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Performance Improvement of Air Traffic Flow Management Ground Delay Program using Machine-learning and Mixed Integer Linear Programming based Algorithm

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ABSTRACT: In India, one of the tools used by Central Air Traffic Flow Management (C-ATFM) to resolve demand-capacity imbalances is to impose ground delays on flights using Collaborative Decision-Making(CDM) measures, commonly known as Ground Delay Program (GDP). This paper proposes a new method which uses machine learning to predict estimated landing time and allocate landing slots in Ground Delay Program (GDP). The performance of a GDP in demand capacity balance depends not only on optimal planning but also on the effectiveness of the intended execution of the scenario in the tactical phase. So the accurate prediction practical capacity and demand during the hours of operation is challenging task, especially when the compliance rate of existing GDP measure in Indian FIR is less than 60 %. Here we propose a combination of machine learning and Mixed Integer Linear Programming (MILP) based algorithm to minimize ground delay and optimise the arrival sequence.

Keywords: Ground Delay, prediction, Demand capacity balancing, airport arrival rate, machine learning, Linear Programming.

I. INTRODUCTION

Indian domestic air traffic in recent years has increased significantly, and this rise has not been accompanied by the corresponding growth of airports and associated systems. As a result, major airports at metro cities of India suffer from increased congestion. C-ATFM has already introduced the ground delay program and ground stop program as a Traffic Management Initiatives (TMI) to reduce or eliminate air traffic congestion at capacity constrained airports in Indian FIR to address the situation. The GDP is a framework to keep the capacity of airport under check, by reducing the rate of input flights. When an airborne delay is likely to occur due to congestion at a particular airport, it would be easier, cheaper and safer for the flight to absorb this delay on the ground. Preceding take-off, instead of in the air. Hence an efficient ATFM necessitates a more predictive and efficient GDP implementation, with minimal optimal delay for all concerned.

II. LITERATURE REVIEW

Formally defined the ground delay programs (GDPs), which have been one of the focus of air traffic flow management studies over the past few decades [1]. Due to the importance of GDPs in ensuring air traffic efficiency, safety and their ability to interrupt operations, in recent years extensive research has been carried out to evaluate and improve them. When faced with an anticipated demand-capacity mismatch at an airport, by applying departure delays to inbound flights, a centralized GDP design optimization problem typically focuses on reducing the amount of ground and airborne de- lay costs. Many previous research studies focused on several different aspects of GDPs, including optimum allocation of ground delays using optimization models, deeper understanding of the underlying system dynamics through data analytic and machine learning. [2-6]. The GDP scenario for demand capacity balancing involves three interdependent processing steps

– Predict Estimated Landing Time.
– Calculate optimum capacity of the airport during the scenario.
– Calculate the revised Calculated Take Off Time (t_{CT}) by demand-capacity balancing.

Most of the work in the ground delay program concentrates on the last step, but the effectiveness of the same depends on the accuracy in calculation of other two processes. The process involved in the ground delay program depends on the rules and regulations applicable to the specific state/region in which it applies. Author studied the impact of GDP parameters on delays and proposed Ration-By-Distance (RBD), allocation approach to be used in the preparation of GDPs for the control of layered airspace traffic flow in the USA [7].

Author proposed a dynamic local search heuristic algorithm for a job-shop model suitable for taking into

account one of the various performance requirements and for incorporating aircraft position changing control techniques to minimize controller/ pilot's workload [8].
Author proposed an improved Ration by Distance (RBD) algorithm, considering Collaborative Decision Making (CDM) attribute Table to flight equity [9]. Under their model, flights with flight distances higher than that of the equity threshold can also be excluded from GDP. Later they proposed a constrained variant of RBD as a realistic alternative to the existing apportionment, minimizing the total expected delay under very wide ranging models of early termination [10]. Author proposed an algorithm for allocating delays in flight departures under predictive airport capacity [11]. The algorithm adapts dynamically to weather forecasts by revising departure delays where appropriate. Author evaluated historical data on weather, traffic and ground delay program decisions at major US airports and recorded the performance of various data mining methods in the three decision-making regions using weather and traffic congestion parameters [12].
By the simulation study carried out in this regards suggested flights to be delayed at departure airports along with the amount of delays (in time) to be applied for such flights [14]. The method is designed to iteratively and progressively alter the departure times in the plan to minimize total airspace delays by using a fast-time simulation to estimate airspace delay of each flight for a given flight schedule. Author proposed a framework for combined optimization of key parameters of GDP including file time, end time and distance [15]. Such criteria are formulated and incorporated into a GDP framework on the basis of which an optimization problem under uncertain airport capacity is addressed. Much of the above-mentioned GDP literature focuses on determining the weather conditions [16, 13] requirement of GDP and optimizing key parameters. However, none considered flights on time performance and the precise predictability of the expected landing time on the basis of which congestion is predicted. Both of these parameters have a significant influence on GDP's degree of effectiveness and complacency.
There has been various research works in recent years exclusively on predicting the arrival time and delay of flights using machine learning. Author proposed Qauntile Regression Forests (QRF) a variant of the Random Forest(RF) that can be used for accurate predictions of aircraft landing times [17].
Later in RF was used in real-time diagnose of turbulence associated with thunderstorms, in aviation operations [18]. Followed by a data-driven model using (RF) method proposed to predict flight's estimated time of arrival (ETA) with improved accuracy at arrival airports [19]. In the air traffic flow management initiative proposed a method for finding similar days [21]. Their study mainly describes a combination of a classification model and a predictive cluster analysis of similar days. Author proposed a two-stage predictive model to forecast delays in departure and arrival, using flight schedule and weather features [20]. The prediction of departure delay had comparatively higher error rates due to a poor selection of features and the prediction was limited to delay or no delay only. Author proposed optimization of nominal flight time by estimation/ resolution of delay [22]. The possibilities of estimating delay by initial traffic statistics were analyzed in their work. Author introduced a predictor automation tool that allows for route adjustments to be operationally appropriate during a flight and recognizes more efficient airspace routes that are influenced by congestion or weather and better meet airline preferences. To enhance predictability, the model uses various data mining techniques [23].
Author proposed a predictive model for on-time arrival utilizing flight information and weather information. This was classified using the correlation between flight data and weather data on arrival time. Since weather phenomena are highly random in nature, the model gives comparatively less predictability with binomial classification only [24].
Author proposed a method for predicting estimated landing time-based machine learning. The method utilizes multi-linear regression model to predict estimated landing time. In this work we extend the above prediction method for ground delay program. Here we propose a machine learning based algorithm uses Exponential moving average to predict the landing time and followed by Mixed linear Integer programming based algorithm to implement ground delay program to improve effectiveness and compliance rate of GDP by minimizing delay [25].

