Estimation of Fuel Consumption Reduction by the SET Operations at Narita Int'l Airport

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***Abstract*—Reducing fuel consumption is one of the issues that airlines are tackling these days. One solution is to apply the Single Engine Taxi (SET) operations that shut down one of the engines during taxiing after landing. In order to predict and evaluate the effect of this operation on fuel consumption reduction with high accuracy, we first developed a machine learning model to estimate the fuel flow during taxiing, using actual flight data from departed and arrived aircraft at Narita International Airport (RJAA). Unlike physically based models, our fuel flow model was designed to incorporate the surface traffic conditions as predictors. This enables evaluation of the SET effectiveness before taxiing, relevant to airlines tactical operations. This fuel flow prediction model suggests that the proportion of taxiing with the SET operations and the aircraft's total weight are main factors that influence the value of fuel flow during taxiing. We additionally discuss how the generated fuel flow model can be incorporated into a Fast-Time Simulation environment, which can assist airlines in real-time fixing of the SET operations starting position. The results show that this predictive model and simulation environment could assist airlines in not only estimating the effects of fuel consumption reduction more accurately, but also determining the starting position of the SET operations and the benefits of this operation in advance.**

***Keywords*—Air traffic control, Fuel consumption, Single engine taxi, Machine learning**

I. Introduction

Recently, airlines have been compelled to focus on reducing aircraft fuel consumption from financial and environmental perspectives, and there is a need for supporting technology or operational techniques that reduce fuel consumption. Aviation demand is projected to recover from the recent pandemic, with RPKs (Revenue Passenger Kilometers) reaching 94.1% of 2019 levels by the end of 2023 [1], and continue to increase into 2024 [2]. In addition to that, expenses for the jet fuel account for 31% of airlines' total expenses, and the preliminary 2024 fuel price per barrel is about 1.4 times higher than in 2019 [3]. Such projected increase in fuel costs associated with increased air traffic demand might pose financial burden on airlines. As for the environmental perspective, the 77th IATA Annual General Meeting in 2021 adopted a joint resolution to achieve net zero carbon emissions by 2050 [4]. The increase in fuel consumption due to rising aviation demand leads to higher carbon emissions, which contradicts this resolution.

In response to this background, one of the measures airlines are adopting to reduce fuel consumption is the Single Engine Taxiing (SET) operations during taxiing. The SET operation is allowing aircraft to taxi on the ground with one engine off and expected to reduce fuel consumption during taxiing. The operation protocol of the SET operations varies by airline, airport, and aircraft type. A study at London Heathrow Airport (LHR) showed that implementing the SET operation during taxiing after landing can reduce fuel consumption by up to two-thirds compared to not doing so [5]. Additionally, Kumar et al [6] suggested that the SET operation could reduce air pollutant emissions by 27% at Orlando (MCO) and 45% at New York LaGuardia (LGA).

To estimate the fuel consumption reduction potential of the SET operation, it is essential to accurately estimate the aircraft's fuel flow or fuel consumption during taxiing because the fuel flow model provided by ICAO, such as the "Aircraft Engine Emission Databank (AEED)", and the "BADA" developed by EUROCONTROL are not designed for estimating fuel consumption during ground operations.

In multiple studies, efforts have been made to develop a fuel flow model that offers greater accuracy than these existing estimation model and database. Khadilkar et al [7] modeled the fuel consumption during ground operations as a multiple regression model based on actual flight data. This model exhibits greater predictive accuracy for fuel consumption compared to both the ideal physical models of engines and ICAO models. Furthermore, they suggested that using actual flight data enables the construction of a highly accurate predictive model.

Recently, there has been an increase in research aimed at developing more advanced fuel flow and fuel consumption prediction models by combining actual flight data with various machine learning techniques.

Jarry et al [8] developed a fuel flow regression model corresponding to various flight phases using Quick Access

Recorder (QAR) data obtained from a range of aircraft. They also conducted a comparative accuracy analysis against existing models.

Metlek et al. [9] applied deep learning techniques to the development of a fuel flow prediction model. They integrated actual flight data with a novel deep learning architecture known as the CNN-BiLSTM model, demonstrating superior performance compared to conventional deep learning models.

Baklacioglu et al. [10] attempted to predict fuel flow using various types of neural network models. They also utilized actual flight data from the cruising, ascent, and descent phases of flight, revealing which neural network model exhibited the highest performance in each flight phase.

These studies have successfully achieved more accurate predictions of fuel flow and fuel consumption compared to traditional models across various flight phases of the aircraft. However, it can be said that there has not been sufficient research on models and prediction methods for fuel flow during aircraft taxiing that take into account interactions between aircraft and the characteristics of taxiing routes. Furthermore, these previous studies utilize information obtained in real time or after taxiing has concluded as explanatory variables in their models, which prevents them from estimating fuel flow and fuel consumption before the taxiing begins. In order for airlines to predict the fuel consumption reduction effects of SET operations in advance, it would necessary to devise prediction methods that utilize only the information available beforehand and reflect the characteristics of airport ground congestion and other factors.

