DEVELOPMENT OF A NEW OPERATIONAL FRAMEWORK TO ACCOMMODATE STOCHASTIC AIR TRAFFIC FLOW AT TOKYO INTERNATIONAL AIRPORT

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Abstract

Departure management is an important congestion mitigation method at airport. This study proposed a new operational framework with 1) machine learning models, 2) departure queuing model using time-varying fluid queue, and 3) reflection of airport-specific characteristics. The framework integrates departure manager, arrival manager and surface manager methods that have been developed separately. The validation of this integrated framework using the AirTOp simulator showed that the proposed framework reduces departure queues by about 53% on average. It was also found that departure manager, arrival manager and surface manager can be integrated and operated without any negative impact on each of them.

Keywords: time-varying fluid queue, decision tree, simulation, airport operation, departure management

1. Introduction

Air traffic is expected to continue to increase, and congestion at major airports is causing many aircraft delays and a corresponding increase in fuel consumption [1]. The bottleneck in the overall air traffic is the limited capacity of runways, which causes queues on the ground before the runway entry point and increases flight distances in the air owing to vectoring and other factors to ensure arrival separation. To solve these problems, it is essential to develop efficient method for using runways. Departure management is an important congestion mitigation method for airports. A particularly important method is departure metering (DM), which predicts congestion before the runway in advance and assigns an appropriate waiting time at the gate to the departure aircraft. This method reduces the queue before the runway entry point while maintaining high runway throughput.

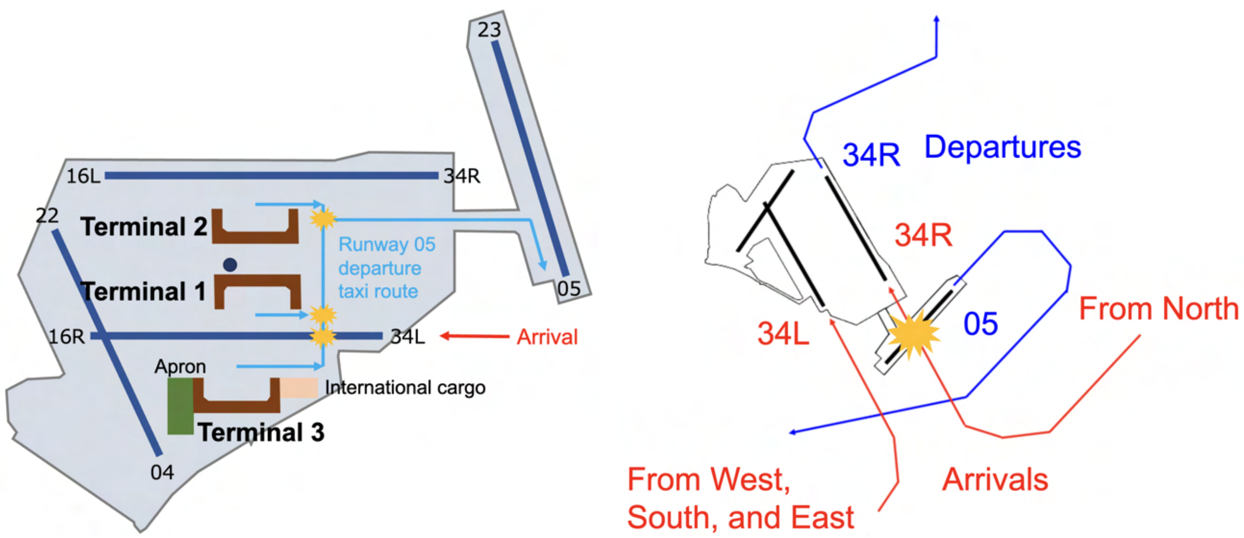
Several studies have been conducted to improve the departure manager (DMAN) ability to estimate departure queues and reduce delays. Itoh et al. proposed a method for calculating the ideal departure rate at a runway entrance and estimating the waiting time, using the $G(t)/GI/S(t)$ fluid queuing model, for departure-only runways [2]. This method is intended to manage the flow of the departure aircraft entering the runway. When a runway is used by a mix of arriving and departing aircraft, the accuracy of the model can be improved by reflecting the information of the arriving aircraft on service times in the queuing model [3]. Moreover, studies have been conducted to predict aircraft ground taxi times. In [4], a machine learning model was used to predict ground taxi times and successfully predicted within an error range of approximately ±2 min for 85% of the aircraft. The study also discussed the importance of building machine learning models that capture the characteristics of each airport. Other studies have been conducted to manage runway flow for arriving aircraft and congestion on airport surfaces to reduce delays in overall traffic flow. A study combined the $G(t)/GI/S(t)+GI$ tandem fluid model with a nonlinear integer programming problem to describe the time variation of aircraft delay in both en-route and terminal airspace to show the delay reduction effect of controlling arrival intervals in upstream arrival traffic flows such as in en-route airspace [5]. Sekine et al. designed an en-route arrival manager (AMAN) using runway flow management with reassignment of arrival runways and aircraft spacing control with speed control, which showed the potential to reduce fuel consumption corresponding to sequence delays by approximately 20% [6, 7]. Moreover, a model-based airport surface manager (SMAN) framework reduced delays on airport surfaces using time-varying fluid queuing networks [9]. The study mentioned that the runway of the departing aircraft can be changed to avoid taxiing at points where congestion is expected, thereby reducing delays for the departing aircraft. Thus, studies have been conducted to reduce the delays in departures, arrivals, and airport surfaces, respectively. In order to implement them into real operation, an integrated operational framework needs to be proposed. In particular, if departures and arrivals use the same runway, the framework must pay attention to how the respective delay reduction methods affect each other.