III. CURRENT STRUCTURE OF A GDP IN INDIA

In India the Central Command Center (CCC) publishes ATFM Daily Plan (ADP), a set of tactical ATFM measures that will be in force the next day in the Indian airspace. The airports which are expecting congestion and duration will be notified on this. On the day after the situation is reassessed before four hours of the actual airport's estimated congestion period, GDP will be implemented by delivering a CDM (Collaborative Decision, Making) scenario to all stakeholders. The CCC will run the CDM Scenario program if the expected demand exceeds the reported AAR for a prolonged period of time. This will be circulated among all stake holder by system as well as email.

A. Process involved in generation a GDP

In an automated process using sky flow system, flights subject to regulation are assigned new calculated take-off times (CTOTs) via ATFM (time) slots. Commonly, the identification of GDP specifications, such as file time, start time, capacity and end time, is decided by the CCC in consultation with the Air Traffic Controller or the relevant airport flow managers, which may be sub-optimal in certain circumstances. If expected landing time predicted by the system is not accurate then the delay introduced to solve demanded capacity imbalance may introduce unnecessary ground delay to inbound flight. Therefore, compliance strategies with cost-effective and optimal GDP require a comprehensive methodology focused on historical data and effective optimization procedures. We initially describe how the CATFM-CCC currently implements GDPs in India.
The CCC regularly tracks and analyses the hourly demand and capacity of each constrained airport. If a reduced airport capacity or increased demand is anticipated for at least two consecutive hours, the CCC will trigger a GDP by issuing a CDM scenario with the start time, the end time, the calculated take-off time (CTOT) and a fixed maximum arrival rate. Once the GDP is enabled, the flights are reassigned to slots to

suit the defined arrival rate. This is done based on programs which sort the flight plans involved in the problem by using the following priority criteria:
– Exempted flights
– Active flights
– Scheduled off Block Time (t_{SO})
– Type of flight
– Expected Off Block Time (t_{EO})
– Flight Distance
– Filed Expected Elapsed Time(E_{ET})
– Submission Time
The GDP uses above priority criteria to Fig. out the flight plans involved in the problem, with the goal of minimizing the occurrence of delays in the most significant flight plans. During the flight reallocation process, the framework considers the exemptions, the aerodrome capability limits, and the minimum separation periods between two movements to determine the flight plan delays within the span of the program. Optionally, when a GDP is implemented, the Flow Manager can pick flight plans that are to be deemed as excluded, thereby granting them a higher priority in the flight reallocation process. In addition, the Flow Manager can cancel the domestic flight schedules.

IV. PROBLEM STATEMENT

Timely updating of the flight delay, which directly affects the planning phase, is one of the main challenges in the current CDM scenario. Current GDP implementation does not consider the possibility of delay in the preceding and subsequent leg operation of GDP-duration flights, particularly when most domestic flights are short-haul(less than 3 hour flying time) in India. Due to this we observed that in addition to reduced compliance rate the participant planned scenario and execution scenario differs. The planned capacity and actual capacity varies and it leads to underutilization or over utilization of airport during the congestion period. Nonetheless, at present this variation is not significant in CDM scenarios (GDP) due to an inherent delay in some of the arrival flights scheduled during the scenario period, which can be sub-optimal in future practice. As the schedule/calculate take of time compliance of flight increases this will cause congestion. One of the other key issues is the predictability of landing time. Since trajectory-based operations are not adopted in India and the estimated landing time varies widely with actual landing time, the CDM scenario would be less successful. Another one hurdle is the declared capacity and practical capacity of airport/runway varies during the scenario it will affect capacity utilization factor. Unlike the Expected time of arrival (ETA), which used previously for deciding sequence, the expected landing time (t_{EL}) will vary with runway and arrival routes from which flight lands. Without accurate trajectory prediction the prediction of landing time is one of the challenging tasks. This paper will address the following issues of currently followed GDP implementation
– Using historical data, propose a novel method for predicting estimated landing time and maximizing an airport's realistic arrival capacity over a span under the specified constraints.
– Propose an efficient GDP algorithm based on maximizing rates of compliance and reducing delays that transcend current GDP limitations.

A. Contributions of this paper

Unlike previous works, by considering all three stages together, this paper considers the problem of optimizing the ground delay program in a more practical aspect. The paper proposes to improve prediction of estimated landing time by introducing additional attribute of exponential moving average in machine learning, where the flying time in Indian scenario varies in large window. Our computational experiments and case study show that the proposed approach can be used to determine very good integer solutions using MILP to minimize average ground delay, compared with the currently used method in Indian airspace. To the best of our knowledge, these simulations are one of the complete GDP process in realistic instances of the ATFM GDP problem optimized in the Indian scenario to date.

B. GDP planning Model and Parameters

A GDP is a consequence of the predicted imbalance in the demand and capacity at an airport over certain duration of time. The airport's arrival capacity is also termed as the Airport Acceptance Rate (AAR) and usually refers to the number of flights that can be landed in a hour. In India all airport has declared the maximum arrival capacity in arrival only configuration and arrival plus departure (mixed mode) operations of the corresponding runway/s of the airport. Here we consider mixed mode operations and assume that the system for Airport Collective Decision Making (ACDM) should take care of departure sequence and departure-based arrival time spacing. This capacity will vary ac- cording to weather, wind and facilities available for the particular airport. For the ease of exposure here, we will generally presume that the predicted AAR is fixed in the GDP range, although this is certainly often not the reality. For the ease of exposure here, we will generally presume that the predicted AAR is fixed in the GDP range, although this is certainly often not the reality. The flights that are scheduled to arrive at the airport between the start and end times are said to be inside GDP range. The parameters just mentioned above are can be expressed in mathematical form.
P= the set of flights whose estimated landing time in GDP period
$\tilde{P}$=the flights in P that are exempted from ground delay
$\hat{P}$= the flights in P which are airborne before t_f.
δP = the flight in P whose preceding legs delayed beyond turn around recovery time and they can't arrive in CDM period
$\vec{P}$ = flights subjected to Ground Delay in GDP
t_f= The file time of CDM scenario
A high-level capacity balancing problem can be modelled mathematically: pick a start time of $\wedge t$, and a set of flights, $\vec{P}$ subject to ground delay, can be described by such that

$$\vec{P} \subseteq P - \tilde{P} - \hat{P} - \partial P \quad (1)$$

The equation (1) identified the initial problem variables for defining the group of flights to be expected to obtain ground delay and to be included in the CDM scenario but not the parameters to be used to set those variables. The criteria involve different factors which directly and indirectly affect the problem. In fact, this is a complex random optimization problem that has to consider the uncertainty involves with both the AAR (which relies on the runway in use, facilities available and weather) and actual departure times of flights (depends on airline operator and Air Traffic Situation at Departure station) along with a complex delay cost function. Once the start time and set of flights are determined, the next step is to predict the imbalance in demand capacity and eliminate the imbalance using a ground delay computation algorithm. This will be discussed in following section. Thus the effectiveness of GDP depends trade off between how actual AAR exactly suits the planned AAR, by keeping the optimum capacity as constant minimize over all amount of delay. The assumption is that these flights are not subjected to air delay.