With this background, we first tried to combine actual flight data from Narita International Airport with machine learning techniques to develop a fuel flow prediction model during taxiing. This approach aims to predict fuel consumption reductions associated with activation the SET operations. Furthermore, we will explore the possibility of constructing a simulation environment that combines a simulator modeling the airport surface traffic conditions with this prediction model. This environment could potentially allow airlines to make decisions about the SET operations activation in advance.

In Section II, based on on-board flight data, we calculate the amount of fuel consumed by aircraft taking off and landing at Narita International Airport (NRT) during taxiing and the taxiing distance. In Section III, we discuss the factors that determine the implementation of the SET operations to reduce fuel consumption, in terms of aircraft taxiing paths. In Section IV, we build a prediction model based on the result of Section II and III. In Section V, we conduct experiments to predict fuel consumption during taxiing by combining an airport-surface modeling fast-time simulator with the prediction model constructed in Section IV, and discuss the potential applications of this simulator environment. Lastly, we conclude the study.

II. Data description and preprocessing

In this Section, we first provide a brief overview of Narita International Airport. Then, we extract and describe the portions of flight data related to taxiing on the ground at Narita International Airport from on-board flight data and calculate necessary values for this study, such as the average fuel flow and taxiing time.

Narita International Airport (RJAA/NRT) is the second largest major airport in Japan after Tokyo International Airport (RJTT/HND) in terms of the number of passengers handled and the number of landings. In addition, the airport handles the largest number of international and cargo aircraft in Japan, and its amounts of fuel supply to aircraft is also the largest in Japan in FY2022 [11]. This airport has two runways: A runway (16R/34L) and B (16L/34R), and it changes the runway used depending on the wind direction. As shown in Fig. 1, for northerly wind configurations, runway 34R/L is used for landing and takeoff. Conversely, during southerly wind configurations, runway 16R/L is used for landing and takeoff. There are two features in runway configurations at Narita International Airport: one is that southerly wind operations are common, and the other is that the B runway is used for arrivals and the A runway is used primarily for departures because the A runway is longer than the B runway. As per this features, in the flight data we used in this study, 65% of the arrival aircraft landed runway 34R or 34L (northerly wind operations), and 75% of arrivals used the B runway.

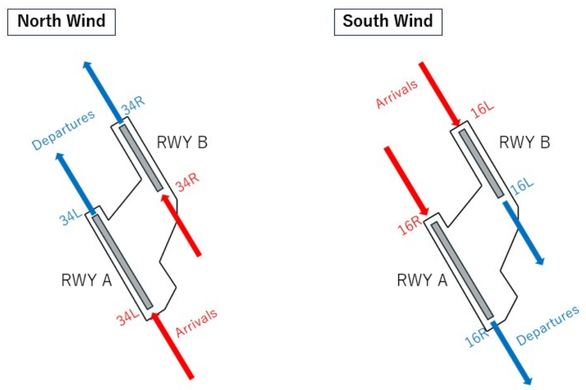

Figure 1. Runway operations depend on the wind direction

In this study, we used flight data acquired from Boeing 787-8 aircraft operated by Japan Airlines (JAL) that have taken off or landed at Narita International Airport between September 2019 and January 2020. There were total 727 flights comprising 356 arrivals and 371 departures.

The flight data contains information such as fuel flow rate and thrust recorded every second during the flight. Since this study focuses on the movement of aircraft on the airport surface, the flight data during taxiing was extracted from the flight data by using the algorithm shown in Fig. 2 and Fig. 3 below. In this algorithm, We monitor the recorded values of fuel flow, GPS coordinates, and Ground Speed to detect the start and end points of taxiing, the locations of parking spots, and the positions where the SET operations are activated. Based on the extracted flight data, the values required for the analysis are calculated according to the following Eq. (1), (2), (3) and (4).

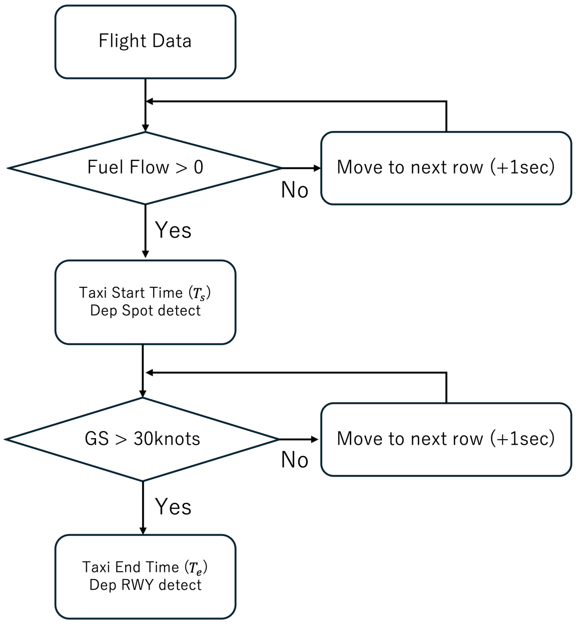

Figure 2. Preprocessing flow for departure aircraft.