Against this background, this study develops a new target start up approval time (TSAT) assignment method accommodate stochastic air traffic flow for the Tokyo International Airport (RJTT) using runway flow control. TSAT is a DM method and is the only one introduced in Japan at RJTT. However, as described in detail in Section 2. under the current TSAT operation, there are still many departure queues, and improvements are required. The proposed operational framework has the following three features. 1) Use of machine learning models. By using machine learning models, it is possible to predict the ground taxi and arrival landing times with higher accuracy and assign appropriate gate departure times. 2) Runway flow control using queuing theory. By introducing a method to control runway flow in a given time frame, it is possible to reduce the queue before the runway entry point to consider the uncertainties in actual operations, that is, the variation in flight time and ground taxi time. 3) Feature designed to express the characteristics of each airport. It is important to capture the operational characteristics of each airport when building machine learning models and improve the accuracy of ground taxi times. In the framework proposed in this study, the northerly wind operation at RJTT was selected as the targeted traffic, and a model was built accordingly. In addition, experiments using the AirTOp simulator were conducted to verify the effect of the proposed TSAT operation method on queue reduction and on the delay reduction of arriving aircraft.

This paper is organized as follows: In Section 2.we provide an overview of the RJTT operation and details of the operational framework proposed in this study. In Section 3.we validate the TSAT assigned by proposed framework using the AirTOp simulator. In Section 4.we discuss future extension of this study. Finally, we conclude this study in section 5.

2. Novel architecture for integrating aircraft operation at an airport

2.1 Current operations at Tokyo International Airport



(a) Schematic of RJTT (b) RJTT northerly wind operation

Figure 1 – Overview of airport surface and operations of RJTT

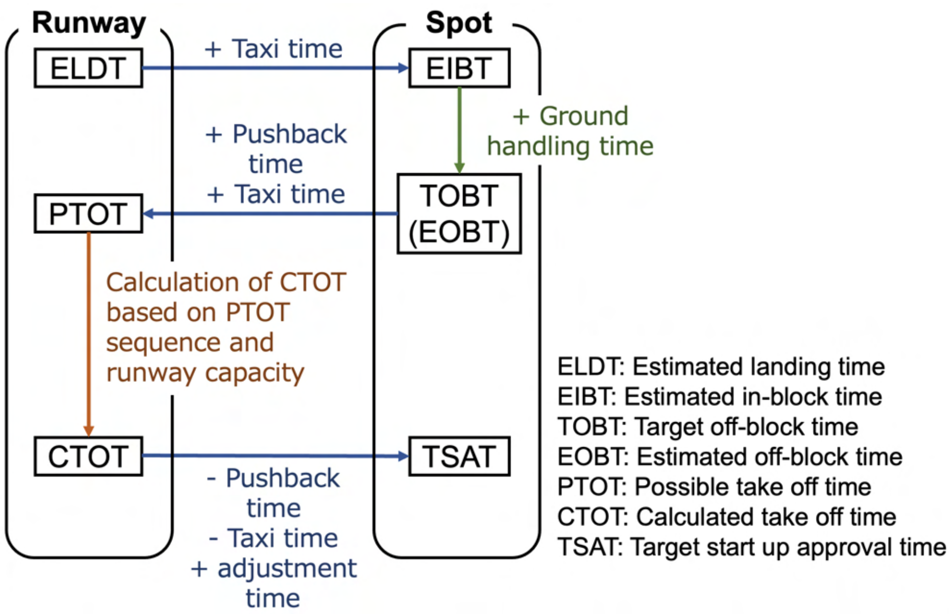


Figure 2 – TSAT operation at RJTT

RJTT is the largest airport in Japan, with four runways. It ranks third in the world in terms of total airline capacity (domestic and international flights) and is the busiest airport in Japan [10]. Figure 1a shows a schematic diagram of the airport surface at RJTT. The RJTT has a parallel-cross structure consisting of parallel north-south runways (34L/16R and 34R/16L) and two southwest-northeast runways (22/04 and 23/05). There are three passenger terminals. Terminals 1 and 2 were mainly used for domestic flights and were surrounded by four runways. Terminal 3 was used for international flights. The runway configuration depends on the wind direction, and there are two main variants: northerly wind and southerly wind. This study focuses on the northerly wind operations, which account for more than half of the total operations. In northerly wind operations, the aircraft land at either runway 34L or 34R and take-off from either runway 05 or 34R. Flights are allocated to these runways according to their origins for arrivals, or according to the destinations for departures. Runway 05 is used only for departures and runway 34R is used for both departures and arrivals. As the arrival course of runway 34R crosses runway 05, air traffic control regulations prevent runway 05 departures from starting their takeoff rolling while runway 34R arrivals are passing overhead. This means that runway 05 departures are held when runway 34R arrivals approach. Figure 1b shows the runway usage of RJTT for departures and arrivals during northerly wind operations.

At RJTT, a DM method called the target start up approval time (TSAT) operation was introduced in July 2018. Figure 2 presents an overview of the TSAT operations at RJTT. It is believed that if an aircraft requests a push-back to this calculated TSAT, the time spent in line waiting for departure will be reduced. However, in actual operations, many aircraft still queue before the runway entry point to depart. In a previous study using data from 2019 and 2020, that is, after the introduction of TSAT, the delay was estimated to be approximately a total of 3.5 hours per day for all departing flights [2, 3]. This can be attributed mainly to the following two time variation sources that affect TSAT calculations. One is the ground taxi time. In actual operations, ground taxi times vary depending on weather, pilot, and traffic situation in the vicinity. However, the ground taxi times used for TSAT calculations (blue arrows in Figure 2) are given in a deterministic way for each spot. The omission of the variance factors may cause the aircraft to arrive at the runway entry point at a time that deviates from the calculated take-off time (CTOT), resulting in a waiting queue. Another factor contributing to errors is the runway occupancy time (ROT). The fixed ROT value based on runway capacity is used to calculate TSAT. However, when looking at individual aircraft, the ROT and take-off intervals vary depending on the type of aircraft, the category of the preceding traffic and whether there are arriving aircraft using the same runway. Not accounting for variation in ROT reduces the effectiveness of CTOT in reducing queues. To eliminate the departure queues before the runway entry point, a new TSAT assignment framework must be developed to address these issues.