C.GDP Statistics

We have analyzed the current GDP program outcome the statics of the same in included in this section. The flights, inside GDP, period can be classified into two sets: those with a positive ground delay, $\vec{P}$ *and* those without delay.

The mean delay is calculated in $\vec{P}$over the flights and is published in the CDM scenario implementation. While the total ground delay for the scenario is roughly constant, the existing GDP rationale therefore an increase in the average delay leads to a distribution of the overall delay over non-exempted flights. The cumulative delay imposed in the period comes around 5-12 hrs for different scenario with average delay 10-25 Minutes for arrival. This leads to a higher overall delay cost as stated earlier. Unrecoverable delay due to inefficient GDP is the extent of ground delay allocated inappropriately to a flight that cannot be recovered during its subsequent service. Another one aspect is the GDP compliance ratio and its effectiveness.

Table 1: Statistics of Block Time and Flying time.

Date/ Period	Total flights	Departure Category	Arrival Count%	Total Delay (HH:MM)	Average Delay (HH:MM)	Max Delay (Min)
06/01/2020 (08 : 00 – 10 : 00) UTC	66	Delay Early On Time	17(50%) 8(24%) 9(26%)	06:08	00:05	18
27/01/2020 (08 : 00– 10 : 00) UTC	64	Delay Early On Time	7(20%) 7(20%) 21(60%)	09:08	00:08	26
03/ 02/2020 (08 : 00 – 10 : 00) UTC	64	Delay Early On Time	12(34%) 2(6%) 21(60%)	04:28	00:04	22
10/02/2020 (08 : 00 – 10 : 00) UTC	66	Delay Early On Time	9(25%) 9(25%) 18(50%)	12:47	00:11	36

Table 1 gives an overall statistics of GDP compliance statics of Mumbai international airport during different CDM periods. It can be observed that compliance rate of current CDM scenario is less than 60% due to different reason. As the compliance rate reduces the airport/ runway utilization factor also may reduce. However, this reduction is offset by the distribution of delayed flights from the previous CDM period and an improvement in capacity utilization factor is observed on the current scenarios. An airline wise CTOT compliance statistics for different CDM period is shown in Fig. 1.

The average delay for the CDM period was around 50 Minutes which is relatively very high value. While tracing reason for the delay it was observed that most of the flights were delayed in their trailing legs. The other statistics used in the paper includes:

Maximum delay: The largest delay assigned to a flight which is participated in CDM scenario; which is shown on the last column in Table 1. This varied in different CDM Scenario.

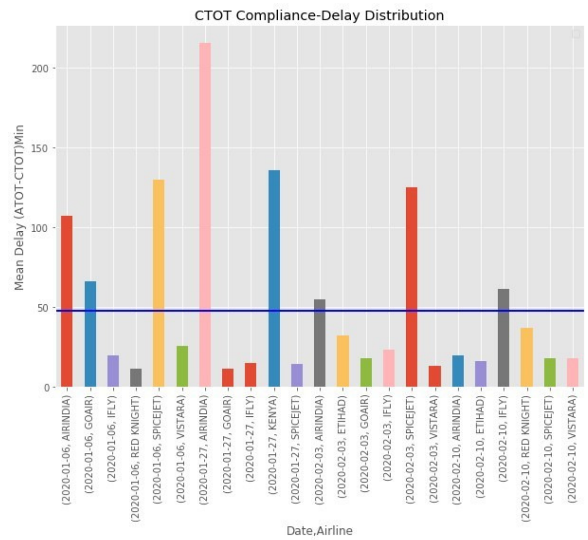

Fig. 1. CTOT Compliance Airline wise.

Table 2: Delay Variability.

Date	Average Delay						
	Air India	Allied	GoAir	Ifly	Red Knight	Spice jet	Vistara
06-01-2020	12.5	14.0	15.0	8.5	15.0	12.7	8.8
27-01-2020	20.7	23.0	19.7	13.1	23.0	16.8	16.4
03-02-2020	9.5	8.0	12.0	4.9	16.0	8.2	8.4
10-02-2020	21.0	27.0	25.3	17.8	12.0	22.8	20.4

Delay variability: The distribution of carrier's mean delay, which can be calculated using standard deviation. This statistics will enable to evaluate the delay distributed more or less equally to all the participating airlines a small value of delay variability means that average delays are very comparable for all carriers, while a high value implies a uneven distribution of average delay among carriers. A statistical analysis was done on different CDM scenario as shown in Table 2. It can be observed that average delay distribution not uniform and airline which operates more number of aircraft will get more delays.

Airborne delay: Then route and terminal arrival delay that can occur even though the flights depart at their scheduled departure times and the actual and planned AAR are equivalent. One of the key objectives of ATFM ground delay program is to minimize the air delay when capacity exceeds demand. Given an AAR matrix and a set of flights with corresponding estimated landing time (Calculated landing time), each flight may be allocated an arrival time/slot so as to reduce unnecessary (airborne) delay. The airborne delay for a single flight is the difference between its estimated /calculated landing time and its actual landing time, if the flight departs at its calculated/estimated take off time. Presently on Ground delay program this air delay is not applied. But there are flights which were flown on the allotted window and incurred air delay due to traffic congestion.

V. PROPOSED MODEL

The decision to establish the set of flights to be included in the program is addressed via the parameters of the GDP decision to impose delay is defined in equation (1). The GDP requirement is first assessed by Capacity vs demand calculation. Once the capacity and demand is calculated and the excess demand has to distribute across the successive hours. Since the effect of the parameters listed in Equation 1 is to decide whether or not a flight is exempted, delayed or not. This decision depends on the predictability of Expected time of arrival and capacity of the airport/runways for particular set of aircraft. There for the accurate prediction of actual landing time is a key challenge. Here we propose a MLR based estimated landing time prediction.

The accuracy of the estimation of landing time minimizes the cost of delay and cumulative delay in the process of execution. Here we reformulate a ma- chine learning based estimated landing of each flight predict $\boldsymbol{t}_{EL(i)}$ proposed by [25]. The model utilizes minimal attributes for Estimated landing time (t_{EL}) for different category of aircraft.