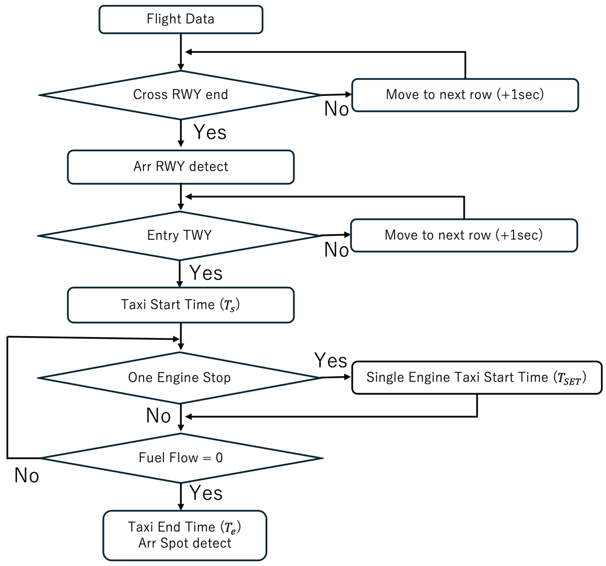

Figure 3. Preprocessing flow for arrival aircraft.

$$t_{total} = T_e - T_s \tag{1}$$

$$t_{SET} = T_e - T_{SET} \tag{2}$$

$$FC_{total} = \sum_{t=T_s}^{T_e} (ff_1 + ff_2) \tag{3}$$

$$FC_{SET} = \sum_{t=T_{SET}}^{T_e} (ff_1 + ff_2) \tag{4}$$

These data are described and cross-checked, as documented below. We first compared the average fuel flow values calculated from the flight data with those estimated by ICAO and BADA used in previous studies. The ICAO model is the predicted fuel flow of a GEnx-1B70 engine at idle thrust from ICAO Aircraft Engine Emissions Databank [12]. The last is the predicted value derived according to Eq. (5) in BADA. BADA is an aircraft performance model developed by EUROCONTROL and used in various air traffic management studies [13].

$$ff_{min} = C_{f3}\left(1 - \frac{H_p}{C_{f4}}\right) \tag{5}$$

where ff_{min} represents minimum fuel flow during idle descent, and H_p is the geopotential pressure altitude. C_{f3} and C_{f4} are constant coefficients determined for each type of aircraft. As shown in Fig. 4 below, if we hypothetically use "Fuel Flow Idle" by ICAO and "minium fuel flow" by BADA as taxing fuel flow and compare these values with the average fuel flow from the flight data, the values from ICAO and BADA model have errors. The ICAO value is in excess of both takeoff and landing aircraft fuel flow, while the BADA value is less than it of takeoff aircraft. In addition, the average fuel flow of arrival aircraft is more varied than that of departure aircraft.

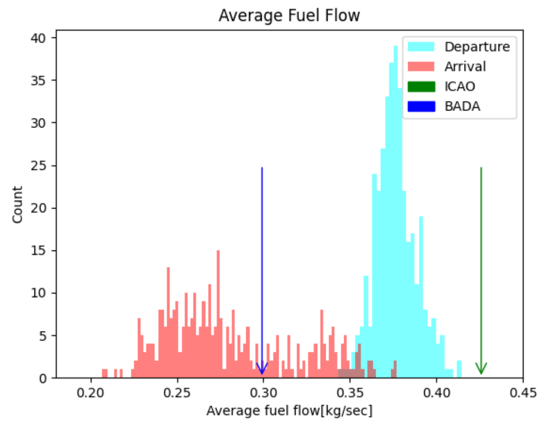

Figure 4. Comparison of average fuel flow

This extracted flight data provides an overview of the current SET operation at Narita Airport. First, Table. I presents the count of arriving flights that activated the SET operations, categorized by each arrival runway.

TABLE I. THE COUNT OF ARRIVING FLIGHTS THAT ACTIVATED THE SET OPERATIONS

	34R (B)	34L (A)	16R (A)	16L (B)	total
Activate SET	210	12	9	31	262
NOT activate SET	40	6	3	45	94
Activation rate	84.0%	66.7%	75.0%	40.8%	73.6%

It is clear that there are differences in the proportion of activating the SET operation across each runway. While over 80% of aircraft landing on Runway 34R (B runway, north winds) activated the SET operation, more than half of the aircraft landing on Runway 16L (B runway, south winds) taxied to the spots without the SET operation. Focusing on the positions where the SET operation was activated during taxiing, although there is some variation in the positions depending on the runway on which they landed, there is a skewed distribution, especially for the aircraft that landed 34R represented by the green dots in Fig. 5.

The observed bias in the locations where one engine is shut down after landing can be attributed to performance-related constraints of the aircraft. The study by Kameníková et al. [14] summarized the constraints encountered when implementing the SET operation on A320 aircraft, highlighting engine operating time as a key factor in deciding whether to start the SET operation. Specifically, it is noted that there are time constraints on the duration for which the SET operation can be continued to avoid weight imbalance between the left and right fuel tanks, as well as the necessity for a certain engine cooling period prior to shutting down one engine after landing. As mentioned in previous research, the flight data used in this study may have indicated that a minimum of 109 seconds is required from the start of taxiing to activation of the SET operation in order to follow such constraints(Fig. 6).