2.2 Designing operational frameworks accommodating stochastic air traffic flow

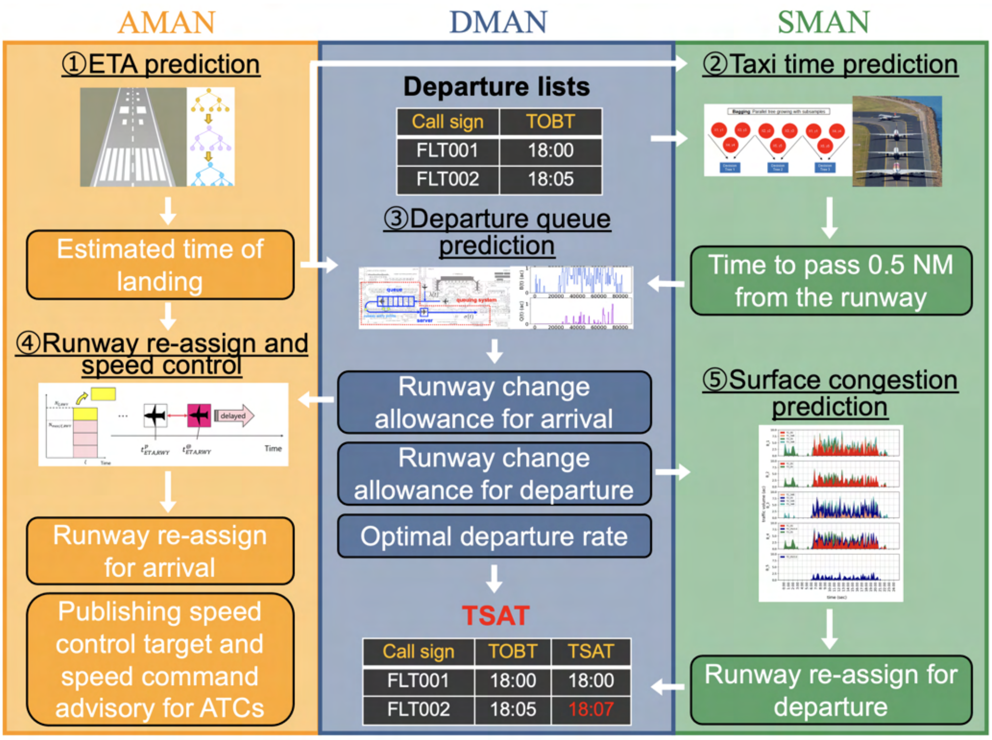


Figure 3 – Operational framework for stochastic variability of traffic flow

The TSAT assignment framework proposed in this study for stochastic air traffic flow is illustrated in Figure 3. The novelty of our proposed new operational framework is that it incorporates a combination of 1) improved accuracy through the use of machine learning models, 2) considering air traffic flow stochastic variability through runway flow control, and 3) reflection of airport specific characteristics. These features aimed to make TSAT operations inclusive of the variability and uncertainty inherent to management of air traffic.

The proposed TSAT assignment operation is carried out in the following steps.

The first step is to predict the landing time of the arriving aircraft (No. 1 in Figure 3). The prediction of arrival time is made approximately 40 minutes before landing. To be precise, this is done when the aircraft passes a defined point on the en route airspace. Prediction results are handed over to AMAN, DMAN and SMAN.

The second step is to predict the ground taxi and push-back time of the departing aircraft using machine learning models (No. 2 in Figure 3). The model is based on airport-specific characteristics, such as airport surface structure and airline characteristics, for example, taxi speed and spot location. The results of this prediction are handed over to DMAN.

The third step is to calculate the optimum departure rate before the runway entry point using a mathematical model based on queuing theory (No. 3 in Figure 3). Based on the estimated landing time of the arrival and the estimated reach time of the departure to the runway entry point, the runway flow is calculated and the departure queue is predicted. From this, the optimum departure rate without departure queues is calculated. At the same time, the number of additional arrivals that do not increase the departure queue when accepted onto a mixed take-off/landing operation runway is handed over to the AMAN, and the number of departures that do not increase the departure queue when the departure runway is changed is handed over to the SMAN.

The last step is the assignment of TSAT. The TSAT is allocated based on the optimum departure rate and the departure runway as coordinated by the SMAN. If no departure queues are expected, the target off-block time (TOBT) shall be TSAT. If a departure queue is expected, TSAT with delay departures is assigned according to the following sub procedure. First, the take-off times are adjusted assuming that the optimum number of departures will take-off at equal intervals within the time frame.

Second, the take-off times are allocated in runway queue sequence is determined according to the expected time of reaching the queue. Third, from the expected take-off time, the time required for ground taxi and push-back as estimated by the SMAN is subtracted to assign the TSAT. Departing aircraft that exceed the optimum number of departures and are not allocated a take-off time are changed to depart within the next time frame. If the optimal number of departures is still exceeded in the next time slot due to congestion, the aircraft is backtracked further to the next time slot. In such cases, priority is given to departures that have been backed out of the previous time slot.
The details of arrival, departure, and surface manager are discussed in the following sections.