A. Calculation of Estimated Landing Time

We analysed improving prediction accuracy by adding the Moving Average value of historical flying time on input attributes of the MLR model. Moving averages tends to smooth out short term irregularity in the data series based on an average of weighted observations. They are effective if the data series remains fairly steady over time. Further analysis was done on the data using Simple Moving average and Exponential Moving Average(EMA) of flying time. In Simple Moving average, since all the data points in the moving average process are given equal weight, this method fails to deal with non-stationary data. Exponential Moving Weighted Average methods are the techniques that place more weights on the recent observations. Holt.C [35] proposed exponentially weighted moving averages (EMA) in dealing with forecasts of seasonal and trends. EMA's reaction directly depends on the pattern of the data. The flying time for each departure destination is calculated by equation 2.

$$FT(n) = t_{AL}(n) - t_{AT}(n) \quad (2)$$

Where $FT_{(n)}$ is the flying time of n^{th} flightand $t_{AL(n)}$, $t_{AT(n)}$ are corresponding actual landing time and actual take off time of flights in Minutes. Fromthis the exponential moving average (EMA) of the previous flying time can be rep- resented by equation 3.

$$\hat{F}T_{(n)} = \alpha[FT_{(n-1)} + (1-\alpha)FT_{(n-2)} + (1-\alpha)^2 FT_{(n-3)} + \ldots \quad (3)$$

Where α denotes a "smoothing constant" (a number between 0 and 1). Current flying time $\hat{F}T_{(n)}$ calculated by the sum of the exponentially weighted average of remaining historical value in the window. Here we have taken a window length of 3. Here all the flight departed from various departure stations to Mumbai International airport is considered. The flights include different airlines, different time and different type of aircraft. The model is developed by taking actual landing time $\boldsymbol{t}_{AL}$as dependent variable. By using backward elimination method actual departure time and exponential moving average of flying time selected as independent variable. The flights are grouped according to type of aircraft and Exponential Moving average of flying time (EMA) for each group is calculated. The data (2655) then split randomly into 80% (2124) training data 20% (531)test data. The regression model for $\boldsymbol{t}_{AL}$ using Ordinary Least Squared (OLS) in machine learning is given below in equation 3.

$$\boldsymbol{t}_{AL} = -2.58 + 1.01 * \boldsymbol{t}_{AT} + 0.99 * EMA \quad (4)$$

Where $\boldsymbol{t}_{AL}$, $\boldsymbol{t}_{AT(n)}$ and EMA are in minutes. The performance matrix of the proposed model for training data shows excellent regression statics with R square= 0.9998 and Adjusted R Square= 0.9998. The 'P' values of both the independent variable are less than 0.05 and approximately zero which indicate that Null hypothesis not valid and these variables dependent on t_{AL}. The RMSE for the data 4.5. The Mean Absolute Error (MAE) is 3.6. The model can be rewritten for predicting expected landing time ($\boldsymbol{t}_{EL}$) from expected time take off($\boldsymbol{t}_{ET}$) as

$$\boldsymbol{t}_{EL} = -2.58 + 1.01 * \boldsymbol{t}_{ET} + 0.99 * EMA \quad (5)$$

The analysis prediction results shows that the proposed model using machine learning gives better results than currently method even without using weather information.

B. Calculating Arrival Capacity

Once the estimated landing time are calculated using above step next to calculate the capacity of arrival airport during the period. The airport capacity is quantified based on the number of allowable landings (Aircraft) per hour, termed as Airport Acceptance Rate (AAR) in GDP. In general, the airport capacity can be estimated based on the details including runway in use, weather conditions and aircraft type scheduled for operation. Hence, Predictive Airport Acceptance Rate (PAAR) is used to characterize airport capacity in GDP [15]. There's usually a target capacity recovery period for a particular GDP start time. The recovery time for capacity also signals the end of GDP and is thus also called the completion time.

Declared capacity is an operational efficiency measure, depends on actual throughput. In principle, it is determined with certain assumptions by the slot coordinator at each slot-controlled airport after a detailed capacity assessment analysis, taking into account different capacity determinants [26]. However, in practice the declared capacity is usually set at 85–90% of the maximum throughput [27]. The capacity analysis proposed here is more practically feasible than the approach currently used, but it is quite difficult to assess a traffic combination and complex distribution of the hourly sequence in capacity analysis, i.e. delays, changes in aircraft and other unplanned factors that affect the hours of operation. However, efforts to fine-tune the departure and arrival sequence will progress in the continuous process of enhancing throughput efficiency. Here we calculate the capacity based on the historical data. The declared maximum capacity of the each runway is published, but practically it will vary according to the type of aircraft, separation and ETA of each arrival. From the historical data, the actual arrival rate over different hours (Fig. 2 of the day with different sequence of pattern analysed. The maximum arrival landed during an hour is 26 and average (mean) is 19 with standard deviation of 5 for the airport in various conditions. The arrival rate of each hour is calculated based on the number of different wake category operated during the hour. From the historical data it was observed that maximum of arrival rate of 26 flights with different combinations of wake

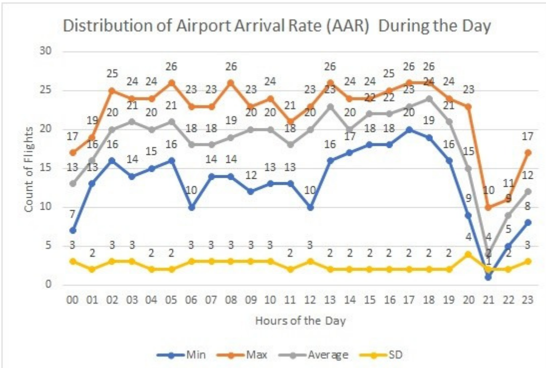

Fig. 2. Distribution of Airport Arrival Rate per Hour.

Category like (22M, 4H), (1L, 21M, 3H) and (1L, 23M, 2H). Here we propose, 90%(in this case it is 24 flights) of the practically attained maximum capacity as optimum capacity, which has been achieved for more than 10% of the total scenarios(hourly AAR) considered for the analysis.

$$C_o = 90\% \text{ of } C_{max} \quad (6)$$

The mean(μ = 18) value of the capacity and standard deviation(σ = 6) also calculated. The different wake category combinations with 20 Medium a maximum of 4 Heavy category can be accommodated in one hour, together with medium category without lowering capacity (Since the light category presence is random due to non-schedule movement). As the number of Heavy category (Light category in rare scenario) increases in mixed mode of operation, the capacity reduces due to more separation requirement. Besides the capacity (ARR/hour), we propose to examine the even distribution of the expected landing time so that air-delay delays can be minimized during the tactical process.

