be improved using a combination of exponential moving average and machine learning models, resulting in improved ATFM efficiency.

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