2.3 Operational framework details

2.3.1 Arrival time prediction and runway flow-based arrival management

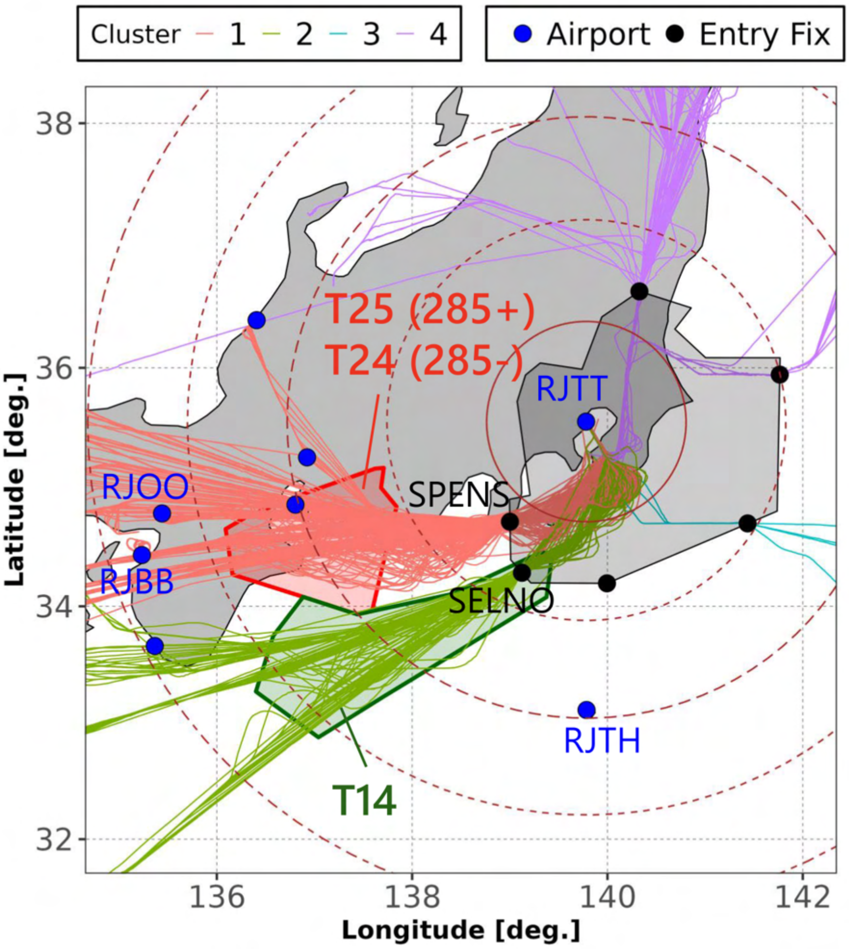


Figure 4 – Tracks of RJTT arrival and associated airspace.

The AMAN embedded in the operational framework have two main tasks. The first is the prediction of arrival times. Figure 4 shows the trajectory of arrivals on one day in December 2019, when northerly operations were conducted all day, clustered by TMA gate points. The grey covered airspace in Figure 4 is the TMA established for RJTT arrivals, with entry gates indicated by black points. The study predicts TMA gate passing times and landing times calculated from statistical data for each of these clusters. Morikawa et al. have developed a prediction method based on the distance from the neighbouring point of the TMA entry fix using a machine learning model, which is also expected to further improve the prediction accuracy [8]. The second is the reassignment of arrival runways and early speed control. At RJTT, aircraft arriving from the west, south and east use runway 34L and aircraft arriving from the north use runway 34R. The number of arrivals using runway 34L is more than three times the number of arrivals using runway 34R. When the arrival flow on runway 34L increases, AMAN reallocates some runway 34L arrivals to runway 34R when it is possible to use runway 34R. At this point, care should be taken to ensure that reallocation onto 34R does not affect the congestion of departing aircraft, as it is a runway with mixed departure-arrival operations. Conversely, if Runway 34L is available, some arrivals on Runway 34R may be allocated to Runway 34L. Such a runway change may result in an increase in flight distance for the aircraft that change the landing runway, as it will land on a more distant runway than usual. However, the vectoring to ensure arrival separation for the aircraft concerned and subsequent aircraft is reduced and the overall flight distance of the traffic flow is reduced. The speed control required to achieve efficient use of each runway is also back-calculated and presented. Details are given in [6].