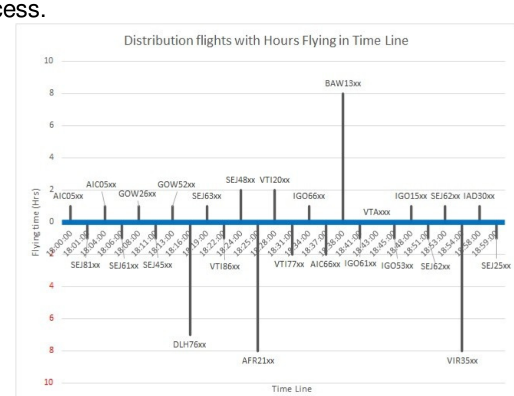

Fig. 3. Distribution of Wake Category during hours.

If the estimated landing time of more aircraft is concentrated on the specific portion of an hour, the delay will be greater, particularly the concentration of long haul flights (in our case more than 3*hrs* EET). In addition to efficient ground delay allocation in GDP computation, this technique helps the Air Traffic Controllers to adjust spacing and spread delay over short haul flights. Fig. 3 indicates the distribution of arrival time observed for the specific hour when the maximum capacity was handled. The optimum, average and Maximum capacity of runway will be tabulated based on the historical data for each hour.

C. CDM Scenario Calculation

Planning for the GDP (CDM Scenario) can best be conceptualized as a process of adjusting flight arrival times. For improving the existing GDP structure here we propose a novel algorithm based on Mixed Linear Integer Programming model. The estimated landing time is calculated based on section 3.1 and optimum capacity based on 3.2. In this proposed algorithm, in addition to the above improvements, additional weight classification criteria for On Time Performance and Trailing flight $\mathbf{t}_{EO}$ (Estimated off block time) to enhance CDM compliance and minimize network delay. When demand exceeds (number of $\mathbf{t}_{EL}$ [Estimated landing time] for the hour) the capacity(optimum capacity) the proposed CDM scenario algorithm will be executed. The first step of the process is to sort the flight plans involved in the problem using the parameters priorities below:

– Estimated Landing Time($\mathbf{t}_{EL}$)
– Exempted flights
– Active flights
– Scheduled off Block Time ($\mathbf{t}_{SO}$)
– Expected Off Block Time ($\mathbf{t}_{EO}$)
– Filed EET
– Weight for regular online performance
– Trailing flight $\mathbf{t}_{EO}$

The $\mathbf{t}_{EL}$ is predicted using 3.1 and will be sorted in ascending order. The flight which comes under the category is given priority over all other aircraft and they will not be given ground delay. It covers VVIP flight, flight owned by state, medical emergency / evacuation as exempted. Active flight is the flights that have already been departed, and the flight that will depart within 30 minutes of the CDM scenario file time (assuming that flight boarding started) can also be exempted from ground delay. Practically for the flight delay departed flights are not possible. Then the preference will be given to flight which is having earlier t_{SO} followed by t_{EO}. The flight with more EET given preference over other this also ensure flight from more distance given priority over short distance.

In the above said the weight for regular on time performance is based on the last three movement of t_{EO} compliance for the same scheduled flight. If the flight is delayed greater than 10 minutes of Expected Time of Takeoff (t_{ET}) then it will indicated by weight 1 and otherwise it will be indicted with weight 0 (no delay in departure). The sum of this weight is treated indicator of recent on time performance. This will ensure the flight which is having more schedule compliance in recent days having more priority. The trailing flight t_{EO} is considered here to assess the delay the flight can take many domestic sector flights in India are hoping through multiple cities and it covers several legs with minimal turnaround time. If the next departure t_{EO} is in 45 minutes and if we give this flight more ground delay, this will cause more accumulated delay for this flight. Those trailing flight which is having earlier t_{EO} given priority.

Once the flight plans are sorted as per the criteria mentioned above next step to optimize the arrival sequence by minimizing delay. A lot of the preceding research has been dedicated to scheduling arrival aircraft at runways. Author proposes the problem in a mixed integer zero-one formulation. There will a time window every flight with a target landing time. If a plane lands after or before its target time, a cost is accounted for. The goal is to minimize the total deviation costs from the target times. Using a linear programming based tree search algorithm the problem is solved optimally [29]. But the experimental findings reported in [29] indicate that the linear relaxation of the LMIP provides a weak relation to the optimum performance of the given Mixed Integer Programming (MIP) method. The problem of air-craft landing was considered as an example of the generic problem of jobshop scheduling [28, 30, 31]. Author suggested the dynamic programming algorithm [32] for single-machine scheduling and extended to aircraft landing. The dynamic programming method in [32] was expanded by [33] into a generalized dynamic system to solve the problem of departure scheduling. Most of the work was for initial scheduling objective. Here we propose a mixed integer linear program (MILP) to minimize the delay in the deterministic scheduling of arrivals in CDM scenario. We reformulate [29] based on GDP criteria and capacity constraints to get a better formulation.

Let F be a set of flights scheduled for arrival at a specific airport during the planning horizon of GDP in order to use the appropriate arrival runway. We use the decision variables

N: is Number of flights arriving on CDM period

F: is the set of arrival flights, sorted by above criteria 3.3 in ascending order of earliest unimpeded(without delay) t_{EL} time.

ET_i: the earliest allowable landing time for plane i(i = 1, ..., N) .

DT_i: the latest allowable landing time for plane i(i = 1, ..., N).

TT_i:the target (predicted) landing time (un impeded landing time)for plane i(i = 1, ..., N).

Sij: the minimum separation time required (>0) between plane i landing and plane j landing (where plane i lands before plane j), i = 1, ..., N ; j = 1, , N ; i = j.

W: is the CDM period over which flights are considered with start time

W_{start}, and End time W_{end}

I: is the interval over which capacity is considered (here hourly)

C_o:is the optimum arrival capacity over the period I

C_I= *maxofi*(XT_i, (XT_i+ I) i = 1, 2, ..N, *and* Number of arrival(X_i) over period I ,

PE_i: *the* penalty cost (>0) per unit of time for landing before the target time $TT_i$for plane I (i = 1,..., N).

PD_i: *the* penalty cost (>0) per unit of time for landing after the target time $TT_i$for plane I (i = 1,..., N).

