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Prediction of Off-block Time Distribution for Departure Metering

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The uncertainties related to Target Off-Block Time (TOBT), the pushback-ready time predicted by aircraft operators, affect greatly airport operations. The accuracy of TOBT is in general difficult to be improved, because there are many uncertain factors in departure process, e.g., delays in the passengers' boarding. Better understanding of TOBT uncertainties, however, may help to improve the airport surface operations. Currently, TOBT is estimated as a single point in time, and updated as necessary by aircraft operators. Instead, the author proposes that TOBT is estimated as a distribution with Johnson-SU distribution. The distribution parameters are estimated with time by neural networks using the history of TOBT updates. The main benefit of the proposed method is found in assigning the better pushback approval time of each departure aircraft for more efficient surface operations, which is demonstrated clearly by the simulation results. Using the proposed method, the aircraft operators can save fuel from improved ground operations via a probabilistic approach at the cost of reporting TOBT as a single point.

I. Introduction

TARGET Off-Block Time (TOBT), the pushback-ready time predicted by aircraft operators, is the major factor of uncertainty in airport surface and departure operations. The prediction accuracy of TOBT is limited due to complicated turnaround and passengers' boarding processes, for instance, so even aircraft operators have limited knowledge of when an aircraft is going to be ready for departure exactly. In the author's past analysis, the accuracy of TOBT is more than 5 minutes of the standard deviation (SD), while the accuracy of Estimated Taxi-Out Time (EXOT) is about 2 minutes of SD[1]. For comparison, the onboard prediction error of flight time, for example, is less than 2% of flight time, i.e., less than 1.2 minutes for 1 hour flight. Once TOBT is not well predicted, the accuracy of the take-off time is also degraded, which also affects the accuracy of the arrival time at the destination airport as well as the air traffic flow management. Therefore, better TOBT predictions are important for the entire air traffic flow management process. [2].

Since the off-block time is calculated as the block-in time plus the turnaround time, the improvement in turnaround predictions is important. The existing studies use a machine learning[3][4][5] or make distribution models in each detailed turn-around process such as unloading[6]. Furthermore, there are several studies which propose improving the accuracy of take-off time prediction directly[7][8][9].

In the airport CDM (collaborative decision making) concept[10], the aircraft operators are asked to report TOBT. The author argues that the accuracy is not the same among the reported TOBTs, while the existing studies often use the latest reported TOBT only. This also means that TOBT is predicted as a single point in time, and does not include the information of the TOBT accuracy and how it has changed over time. If the reliability of TOBT is determined, airport operation can be improved. Therefore, the author proposes to predict TOBT as a distribution for each flight.

If all information relevant to TOBT is available, TOBT accuracy can also be predicted. However, as noted by other researchers in the past [7], data and information availability are also important factors in predicting TOBT. The most information related to turnaround process is confidential and limited to the knowledge of aircraft operators only. Therefore, the author proposes to predict TOBT distribution by using the history of TOBT update. The reported TOBT is often updated once the flight situation changes, which is recommended in the airport CDM concept. On the other hand, the TOBT update means the change of the flight situation, and the frequent TOBT update may mean that the

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reported TOBT is not so reliable. Therefore, the TOBT update history may include the sufficient relevant information to estimate the accuracy of TOBT. The accuracy of the TOBT can be represented as a TOBT distribution.

In this paper, TOBT is assumed to follow a certain distribution function whose parameters are estimated by a neural network (NN). The estimated TOBT distribution is applied to determine Target Start-up Approval Time (TSAT). TSAT is the time when each departure aircraft is allowed to leave the spot to minimize the runway congestion. There have been several studies to assign the best TSAT under uncertainty[11][12][13][14], all of which focus on the TSAT assignment algorithm, not the prediction of uncertainty itself. In this paper, the benefits of predicting the TOBT distribution are illustrated with an application to the TSAT assignment problem. TSAT operations can provide benefits to encourage operators to report TOBT. TSAT reduces the taxi-out time potentially, but it may also delay the take-off time. In the proposed approach, TOBT is estimated as a distribution, and it contributes to the reduction of taxi-out time as well as the fuel saving on the ground while keeping the take-off delay small. The proposed method does not demand the change of the TOBT report style; the aircraft operator is still asked to provide TOBT as a single point, and obtain the benefits of the proposed probabilistic approach, i.e., minimizing the take-off delay by TSAT.