2.3.2 Estimating available aircraft arrival/departure rate using time-varying fluid queue

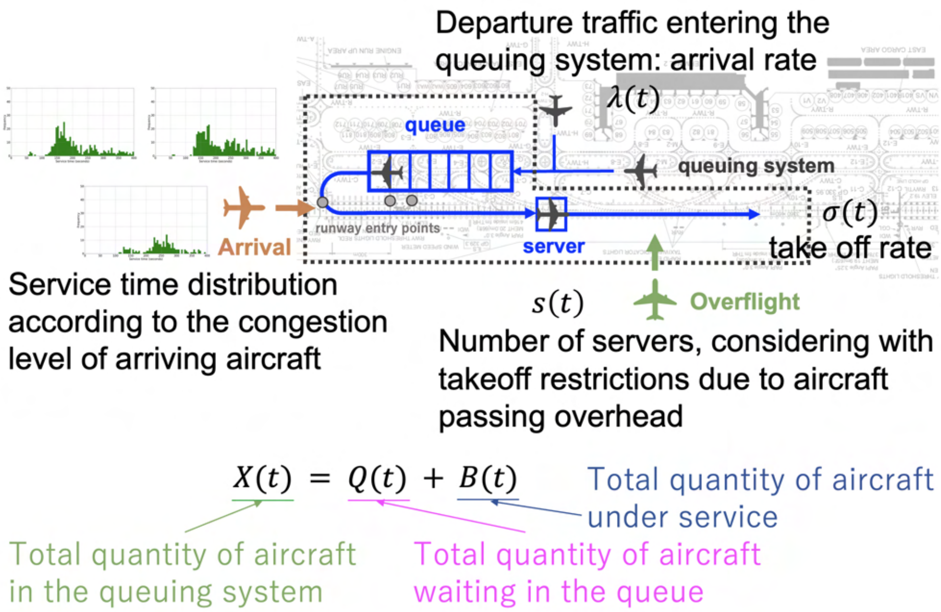


Figure 5 – Departure queuing model at RJTT using time-varying fluid queue

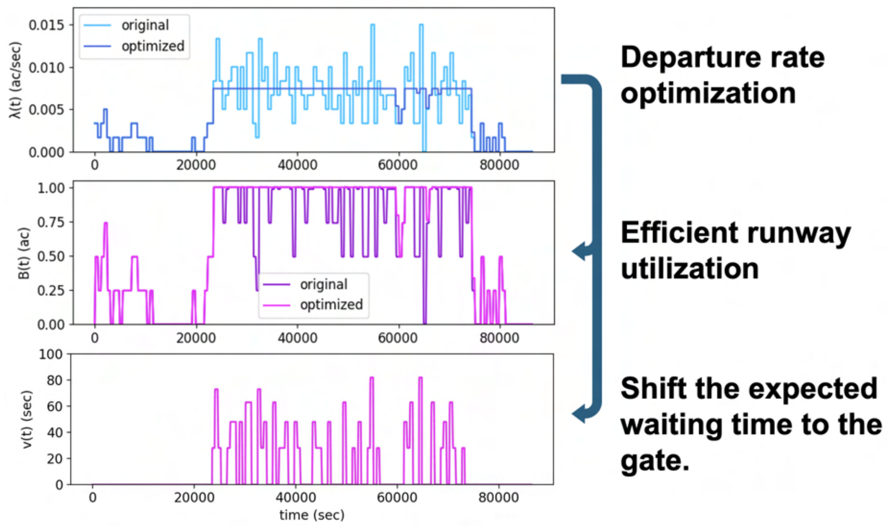


Figure 6 – Departure queue prediction results

The aircraft departure queuing model in the second step of the proposed framework was designed using $G(t)/GI/s(t)$ time-varying fluid queues [2, 3, 13]. This model is used to estimate the time-varying length of the departure queue and the waiting time at the runway entry point. Figure 5 shows the departure queuing model at RJTT. In this model, the arrival rate (the rate of departure traffic entering the queuing system) is determined by designating a location 0.5 NM from the runway entry point as the system entrance and the interval between two consecutive aircraft passing that point as the time interval into the system. The arrival rate is updated for every 10-min time frame. By predicting the departure queue in 10-min increments and controlling runway flow of departure and arrival, the system is able to consider the uncertainties of aircraft operations (variation in flight times and ground taxi times due to weather and individual differences in human operation). The service time is defined as the sum of the ROT and the interval time between proceeding aircraft at the runway entry point. Because runway 34R at RJTT is operated by a mixture of departing and arriving aircraft, the distribution of service times varies with the number of arriving aircraft using the same runway in the same time frame. This allows the system to account for variations in ROT and take-off intervals that occur in actual operations. Furthermore, the number of servers is given as the number of departures that can use the runway for take-off. Because of RJTT runway 05 departures are restricted to take-offs when runway 34R arrivals pass overhead, the number of servers varies over time and is always less than 1.0, depending on the number of aircraft passing overhead in a 10-min time frame. The total number of aircraft in the queuing system at time t, $X(t)$, is given as the sum of the total number of aircraft in service, $B(t)$, and the total number of aircraft waiting in the queue, $Q(t)$. The algorithm is summarized in [2]. This prediction is used to optimise the departure rate, as shown in Figure 6, so that the waiting time incurred at the runway entry point can be consumed at the gate

2.3.3 Aircraft taxi-time prediction and runway reassignment for departure

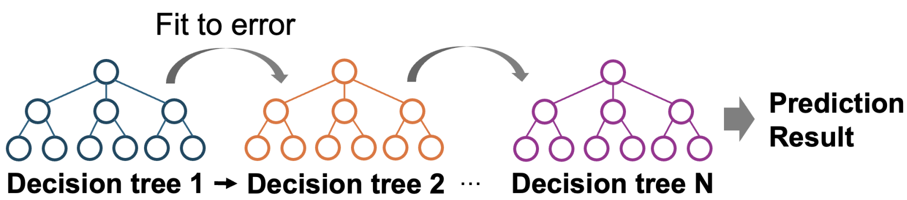


Figure 7 – Boosting in GBR

In proposed framework, SMAN mainly has two tasks.