Thus, such constraints associated with activating the SET operation may contribute to the relatively low activation rate of the SET operation for aircraft landing on Runway 16L, as shown in the Table. I. Specifically, aircraft landing on Runway 16L are typically flights arriving at the B runway toward the terminal, which suggests that they may enter the apron area relatively quickly after leaving the runway. Consequently, pilots may determine that they cannot secure the necessary engine cooling time required by operational constraints, leading to the decision made before landing to taxi to the gate without the SET operation.

III. Estimated fuel consumption reductions of the SET operations

In this Section, we attempt to estimate the fuel consumption reduction of the SET operations by focusing on the taxiing distance during the activation of this operation, based on the flight data obtained in Section II. The fuel consumption for Case2 (FC_{total}) represent the total amount of actual fuel consumption during taxiing. The fuel consumption for Case1 (FC_{est_T}) and Case3 (FC_{est_S}) are estimated values, and as shown in Eq. (6) and Eq. (7), they are calculated by linearly extending the value of FC_{total} based on the total taxiing length (l_{total}) and the taxiing length with the SET operations activation (l_{SET}). Fig. 7 shows an example of calculation result for one flight.

·Case1 Running both engines during taxiing. (FC_{est_T})
·Case2 Stopping one engine during taxiing. (FC_{total})
·Case3 Running only one engine during taxiing. (FC_{est_S})

$$FC_{est\_T} = (FC_{total} - FC_{SET}) \cdot \frac{l_{total}}{l_{total} - l_{SET}} \tag{6}$$

$$FC_{est\_S} = FC_{SET} \cdot \frac{l_{total}}{l_{SET}} \tag{7}$$

For a finer look into the data, we first filtered the available data for arrivals via Runway 36R. This is because the arrivals exhibit greater variability in fuel flow data, and because arrivals via 36R are the majority traffic, as discussed in Section II. We further dissect the data according to the arrival spot.

By classifying arrival aircraft by arrival spot, it would be possible to consider the impact of the geographical characteristics of the taxiing path from the runway to the spot and the location of the spot on fuel consumption. Table. II shows the average fuel consumption for aircraft landing on runway 34R and arriving at the top six most frequently used spots, assuming the above three cases of operation. Focusing on fuel consumption reduction, the difference between the estimated values in Case 1 and Case 2 corresponds to the estimated fuel consumption reduction due to activation the SET operations, which is inferred based on the fuel consumption and the taxi length in the flight data. The aircraft arriving at Spot 84 have

TABLE II. Estimated average fuel consumption for each cases[kg]

SpotNo.	Count	Case1	Case2	case3	Case1-Case2
68	27	189.3	173.8	156.1	15.5
94	16	193.6	182.0	171.7	11.6
66	16	180.9	169.1	156.3	11.8
84	10	144.6	145.4	149.6	-0.83
91	9	159.9	156.5	153.2	3.32
95	9	166.3	160.6	151.7	5.66
total	87	178.0	168.0	157.5	9.92

TABLE III. Max and minimam fuel reduction [kg]

Spot No.	Max reduction	Minimum reduction
68	36.0	-6.71
94	30.9	-4.74
66	21.3	-0.44
84	3.08	-6.51
91	14.6	-6.40
95	9.09	1.11

significantly lower fuel consumption reductions compared to the average value by adopting the SET operations, and we discuss the reasons for this result in this Section.

The estimated reduction value is calculated as following Eq. (8) using Eq. (6).

$$\begin{aligned} FC_{est\_T} - FC_{total} &= \frac{FC_{total} \cdot l_{SET} - FC_{SET} \cdot l_{total}}{l_{total} - l_{SET}} \\ &= \frac{\rho_l - \rho_{FC}}{1 - \rho_l} \cdot FC_{total} \\ &= k \cdot FC_{total} \end{aligned} \tag{8}$$

where ρ_l represents $\frac{l_{SET}}{l_{total}}$, and ρ_{FC} represent $\frac{FC_{SET}}{FC_{total}}$. The k value in Eq. (8) is an indicator of the fuel consumption reduction effect of the SET operations during taxiing. In other words, a larger value of k can be interpreted as indicating that the SET operations is more effective, while a negative value of k can be interpreted as the SET operations increases fuel consumption instead.

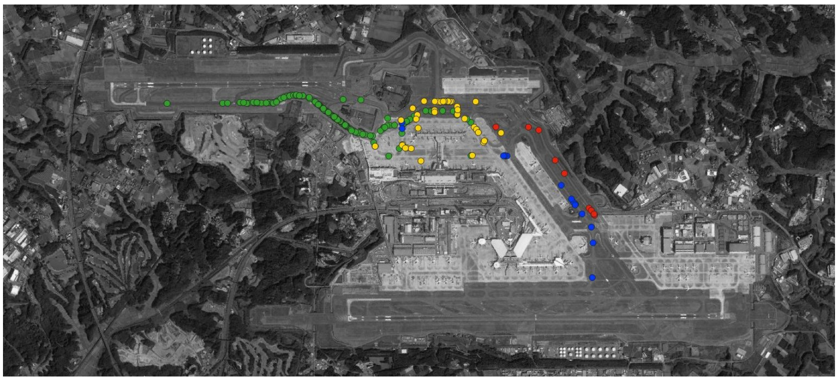

Figure 5. Positions where arrival aircraft started the SET operations.
The green dots represent aircraft that performed the SET operations and landed on 34R, the yellow dots represent aircraft that landed on 16L, the blue dots represent aircraft that landed on 34L and the red dots represent aircraft that landed on 16R.