ZE_i= *max*[0, TT_i– XT_i], I (i = 1, ..., N)

ZD_i= *max*[0, XT_i– TT_i], i(i = 1, ..., N)

M = *max*(DT_i) –*Min*(ET_i)

XT_i the landing time (≥ 0) for aircraft i, a decision variable

$\delta_{ij} = \begin{cases}1\\0\end{cases}$ if plane ilands before plane j (i = 1, ..., F; j = 1, ..., F;i 6= j) otherwise

Minimize $\sum_{i=1}^{N} ZEi * P\,Ei + ZDi * P\,Di$ (7)

$T\,E_i \le T\,X_i \le T\,L_i \in F$ (8)

$T\,X_N \le W_{end}$ (9)

$ZE_i \ge T\,Ti - T\,x_i \forall_i \in F$ (10)

$0 \le ZE_i \le T\,T_i - T\,E_i \forall_i \in F$ (11)

$ZD_i \ge T_{\,Xi} - T\,T_i \forall_i \in F$ (12)

$0 \le ZD_i \le T\,D_i - T\,T_i \forall i \in F$ (13)

$T\,Xj - T\,Xi > T\,S_{ij}\delta_{ij} - M\delta_{ji} \forall i, j \in F$ (14)

$0 < XT_i + I \le XT_N$ (15)

$C_I \le C_o$ (16)

$\delta_{ij} + \delta_{ji} = 1$ (17)

Equation (7) is the objective function that minimizes all planes' cumulative costs. When the optimal solution chooses a feasible sequence Xi, the flights involved in this sequence should land at the appropriate landing time, thereby reducing the overall cost of the landings. Here the cost is allotted as per the type of aircraft and priority in the sequence.

Time–Window Constraints (Eq. 8): Time–window is a hard constraint to ensure that the flight lands between its earliest and the latest possible time of landing, which is denoted by [$TE_i \le TX_i \le TD_i$]. The earliest possible landing depends greatly on the restraints such as maximum speed, runway availability, and potential manoeuvres, maximum early departure, whereas the latest possible (TD_i) landing time depends on fuel restriction, maximum permitted delay, minimum airspeed, maximum departure delay etc. For GDP period on time compliance window is declared for an aircraft. Here we assume that aircraft can depart −5/+10 of CTOT the same variation may come in the landing time and same variation (**t**$_{EL}$ +−5/+10 minutes) can be considered as time window . Equation 9 refers the end of the CDM period will be the landing time last aircraft involved in the CDM scenario. The constraints in (Eq. 10) and (Eq.11) ensure that Z_{Ei} is at least as big as zero and the time difference between TT_i and XT_i, and maximum the time difference between TT_i and ET_i .Similarly for delayed case TD_i can be represented using constraints Eq. (12) and (13).

Minimum Separation Time (MST) Constraints (Eq.14) MST is a hard restriction to guarantee standard separation and safety in line with ICAO (International Civil Aviation Organization) requirements [34]. One of the key separations is separation based on the wake turbulence of preceding aircraft. When an aircraft flies get airborne and until it lands, it generates wake-vortex (WV). However, WV can cause the following aircraft to become unstable (to shake or lift) [36]. To prevent this, an MST is strictly kept between successive landings. A standard MST requirement between four major aircraft types is shown in Table 3. Generally, wake separation is applied to larger one follows smaller one. For instance, after landing a heavy aircraft, a light aircraft must wait 3 minutes (6 Nautical Mile [NM]) in distance-based separation under radar/surveillance environment). Practically this will be prescribed based the minimum lateral spacing (3NM/5NM for approach radar in Metro airports/Non metro) and runway occupancy time of preceding landing, and will vary for different Airport (Runway in use). Here we assume that minimum 1 Minute (3NM minimum separation in approach surveillance area) lateral separation required for if preceding aircraft is smaller than succeeding one. One explanation is that larger aircraft produce more turbulent air and tolerate it, whereas smaller aircraft produce and tolerate less. MST's asymmetric nature results in a need for appropriate scheduling strategies and which might save a great deal of landing time.

Equation 15 refers to constraint for calculating hourly capacity. Here the capacity is calculated in revolving manner so that every hours from start point (X_i) the capacity for the next hour(or period over capacity is calculated) will be remain in the maximum hourly capacity which over comes the Drawback (start point only on beginning of hours of the day) of conventional hourly capacity. The maximum value of end of the hour is the X_N that is value of maximum value i corresponds to X_N – I Finally equation 17 limits the hourly arrival rate less than or equal to Optimal Capacity of the hour (C_o). By minimizing the objective function we will get optimum arrival sequence and calculated landing time. From the revised calculated landing time will calculate the calculated take off time by adding the revised delay time to departure time. Ground delay will be introduced for the flights whose delay is more than +10 minutes, since the on time window varies +10 minutes of target time.

Table 3: Minimum Wake separation criteria.

Trailing	Maximum Certified take off mass(Ton)	Separation Minim(Minutes/Distance)			
		Super	Heavy	Medium	Light
Super(A388)	560	-	- (6NM)	3Min(7NM)	4Min(8NM)
Heavy	≥ 136	-	- (4NM)	2Min(5NM)	3Min(6NM)
Medium	136 > MAUW > 7	-	-	-	3 Min(5NM)
Light	≤7	-	-	-	-

D. Proposed model to Optimize ATFM Ground Delay Program

The Fig. 4 depicts the proposed GDP optimization method that integrates machine learning techniques to enhance the accuracy of landing time estimation and efficiency of MILP to optimize the sequence with minimal delay. The methodology consists of a novel MLR model, which uses EMA of flying time to predict the actual arrival time based on the departure information. Earlier GDP studies either focus GDP criteria and capacity parameters or scheduling processes in GDP. Here we take into account the whole process in three segments. In the initial segment of the algorithm we propose a novel method for predicting landing time with minimal constraints and our previous studies indicated that the prediction accuracy is higher, particularly the EMA of flying is able to trace the random variation in flying time. On the next segment we calculate the capacity based on the historical data. We proceed to the third segment based on these outcomes of these two segments, which calculation of the GDP/CDM scenario.

The process involved this explained in detail on section-V. Finally, the outcome of GDP is the calculated take off time (**t**$_{CT}$) generation, which will be disseminated via electronic network including emails to all stakeholder. The proposed approach, in the functional sense, attempts more or less from a realistic point of view at the problem and offers a practical algorithm.

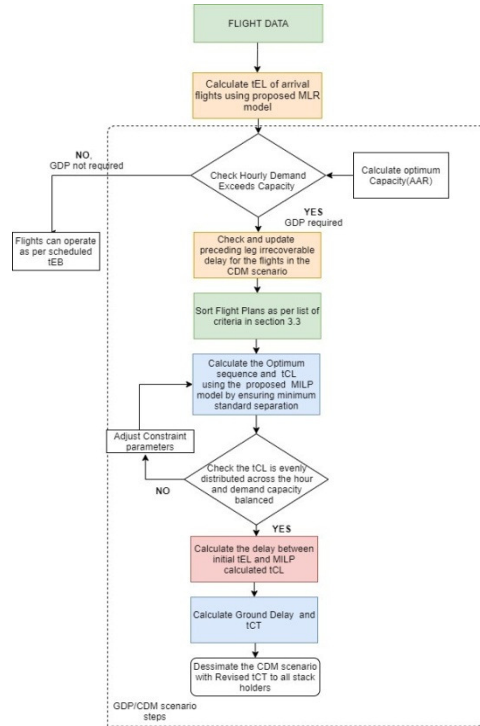

Fig. 4. Proposed GDP algorithm flow chart.