The first is the taxi-time prediction using the machine learning model [4]. For the DM system to work, the ground taxi time of each departing aircraft must be accurately predicted before it leaves the gate. For this reason, the ground taxi time prediction was performed using features obtained while the aircraft is still at the gate. Basically, we employed the features that have been shown to be important in previous studies [14, 15, 16]. However, we did not use the most important features in the previous studies, i.e., the ground taxi route and the number of turns in the route. This was because the ground taxi route is not confidently known before departing from gate in the RJTT operations, and it was considered inappropriate to incorporate it into the DM system. Instead, the straight line distance from the gate to the runway entry point was used. Since the departure runway is predetermined according to the destination, the direct distance to the runway can be calculated while the aircraft is still at the gate. The gates were additionally divided into several zones and used as categorical features. For northerly wind operations at RJTT, as shown in Figure 1a, the departures from Terminal 3 interfere with the departures from Terminal 1 and Terminal 2, and also require crossing runway 34R, which is used by arriving flights. As a result, departures from Terminal 3 require longer ground taxi times. To incorporate this terminal-specific character, zoning as well as distance was incorporated into the categorical features. In addition, a machine learning method called Cat Boost (CAT) was used in this study. CAT is a decision-tree-based method and an improved version of Gradient Boosting Regression (GBR). Decision-tree-based methods are beneficial in that they are easy for humans to interpret because they output results based on various conditional branches. On the other hand, they are prone to over-fitting. To overcome this, GBR incorporates a technique called boosting. As shown in Figure 7, the boosting is a method that arranges trees in series, with one tree fitting the error of the preceding tree, and the result using all trees is the output. Combining the results of various trees reduces the risk of over-fitting. Prior research has shown that decision-tree-based methods are

more suitable and accurate for predicting the ground taxi times and the flight times. Radar data and spot assignment charts of actual flights departing from RJTT on 38 randomly selected days between September 2019 and February 2020 were used to build the machine learning model.
The second is the coordination of departure runways to reduce ground surface congestion. If many aircraft depart from the same runway at the same time frame of day, the taxiway from the spot to the runway will also be congested. This causes queues on the taxiway outside the runway frontage. To avoid this, the queuing model is used to estimate the flow rate at a representative intersection on the taxiway, and if the flow rate exceeds a certain level, the departure runway is changed to reduce the flow rate [9]. At this time, the SMAN coordinates with the DMAN to ensure that the flow on the new departure runway does not increase the queue at the runway entry point as a result of the increased flow.

3. Performance evaluation through simulation experiments

3.1 Experimental design

3.1.1 Simulator tool

To evaluate the effectiveness of the proposed operational framework for reducing departure queues, we conducted simulation experiments using AirTOp software, an agent-based simulator [11]. By loading a flight plan that specifies departure time, departure airport, departure spot, destination, aircraft type, flight route, and cruising altitude, the AirTOp simulator spawn the aircraft at the specified location at the departure time and begin moving. In the AirTOp simulator, each aircraft moves according to the BADA model [12]. Moreover, the AirTOp simulator has the function to control the separation between aircraft like ATCOs. When there is a risk of collision between aircraft on the airport surface or in the air, the simulator follows certain rules to stop or vector one of the aircraft to maintain separation. This function reproduces movements similar to actual air traffic flow. Furthermore, various scenarios could be reproduced by changing the flight plan to suit the purpose of the experiment. By analyzing the data acquired in each scenario, the waiting time can be verified before the runway entry point for departing aircraft, delay in arriving aircraft, and flight extension distance due to vectoring.

3.1.2 Experimental scenarios

Table 1 – List of AirTOp simulation scenarios.

Scenario number	Departure	Arrival
1	Original	Original
2	V1	Original
3	V2	Original
4	V3	Original
5	Original	AMAN
6	V1	AMAN with DMAN
7	V2	AMAN with DMAN
8	V3	AMAN with DMAN

The AirTOp simulation experiment validation was conducted flight data for seven days (Sep. 13, 14, Oct. 18, and Dec. 10, 2019 and Jan. 10, 11 and Feb. 8, 2020) when all-day northerly operations took place after the start of TSAT operations at RJTT.
For each of these days, four different sets of departure aircraft flight plans were prepared. The first set was the existing TSAT operational flight plan (Original). The flight plan based on the radar data for the day of the experiment to identify the time at which the aircraft starts its push-back and uses this as the departure time. The second set applies the optimum departure rate according to the proposed operational framework (V1). The departure time in first plan as TOBT, and the flight plan uses the new TSAT as the departure time, which is assigned to maintain the optimum departure rate using the proposed framework. The third set is a scenario where the optimal departure rate calculated in the proposed framework is allowed to be temporarily exceeded (V2). Specifically, if not consecutive, allow one more departure per time frame than the optimal number of departures per time frame (e.g.

if the optimal number of departures is four at the time frames, allow 5 → 4 → 5 → 4 departures per time frame). This scenario is designed to prevent unused slot, where a departing aircraft is not present at the runway approach point at the time when the departing aircraft can utilise the runway, due to time variations present in real operations (e.g. variations due to human operations, variations due to weather conditions, etc.) The fourth set is a scenario that always allows one more departure per time frame than the optimum number of departures per time frame (e.g. if the optimum number of departures is four time frames, the number of departures per time frame is allowed to be 5 → 5 → 5... per time frame (V3)). In order to keep the verification simple, for SMAN, only the ground taxi time prediction was applied, and runway changes for departures were not applied in this simulation experiment.

Three sets of flight plans for arriving aircraft were prepared. The first reproduced existing operations based on radar data on the day of the experiment. The second was the result of an application of AMAN, in which runway allocation and speed control were carried out without considering DMAN, but only with a view to improving the efficiency of the arriving aircraft (AMAN). The third applies an AMAN that implements runway allocation and speed control based on the efficiency gains of departing aircraft due to DMAN, to the extent that these gains are not adversely affected (AMAN with DMAN).

Table 1 lists the scenarios implemented. In all, eight different departing and arriving traffic combinations were simulated. Due to lack of resources, a limited number of combinations of flight plan sets were used in the simulations. However, with these combinations, the study's objective can be achieved.

3.1.3 Measurement

In this study, the following indicators are used to verify the effectiveness of the proposed new TSAT assignment method in reducing departure queues. For departing aircraft, the indicators are the waiting time at the runway entry point and at the gate compared to existing operations. For arriving aircraft, the indicator is the increase or decrease in flight time compared to existing operations.