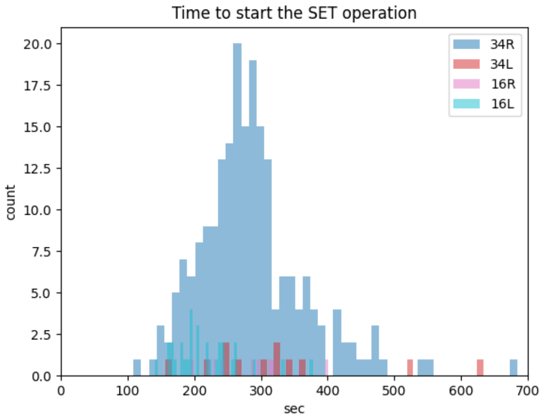

Figure 6. Time to start the SET operation after landing

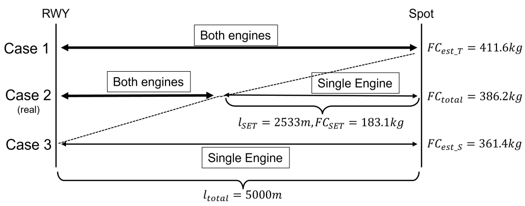

Figure 7. Example values of each cases

Therefore, the estimated reduction value is determined by the product of a scalar k and the total fuel consumption FC_{total} according to the Eq. (8). Furthermore, by dividing both sides of Eq. (8) by FC_{total}, the fuel consumption reduction for each spot can be evaluated regardless of the magnitude of the value of FC_{total}. In other words, it can be argued that the value of k defined in Eq. (8) allows for a quantitative evaluation of the fuel consumption reduction effect of each spot. As shown in Fig. 8, the value of k in Spot 84, where the fuel savings from the SET operations are lower as shown in Table. II and III, show a smaller distribution than in the other spots.

It seems possible that this phenomenon may be due to the spot's geographic location at the airport. Fig. 9 shows the location on the airport of each of the spots listed in Table II and III and the direction in which aircraft landing at 34R are taxiing on the airport. As represented in Fig. 9, Spot84 has a shorter taxi distance from the runway than the other spots.

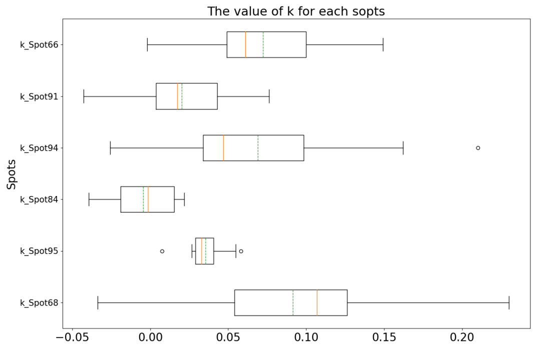

Figure 8. The k values for each spots.
The orange lines represent median values, and green dots represent mean values.

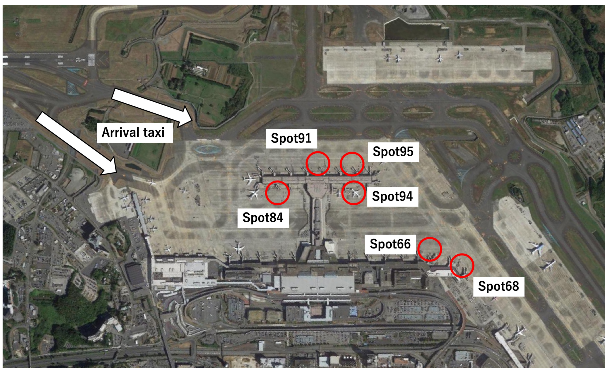

Figure 9. Spot positions at Narita Int'l Airport

As shown in Fig. 5, since the locations where 34R arrivals begin the SET operations are somewhat coherent, we can expect that the longer the total taxi length, the larger the value of ρ_l, and consequently the larger the value of k. In fact, as shown in Fig. 10, which illustrates the distribution of ρ_l values by spot, the value of ρ_l at spot84 is considered to be smaller than that of other spots. It can therefore be assumed that we can not only quantitatively estimate the effect of the SET operations at a spot by determining the value of ρ_l for each spot based on real data, but also but also answer how much difference in fuel consumption a hypothetical the SET operations might make, irrespective of the arrival spot.

The results of the ρ_l and the k values plotted for arrivals landing on all runways, not just runway 34R, are shown in Fig. 11. As suggested in the previous discussion, when ρ_l is less than a certain value, the value of k becomes negative. It therefore follows there would be no fuel consumption reduction effect. The ρ_l value is determined by four conditions: landing runway, the SET operations start position, taxiing trajectory, and arrival spot. Therefore, if the SET operations start position and taxiing trajectory are determined prior to landing, the value of ρ is also decided, and it is possible to estimate how much fuel consumption will be reduced by the SET operations.