This paper is extended research of Ref. [15]. In the previous paper, the general idea of this method is proposed. In this paper, the following extensions have been made. 1) In the initial assessment of the proposed method, the more complex distribution is used. 2) The discussion of the feature importance is added. 3) The simulation conditions of the application of TSAT assignment are set more stringent and in-depth analysis of the result is added.

II. TOBT prediction based on TOBT history

A. Data available

This research uses airport operation data at a French airport in January 2018. The data set used here is the same as the one used in Ref. [1]. The target airport has two runways, with departures and arrivals being operated on each runway independently. This allows the author to consider departure aircraft only. The data includes more than 3000 departure aircraft, and the following information is available: all TOBT update histories, EXOT, SOBT, AOBT, and ATOT. SOBT, AOBT and ATOT denote Scheduled Off-Block Time, Actual Off-Block Time, Actual Take-Off Time, respectively. At each moment, TOBT distribution is predicted using the information available until then.

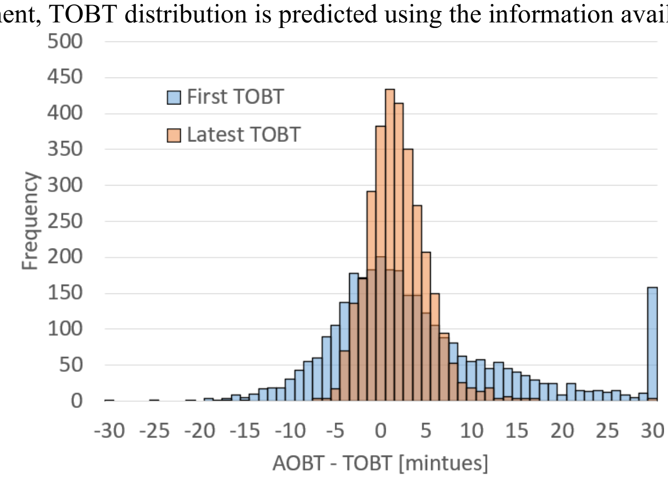

Fig. 1 Frequency of TOBT accuracy (= AOBT – TOBT) of the first and latest reported TOBT.

B. Accuracy of TOBT

The first TOBT is usually reported 35 minutes before TOBT, and the TOBT can be updated anytime later as needed. Fig. 1 shows the difference of the TOBT accuracy between first and latest reported TOBT where TSAT is not assigned. Some aircraft report the TOBT only once, so the first and last TOBT is the same. AOBT-TOBT = 0 indicates that the estimated TOBT and AOBT is the same, and the peak of distribution is seen around here. As for the first TOBT, AOBT is more than 30 minutes later than the TOBT with 5.0 % aircraft, and the SD of AOBT-TOBT is 19.6 minutes. The SD of AOBT-TOBT is still 7,2 minutes even if the data with more than 20 minutes error are excluded. On the other hand, using the latest TOBT, the TOBT accuracy has been significantly improved. Since the aircraft operators update TOBT to reflect the most recent aircraft state, as time progresses, the reported TOBT is more accurate. However, the SD of the latest TOBT is still 4.4 minutes, while the accuracy of flight time prediction in the enroute phase is in the order of 1 minute per hour[16]. The departure time uncertainty is much greater than that of flight time after the departure even using the latest reported TOBT.

In addition, both distributions are skewed. More data are observed at the positive tail than the negative tail. This makes sense because it is difficult to start pushback too early while the delay of the pushback unlimited.

C. Features which can affect TOBT accuracy

In this research, the TOBT is predicted as a distribution using NN, so the useful features must be selected as NN inputs. Here, five possible features that may potentially affect the TOBT accuracy are selected.

1. The time to the latest TOBT

If the pushback-ready time is changed, TOBT will be reported by aircraft operators. Therefore, as the time approaches to TOBT without updating TOBT, the TOBT accuracy will be improved. Here the time to the latest TOBT is the time difference between the current time and the latest reported TOBT when the prediction is computed.

2. The time since the latest TOBT update

Since the aircraft operators update TOBT once the aircraft situation changes. This also means that not updated TOBT will be more reliable. Here, the time since the latest TOBT update is the time difference between the current time and the latest TOBT update when the prediction is computed.

3. Number of TOBT updates

The frequent update of TOBT means that the aircraft situation changes very often, which may imply the further change in the future. Here, the number of TOBT updates is the number of updates prior to time t when the prediction is computed.