3.2 Result

3.2.1 DMAN+SMAN

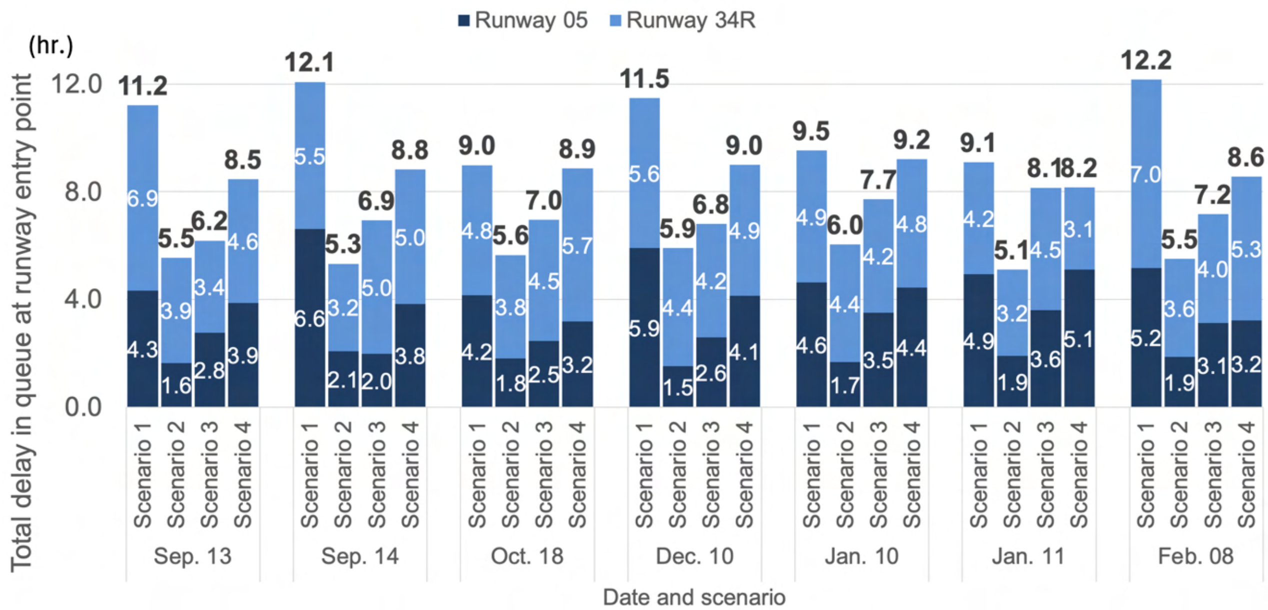
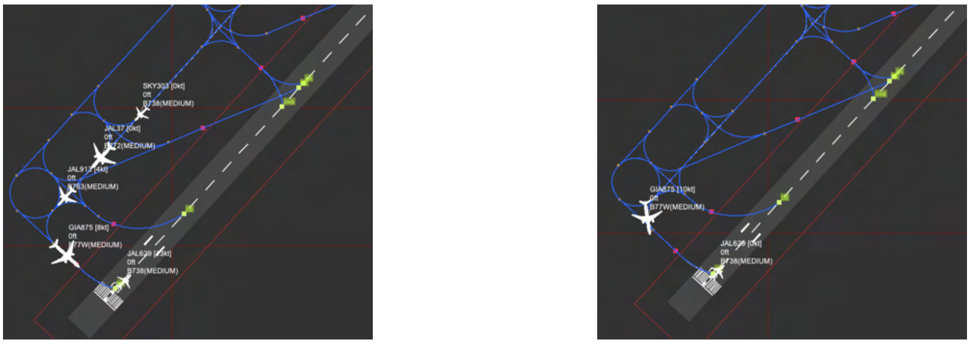


Figure 8 – Comparison of departure delays in scenarios 1 to 4.



(a) Original departure time (b) With new TSAT

Figure 9 – Effect of new TSAT on queue reduction

Table 2 – Additional waiting time at the gate for departing aircraft due to new TSAT

Date	Scenario number	Mean (s)	Percentage of departing aircraft waiting at the gate due to new TSAT
Sep. 13	1	–	–
	2	2157	87 %
	3	523	67 %
	4	73	22 %
Sep. 14	1	–	–
	2	2301	90 %
	3	507	66 %
	4	57	21 %
Oct. 18	1	–	–
	2	2386	89 %
	3	419	66 %
	4	70	24 %
Dec. 10	1	–	–
	2	2244	88 %
	3	496	66 %
	4	76	26 %
Jan. 10	1	–	–
	2	2362	85 %
	3	398	62 %
	4	55	21 %
Jan. 11	1	–	–
	2	2468	86 %
	3	533	67 %
	4	61	20 %
Feb. 8	1	–	–
	2	2237	82 %
	3	445	64 %
	4	67	21 %

Figure 8 shows the total waiting times of the queue of departing aircraft at the runway entry point for scenarios 1 to 4. On all days, the waiting times were reduced with our proposed TSAT assign framework compared to conventional operations. In scenario 2, where the queues were reduced the most, up to 56% and on average 47% of queues were reduced. A comparison of the queues generated for a given departure flight is shown in Figure 9, where the departure sequence remained the same, but the queues were reduced. Looking at the waiting times by runway, there were cases where the waiting times are shorter in scenario 3 than in scenario 2. This is considered to be the result of avoiding more unused slot than in scenario 2. The average waiting time at the gate due to the new TSAT assignment and the percentage of aircraft subject to the assignment are shown in Table 2. Although scenario 2 demonstrated high queue reduction, it was found that more than 80% of departing aircraft had to additionally wait an average of more than 30 minutes at the gate. On the other hand, it was also found that simply adjusting departures appropriately by two minutes for just under 30% of aircraft, as in scenario 4, could reduce queues. In terms of delays for arriving aircraft, the application of the new TSAT did not increase delays due to the simulator specifications, as the flight plan was not changed.