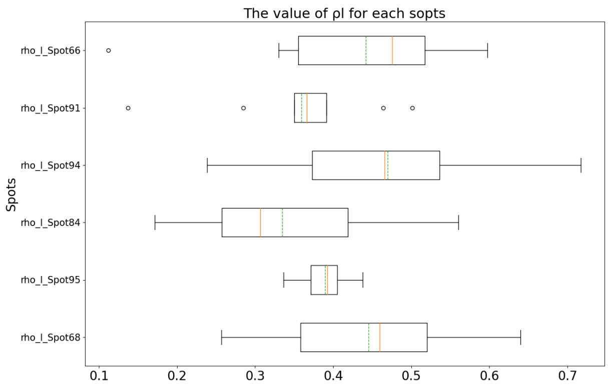

Figure 10. The ρ_l values for each spots

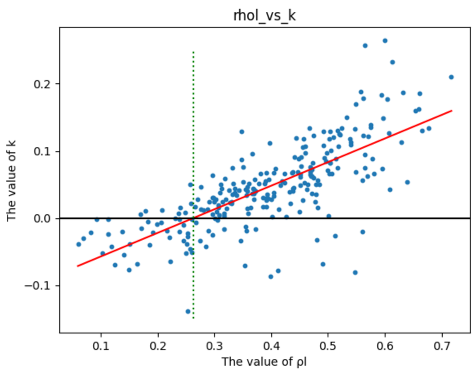

Figure 11. Relationship between the value of ρ_l and k.
The red line represents a linear approximation.:$y = 0.351x - 0.092$
The green line represents the x coordinate where the linear approximation and $y = 0$ intersect.: $x = 0.263$

IV. Fuel flow prediction modeling

According to previous studies [15] [7], using actual flight data may enable to build a model that can estimate fuel flow rates more accurately than existing databases. In this Section, we build a machine learning model to predict average fuel flow during taxiing at NRT based on the extracted flight data in Section II.

A. Feature selection

TABLE IV. Prediction features

Feature name	Main purpose	Data type
Date	Expression of congestion	Categorical
Taxi start time		Numerical
Departure or arrival	Expression of taxi length	Categorical
Runway		Categorical
Spot number		Categorical
ρ_l		Numerical
SET activation	Expression of engine performance	Boolean
Gross weight		Numerical
Temperature		Numerical
Rainfall		Numerical
Wind-speed		Numerical

Table. (IV) shows the features we used in this study. “Date” and “Taxi start time” are considered to reflect changes in airport surface congestion over time. “Departure or Arrival”, “Runway”, “ρ_l” and “Spot number” are thought to provide information related to taxiing distance. Additionally, features related to weather and “Gross weight”, which have been used in previous study by Atasoy [16], and the SET operations activation are potential factors that could influence engine performance. The previous study by Zhang, M et al. [17] have identified acceleration/deceleration and pauses on taxiways as factors that increase fuel consumption during taxiing, and the number of these events is used to estimate fuel consumption, but we did not use such factors as prediction model features in this study because they are known consequently only after the taxiing. On the other hand, as mentioned in Section III, since ρ_l is a factor in determining fuel consumption reduction during taxiing, ρ_l is also considered to be an important feature when predicting fuel flow. At Narita Airport, as long as the runway and spot to be used by the aircraft are determined in advance, the taxiing route is almost uniquely determined according to the AIP instructions. Therefore, if the position where the SET operations starts is determined in advance, the value of ρ_l can also be obtained as an explanatory variable known in advance.

B. Learning methods

We employed 2 learning methods: CatBoost Regressor and Statistic method. CatBoost Regressor is a machine learning model included in the CatBoost library and based on gradient-boosting algorithm like Gradient Boosting Regressor. CatBoost Regressor introduces a novel algorithm known as “Ordered boosting” to mitigate the issue of target leakage present in existing gradient boosting algorithms. Additionally, it enables the numerical encoding of categorical variables. These advantages collectively confer a significantly greater performance compared to conventional gradient boosting models [18].

In the statistical model, the average fuel flow during taxiing of the departure or arrival aircraft is calculated from actual data and used as the predicted value.

In each method, 80% of the total data was allocated to the training dataset, with the remaining 20% designated as the test dataset. CatBoost was implemented using the CatBoost library, which operates in Python3. The three hyperparameters considered to affect model accuracy were “iterations”, “learning rate”, and “depth”. Optimal parameter selection was performed using five-fold cross-validation.

C. Model evaluation

In this study, we used following four metrics to evaluate the prediction accuracy of each model, similar to the study by Kato et al [19].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\|y_i - \hat{y}_i\| \tag{10}$$

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\|y_i - \hat{y}_i\|}{y_i}\right) \times 100 \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{12}$$

where y_i is an actual value, and $\hat{y}_i$ is a predicted value, and $\bar{y}$ is the mean of actual values. $RMSE$ and MAE signify the magnitude of the error. In particular, $RMSE$ is an evaluation item that is sensitive to outliers. $Accuracy$ is a dimensionless quantity that represents the accuracy of the predictions, and R^2 value are used to quantify the goodness of fit of the model, with a value of 1 indicating a perfect fit and a value of 0 indicating no fit at all.