VI. RESULTS AND DISCUSSION

We perform a case study of the proposed approach for GDP and its key metrics in this section. Actual data from a certain day's (10/02/2020) operation at Mumbai International Airport is used for GDP simulation, which includes actual flight schedules. Due to runway closure demand from 08: 00 to 10: 00 to exceeded predicted airport capacity and total 36 arrival flights in total are affected. In this study we considered the Ground delay requirements of arrival to Mumbai International airport is considered by assuming departure from this airport during this period is scheduled by ACDM system. From the historical data the capacity and Estimated Landing Time are calculated using methods mentioned in previous sections. Here we have considered optimum capacity as 24 arrivals per hour. Maximum 26 arrivals per hour.

Table 4: t$_{EL}$ prediction Comparison.

	Proposed Method	Existing system	Percentage improvement
MAE	6.31	13.21	52.2
RMSE	8.31	16.28	48.2
RMSE(On time Departure)	5.30	11.2	52.6

A. Result of predicated estimated landing time

The estimated landing time is calculated using linear regression model using machine learning algorithm. The data is grouped based on the departure station and type of aircraft. The **t**$_{EL}$ was predicted using proposed algorithm and a comparison was done (Table 4). The proposed model has better Mean Square Error and Mean absolute Error.

The above results are based on t_{ET} prediction of t_{EL} and comparison with actual landing time t_{AL}. Among this the predictability of flight departed on time (−5/+10 Minutes of t_{ET}) the RMSE got improved. Due to congestion the flights experienced air delay. The predictability will further improve when the training data set and flights on time performance increases.

B. Result of Ground Delay Optimization

The four aircraft weight categories are used for which Manual of Air Traffic Services (MAT S−I) [37] in India mandates minimum separation criteria based on wake vortex separation. This separation can provided in terms of both distance and time, here we adopted time − based separation considering average runway occupancy times, average speed in decent and horizontal phase for each aircraft weight class based on historical data collected for Mumbai airport. From the statistical analysis of flight plans (00:00 to12: 00 UTC) most of the instances it is observed that more than 80% of flights are of same type (Medium) operated during the hours. Thus in present case the airport's AAR does not vary significantly based on the type of aircraft variation, which was considered in most of the previous scheduling algorithm. The resulting time-based separation matrix is used in proposed model in Table 3. The estimated landing time (t_{EL}) of flights are generated by a MLR model. For simulation of the algorithm and its effectiveness we considered the arrival flight whose t_{EL}(Calculated by existing system) comes between 08: 00 − 09: 00 for a preciously executed scenario. At present the CDM Scenario is calculated 4hr before predicted congestion and is published before 3hr. But it is observed that more than 50% of flights having less than 120 minutes of flying time and its previous leg lands after the CDM scenario and some of them already experienced irrecoverable delay during turnaround time. Here we propose this delay shall be updated especially if it is more than 30 Minutes. Along with this status of flight delayed previous hours are calculated the flight t_{ET} /t_{AT} (For flight already departed) updated. Based on analysis of participating flights (Flying time and t_{EOs}) in different CDM scenario we propose that the GDP file time 2 hr before CDM period(Anticipated congestion period) will be optimal and ensure maximum compliance rate. The estimated landing lading time (t_{EL}) of the flights were calculated using proposed model which given in the column 11 of Table 6. There are 23 arrival flights are planned for the hour as per the existing system estimated landing time (t_{EL}). In this particular scenario there was a situation at VABB airport that in addition to capacity reduction there is an anticipated delay 15 Minutes from 08: 15UTC due runway changing procedure. Here we considered same in CDM generation along with the capacity reduction for the period. Once the t_{EL} calculated now following assumption are made for executing GDP algorithm before sorting the Flight plan based on the criteria mentioned in section-V to obtain the result.

– Optimum capacity during the hour is 18 (75% of hourly maximum capacity) flights due to capacity constraints (15 Minute runway non availability)

–t_{ET} = t_{AT} for flights already departed and no early time available for landing ie. t_{EL} + 10 minutes is deviation only

– Minimum separation between all arrival flight kept 2Minutes in except for Medium behind Light(3 Minutes), which can be varied

– On time departure is (−5/+10) Minutes of t_{CT} /t_{ET}

– Estimated landing time−5/+10 Minutes of t_{EL}/t_{CL}

A sample GDP (CDM scenario) output for 1 hr between 08 : 00 − 09 : 00 UTC on 10/02/2020 is given Table 5. The Call Sign is indication flight name, ADEP indicates the departure station, WC is the wake turbulence category of the flight. The terms t_{EO} indicates the time at which flight is expected to commence movement from its gate (Expected off Block Time) and t_{ET} indicates Estimated Take off time, is the time at which flight expected to depart. Normally t_{ET} is t_{EO} + 10 Minutes by assuming that average taxi time is 10 Minutes. The Table further compares the outputs of the currently used system with the proposed model output. The t_{CT}, and t_{CL} reflect calculated take-off time (revised take-off time as per GDP) calculated landing time (revised landing time based on GDP calculation). The suffix "p" in the columns proposed method indicates the result obtained using proposed method. FT is flying time from departure to destination calculated by exponential moving average. The t_{CL} is calculated (Table 5) using the MILP model With the Gurobi Python Interface. The model found Optimal solution with tolerance 1.00 exp−04, Best objective 1.380 exp+03, best bound 1.3800 exp +03 and gap 0.0000%.

Table 5: GDP performance Comparison.

	Proposed Method	Currently used Method	Percentage Improvement
Average GD	~7 Minutes	26Minutes	73
Maximum GD	10 Minutes	36Minutes	72
Total GD for the scenario	01Hour 48Minutes	08 Hours 15 Minutes	78

Once the t_{CL} is obtained the delay in landing time is calculated and same delay is applied to the flights which are yet to depart. The delay which is applied is added to any flight on the basis of CDM measure is called Ground Delay(GD). A comparative analysis of performance proposed GDP and the currently used GDP is compared in Table 5. The average ground delay for the flights included in the GDP using the proposed model is ~7 Minutes, maximum GD 10Minutes and total GD 01 Hour 48 Minutes, while the existing method imposes an average delay of 26Minutes, maximum GD 36 Minutes and total GD 08 Hours 15 Minutes. Since the CDM scenario applied for a given time and flights are redistributed according to the GDP generated by the current method, the comparison with the actual flight timings do not produce valid results. However, we compared the results of the flights departed On Time (t_{CT} − 5 ≤ t_{AT} ≤ t_{CT} + 10) during this duration and observed that the proposed method gives MSE of 14.49 whereas present method gives only 19.95 (without considering air delay for both cases). Which indicates that with in a window (On Time) of 15 minutes of departure time variation the proposed method gives better predictability landing time.