3.2.2 DMAN+SMAN+AMAN

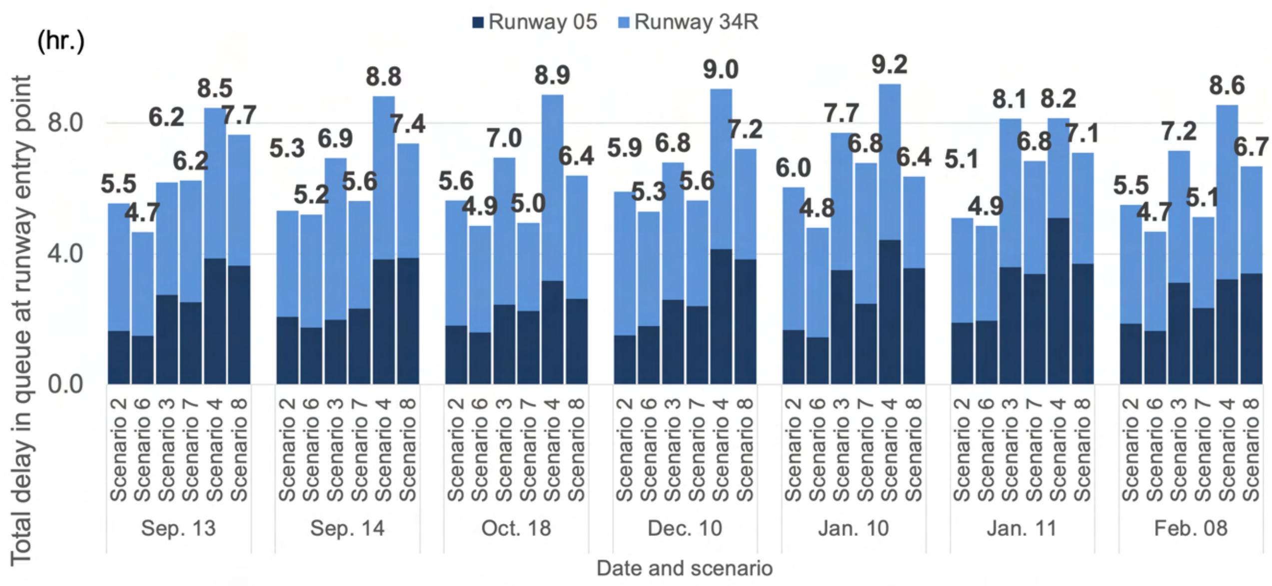


Figure 10 – Comparison of departure delays in scenarios 2 to 8 (except 5)

Table 3 – Comparison of flight times of arriving aircraft

Scenario number	Mean (s)	Median (s)	Standard deviation (s)	Max (s)
1	1342	1359	245	2305
5	1352	1334	275	2372
6	1351	1331	276	2373
7	1357	1338	275	2372
8	1366	1364	271	2518

Figure 10 shows a comparison between the total waiting times of the departure queues at the runway entry point for scenarios 2 to 4 and scenarios 6 to 8. On all days, the application of AMAN in addition to DMAN and SMAN did not increase the departure queues. This indicates that AMAN in our proposed TSAT allocation framework does not have a negative impact on DMAN. Further reductions in departure queues were observed in most scenarios applying AMAN. It may be due to the effect of the AMAN changing the arrival runway from 34R to 34L. In other words, this is because fewer arrivals on runway 34R allowed more departures to depart from runways 34R and 05. The scenario with the highest queue reduction, scenario 6, reduced queues by up to 62% and 53% on average.
Table 3 shows the change in flight time of arriving aircraft for all periods combined, scenario 1 and scenarios 5 to 8. A comparison of scenarios 1 and 5 shows that the median flight time decreases when AMAN is applied. Scenarios 6 and 7 show that the effect of reduced flight time due to AMAN remains almost the same when DMAN is applied. In scenario 8, the flight time increased compared

to scenario 1. This may be due to the fact that the change from runway 34L to runway 34R was not possible due to the high number of departing aircraft in the scenario. This may be because, in this scenario, the large number of departing aircraft often prevented the change from runway 34L to runway 34R, so the vector reduction effect of the runway change was not as significant as it could have been.

4. Discussion

In this study, simulation experiments were conducted with several variations on the number of departing aircraft in time frame. In all cases, a delay reduction at the runway approach point was observed, but there was a trade-off between the effect of reducing queue and the waiting time at the gate. In some scenarios, runway unused slot occurred, which required extra departing aircraft to fill it. On the other hand, having extra aircraft depart when there were no unused slots would naturally create waiting queues. In implementing the proposed new TSAT operation, it is necessary to consider how much extra departures should be allowed and to what extent the loss of passenger convenience due to waiting time at the gate should be tolerated.

5. Conclusion

This study proposed a new operational framework to accommodate stochastic air traffic flow with 1) improved accuracy through machine learning models, 2) consideration of stochastic variations in air traffic flow through runway flow control, and 3) reflection of airport-specific characteristics. Validation of seven days of data from the AirTOp simulator showed that the scenario with the highest reduction in waiting times reduced departure queues by an average of about 53%. It was also found that the DMAN, AMAN and SMAN could be integrated and operated without any negative impact on each of them. In order to apply this operational framework to real operations, it is necessary to discuss to what extent extra departures are allowed to prevent runway unused slot and to what extent the loss of passenger convenience of waiting at the gate is acceptable.

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