D. Prediction results

Table. (V) shows the prediction accuracy for each model. The prediction model made by CatBoost shows high accuracy across all evaluation metrics. In particular, the high R^2 value indicates strong adaptability to unknown data, suggesting that this model holds potential for future use. Additionally, Table. (VI) shows the accuracy of cumulative fuel consumption during taxiing based on these models. Even when the fuel flow is converted to fuel consumption using the actual taxiing time, it can be argued that the predictions made by Catboost have smaller errors than those made by other models.

The five features with the highest feature importance in the Catboost model we constructed in this study are listed in the Table. (VII). The feature importance was computed as the gain difference that a feature contributes. The results of the fuel flow prediction modeling in this study suggest that while date and time information, which was assumed to reflect airport congestion, was not considered a highly important feature. On the other hand, information on whether the SET operations had been activated (if so, its starting position) and the gross weight of the aircraft were highly important.

TABLE V. COMPARISON OF PREDICTION ACCURACY[KG/SEC]

Model	RMSE	MAE	Accuracy(%)	R^2
CatBoost	0.033	0.02	97.2	0.92
Statistic	0.041	0.03	95.7	0.87

TABLE VI. CONVERTED TO FUEL CONSUMPTION[KG]

Model	RMSE	MAE
CatBoost	29.5	18.9
Statistic	39.5	27.6

TABLE VII. FEATURE IMPORTANCE IN CATBOOST[%]

ρ_l	SET implementation	Gross Weight	Runway	Temperature
43.1	21.1	10.5	10.3	5.7

V. PRELIMINARY SIMULATION WORK

In this Section, we will discuss the construction of a fast-time simulation that recreate the structural layout of taxiways and parking spots. We will also discuss prediction capability of fuel consumption during taxiing by combining this simulation environment with the fuel flow prediction model constructed in Section IV. Additionally, we will compare the predicted fuel consumption from this simulation with actual fuel consumption to evaluate the reliability of the simulation environment and discuss potential future applications.

A. Simulation environment

The taxiing trajectories on the surface of RJAA are modeled in the AirTOp simulator [20]. We modeled the airport surface structures such as taxiways, runways and parking spots according to the information supplied by Japan Aeronautical Information Service Center (AIS Japan) published by Ministry of Land, Infrastructure, Transport and Tourism (MLIT). [21](Fig. 12) This simulator automatically calculates the taxiing paths, taxiing time, taxiing length, and fuel consumption by inputting the departure and arrival spots, the runways used, and the departure and arrival times for each flight. Additionally, since the simulation includes calculations to avoid collisions between aircraft, it is considered capable of simulating ground air traffic that closely resembles real-world conditions. In this simulator, aircraft maneuvering performance is calculated according to the BADA model, but the value of fuel flow can be set arbitrarily for each flight. Therefore, in this simulation environment, we set the fuel flow predicted in Section IV for each flight and attempted to achieve accurate fuel consumption predictions.