The highlighted flight in Table 6 indicates international flights which are exempted and no ground delay applied, however the proposed model calculate the estimated landing time of same in the scenario with minimal air delay. This enables to assess the sequence of landing as more international flights are simultaneously clumped. Finally, we examined the landing time distribution (Fig. 5) for every 15 minutes with the assumption that the arrival capacity is 7(in case of only arrivals for the period it can be 8) flights and the optimum is 6in the interval of 15minutes. If more departures to be accommodated by increasing the separation number of arrivals can be further reduced. For this sample analysis, in-order to accommodate maximum arrival, we optimized the landing time using 2 minutes separation between same type (Medium) and 3 Minutes for light after medium MST (Minimum Separation Time) is set as per the Table 3.

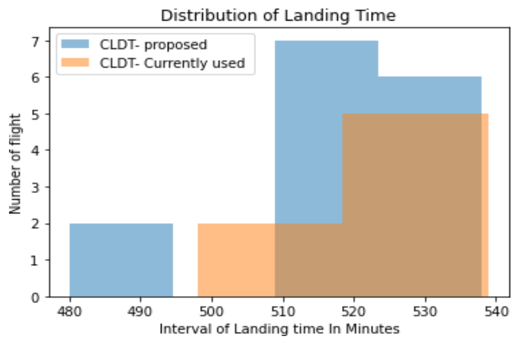

Fig. 5. Histogram of Landing Time.

In some cases there will be gap of 5–8 minutes between the arrivals since flight can't depart early this gap can't be covered, in this case effective capacity may reduce, the same can be observed in the first quarter of the hour. The proposed model also ensures that flights landing time are spread uniformly over the period inside the hour. The proposed model gives better practical efficiency compared to the currently executed CDM scenario.

VII. CONCLUSION

This paper proposes a paradigm based on machine learning and MILP optimization methodology for a functionally efficient GDP. The key parameters of interest are maximizing compliance rate, predicting more accurate t_{EL}, practical capacity prediction and optimizing the arrival sequence to minimize delay. In contrast to existing GDP studies, this paper explicitly presents a novel method for predicting estimated landing time and flight preference that maintains timing performance that could significantly reduce delay times and increase compliance rate. We also propose timely updation of irrecoverable delays preceding legs of short-haul flights that covers more than 50% of hourly traffic, which in turn increases CTOT compliance rate. The proposed model uses the historical data effectively and uses machine learning algorithm to predict actual landing time, which gives better results as compared to currently used GDP model. The MILP based model gives optimal arrival sequence with given constraints including optimal capacity. The proposed model, distinguished by its predictability and effectiveness, takes into account not only the operational efficiency of GDP, but also flight equity, airline equity and even distribution of arrivals over the hours of the scenario duration. The model's effectiveness has been validated by simulation analysis of the proposed GDP strategy with actual flight data. The model outperformed currently used method in predictability and minimizing the ground delay.

Table 6: A sample CDM Scenario comparison.

Call Sign	ADEP	WC	t_{EO}	t_{ET}	Current Practice				Proposed GDP				
					t_{CT}	t_{EL}	t_{CL}	GD	FTp	t_{EL}p	t_{CL}p	t_{CT}p	GD'p
AIC62xx	VILK	M	05:35	05:45	06:03	08:16	08:34	00:18	125	07:22	07:22	05:18	00:00
GOW38xx	VICG	M	05:55	06:05	06:26	08:16	08:37	00:21	115	08:00	08:00	06:05	00:00
VTI94xx	VIDP	M	06:10	06:20	06:41	08:18	08:39	00:21	112	08:12	08:12	06:20	00:00
IGO34xx	VOHS	M	06:45	06:55	07:28	08:19	08:52	00:33	87	08:23	08:32	07:04	00:09
IGO42xx	VECC	M	05:25	05:34	06:08	08:21	08:55	00:34	171	08:24	08:30	05:40	00:06
AIC67xx	VECC	M	05:30	05:40	06:13	08:31	09:04	00:33	168	08:27	08:34	05:47	00:07
IAD71xx	VIDP	M	06:25	06:35	06:47	08:29	08:41	00:12	113	08:28	08:36	06:43	00:08
SEJ63xx	VOCB	M	06:30	06:40	07:12	08:18	08:50	00:32	110	08:30	08:38	06:48	00:08
SEJ63xx	VEBD	M	05:30	05:40	05:42	08:45	08:47	00:02	180	08:39	08:40	05:41	00:01
AIC92xx	OERK	M	05:15	05:05	05:15	08:43	08:43	00:00	218	08:41	08:42	05:05	00:00
IGO17xx	OKBK	M	05:10	05:12	05:10	08:18	08:18	00:00	212	08:42	08:46	05:12	00:00
ETD20xx	OMAA	M	06:00	06:00	06:00	08:28	08:28	00:00	163	08:42	08:44	06:00	00:00
VTJxxxx	VOMM	M	06:45	06:55	07:27	08:25	08:57	00:32	108	08:43	08:48	07:00	00:05
AIC64xx	VAJM	M	07:20	07:30	08:03	08:26	08:59	00:33	74	08:45	08:55	07:40	00:10
VTI82xx	VOMM	M	06:50	07:00	07:27	08:52	09:19	00:27	106	08:47	08:52	07:05	00:05
SEJ64xx	VARK	M	07:40	07:50	08:19	08:40	09:09	00:29	55	08:47	08:50	07:53	00:03
SEJ28xx	VAJB	M	06:50	07:00	07:20	09:10	09:30	00:20	110	08:51	09:00	07:09	00:09
IGO91xx	VOMM	M	06:55	07:05	07:41	08:31	09:07	00:36	106	08:52	09:02	07:15	00:10
IGO60xx	VOGO	M	07:40	07:50	08:20	08:42	09:12	00:30	64	08:55	09:04	07:59	00:09
IGO02xx	WSSS	M	03:30	03:42	03:42	08:43	08:43	00:00	320	08:58	08:58	03:42	00:00
GOW47xx	VOGO	M	07:45	07:55	08:22	08:47	09:14	00:27	64	09:01	09:09	08:03	00:08
IGO26xx	VICG	M	06:40	06:50	07:18	09:00	09:28	00:28	132	09:02	09:06	06:54	00:04
VTLxxxx	VAPO	L	08:30	08:40	09:07	08:59	09:26	00:27	23	09:05	09:11	08:46	00:06

VIII. FUTURE SCOPE

Further work involves carry out more extensive mathematical analysis to clarify the trade-offs in the optimization problem between different goals, including dynamic optimal AAR under various attribute change. Using machine learning techniques, further improvement in prediction accuracy of estimated time of landing using other parameters such as runway, track distance etc has also been proposed as future work.

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