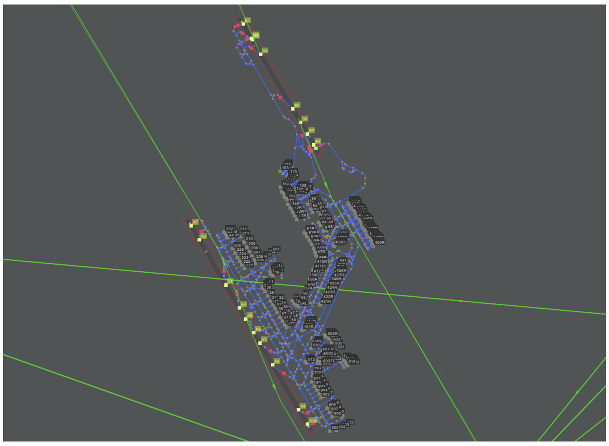

Figure 12. The AirTop model of RJAA

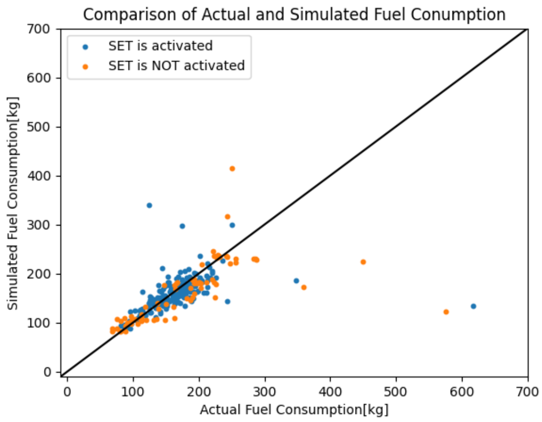

Figure 13. The comparison of Actual and Simulated fuel consumption

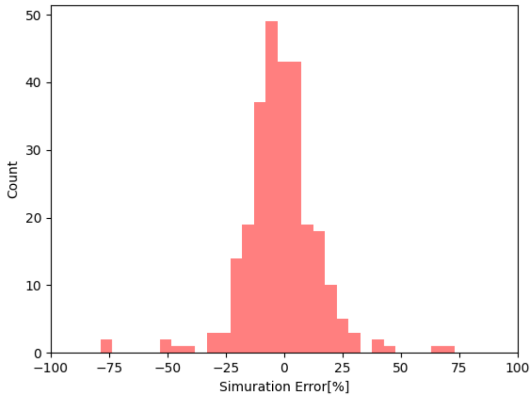

Figure 14. Simulation error

B. Simulation scenarios

In the simulation experiment, we focused on arriving aircraft from the flight data used in this study. In this simulator, we prepared simulation scenarios for arrival aircraft by referring to actual flight data. For arrival aircraft, the time of entry into the terminal airspace, the STAR used, the landing runway, and the arrival spot follow the actual data. Furthermore, for each of the flights, we assigned the aircraft performance data with the average fuel flow $[kg/min]$ predicted in Section IV to each of the flights and calculated the fuel consumption during taxiing. When focusing on the amount of fuel consumption during taxiing, the choice of taxiing route between the runway and the spot is an important factor. In this simulator, each taxiway has its own transit cost index, and each aircraft chooses the trajectory that minimizes the sum of its costs for taxiing in the simulation. Therefore, when modeling the airport, we set those cost values so that the simulated taxiing trajectories are close to the actual ones.

C. Simulation capability

Fig. 13 and Fig. 14 show a comparison of fuel consumption during taxiing obtained from the simulation results and fuel consumption obtained from actual flight data.

As shown in these figures, simulated fuel consumption was close to that of actual data, as 92.1% of all flights achieved an accuracy within 25% of the prediction error. In some flights, the prediction values were either under-estimations or over-estimations compared to the actual values. One possible reason for the prediction error observed in some flights is that the actual flight took an irregular taxiing route. For example, Fig. 15, which shows the taxiing routes of the flight with the largest prediction error, indicates that the actual taxiing route involved passing through longer, more circuitous taxiways.

In this simulation, non-nominal taxiing routes caused by aircraft routing conflicts was not yet fully replicated. The accuracy of fuel consumption prediction is limited if the aircraft is routed in an irregular manner during the taxiing. On the other hand, for aircraft following standard taxiing routes, this simulation was considered to accurately represent real ground air traffic.

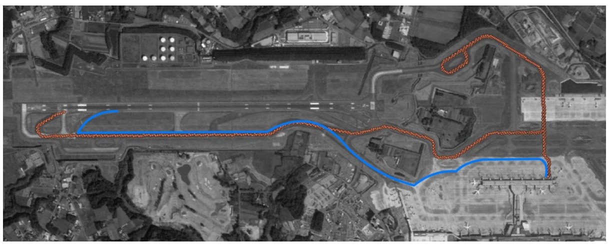

Figure 15. Actual taxiing route (Orange) and simulated taxiing route (Blue)

As a future application of this simulation environment, it might be possible to estimate the fuel consumption reduction of activating the SET operations or the value of ρ_l with high accuracy before landing. This could assist airlines in determining the optimal activating position for the SET operations or estimating the economic benefits of such operations before landing.

VI. Conclusion

In this study, we estimated fuel consumption during taxiing by combining machine learning techniques with a fast-time simulation environment. We applied a machine learning model to predict average fuel flow during taxiing before takeoff and landing at Narita International Airport using only information available before starting taxiing. The fuel consumption reduction effect of the SET operations, in which one engine is shut down while taxiing, was quantitatively evaluated using the actual flight data. It was confirmed that the percentage of the distance in which the SET operations activation among the total taxiing distance is a feature that has a significant impact on fuel flow prediction model. Furthermore, this study also confirmed that the estimated fuel consumption obtained from the simulation results is close to the actual value when ground air traffic at the airport was simulated.

We suggest that this prediction model and simulation environment enable an efficient prediction of fuel consumption during arrival taxiing in advance with its relatively fast calculation time while maintaining accuracy.

It is also important to acknowledge certain limitations of this study include the following. The fuel flow prediction model which we developed in this study requires prior calculation of ρ_l. This means that not only pilots or operation managers must determine where they start the SET operation in advance, but also that they must follow the AIP-recommended taxiing route to the greatest extent possible. In addition to that, not all the factors affecting fuel consumption in reality might not have been fully considered. For example, the slope of the airport's ground surface was not considered in this study.

From the perspective of improving the simulation environment, we can achieve more realistic simulations of actual operations, such as irregular taxiing routes and intermittent stops on the taxiway, by adding departing aircraft and flights from other airlines to the simulation scenarios.

As for ground operations specific to Narita International Airport, the results at this point suggest that activating the SET operation for arrival aircraft at the most frequently used Spot68, as shown in SectionIII, is the most effective way to reduce fuel consumption. Therefore, we can recommend the active implementation of the SET operation for arriving aircraft utilizing this spot. Conversely, at Spot84, the activation of the SET operation is not expected to yield significant fuel savings.

The ultimate goal of this research would be devising a framework that assists airlines in deciding how to implement the SET operation. This framework should receives input from pilots or operation managers regarding the aircraft's states, the takeoff or landing runways and spots, and the planned location to activate the SET operation. It then outputs the estimated fuel consumption reduction and more suitable starting locations for the SET operation. This system would assist airlines in estimating specific fuel consumption reduction effects and in implementing fuel-saving measures in the operations.

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