4. Aircraft operator

The above TOBT update policy may depend on aircraft operators.

5. Scheduled Off-Block Time (SOBT)

SOBT is the scheduled time of off-block, which is part of the official flight schedule. SOBT represents the planned time for the aircraft to start moving away from the gate, so the initial TOBT is often equal or close to SOBT. The difference between SOBT and TOBT means the delay from the schedule, so SOBT will affect the TOBT distribution.

III. DENSITY PREDICTION BY A NEURAL NETWORK

A. Johnson distribution

As stated above, airport operation is potentially improved by predicting TOBT as a distribution. The normal distribution is often used to model such uncertainty, but Fig. 1 shows that the TOBT accuracy is asymmetrical. Therefore, this research uses Johnson's-SU distribution instead. Johnson's-SU distribution is a transformation of the normal distribution, and is denoted by Johnson distribution here. The Johnson distribution can represent a skewed distribution[17], so it is more appropriate to estimate the TOBT distribution. First, Johnson distribution is introduced. The probability density function $f(x)$ and the cumulative density function $F(x)$ are calculated by the following forms with four parameters (γ, ξ, $\delta(>0)$, and $\lambda(>0)$).

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}} \frac{1}{\sqrt{1+\left(\frac{x-\xi}{\lambda}\right)^2}} \exp\left[-\frac{1}{2}\left(\gamma + \delta \sinh^{-1}\left(\frac{x-\xi}{\lambda}\right)\right)^2\right] \tag{1}$$

$$F(x) = \Phi\left(\gamma + \delta \sinh^{-1}\left(\frac{x-\xi}{\lambda}\right)\right) \tag{2}$$

where Φ is the cumulative density function of the standard normal distribution. The average $(\bar{x})$, SD(σ), skewness ($({\beta_1}^{1/2})$), and kurtosis (β_2)) are calculated by the following forms.

$$\bar{x} = \xi - \lambda\sqrt{\omega} \sinh \Omega \tag{3}$$

$$\sigma^2 = \frac{\lambda^2}{2}(\omega - 1)(\omega \cosh 2\Omega + 1) \tag{4}$$

$$\beta_1{}^{1/2} = \sqrt{\omega(\omega-1)\frac{[\omega(\omega+2)\sinh 3\Omega+3\sinh\Omega]^2}{2(\omega\cosh 2\Omega+1)^3}} \tag{5}$$

$$\beta_2 = \frac{\omega^2(\omega^4+2\omega^3+3\omega^2-3)\cosh 4\Omega+4\omega^2(\omega+2)\cosh 2\Omega+3(2\omega+1)}{2(\omega\cosh 2\Omega+1)^2} - 3 \tag{6}$$

where $\omega = \exp(\delta^{-2})\ (>1), \Omega = {}^{\gamma}/_{\delta}$.

B. NN outputs and objective function

In this research, the TOBT is modeled by using Johnson distribution, and its parameters are estimated by NN. The flow to determine the parameters of Johnson distribution is explained here.

As for the density estimation used in the objective function, , the maximum likelihood estimation is often used, so the log-likelihood is used as an objective function (L) here.

$$L = -\sum_i \log\left(f(y_i)\right) \tag{7}$$

where y_i is the i th output (AOBT) in the training data.

As for NN outputs, while setting the four parameters as NN outputs might seem straightforward, according to the author's preliminary calculations, this approach did not lead to satisfactory results. The problem lies in the fact that Johnson distribution can represent the distribution with too much freedom. For example, Eq. (6) shows that the kurtosis becomes infinity as ω increases. The large kurtosis indicates the spike distribution at a single value, like the gamma distribution. The NN tends to estimate the exact value at several points with a large kurtosis, which minimizes the objective function and fails to estimate the TOBT distribution. A large kurtosis function becomes close to a gamma function, which gives infinity at a single point, which reduces the objective function defined in Eq. (7) significantly. Therefore, it is inevitable to avoid this situation even when the amount of training data increases.

Therefore, the range of parameters are limited to solve the problem. Table 1 which shows the skewness and kurtosis of well-known distributions is used to estimate the ballpark parameter figures. According to this table, the Johnson distribution covers the wider ranges of both the skewness and the kurtosis. The range of the skewness and the kurtosis of these well-known distributions may be appropriate when using Johnson distribution. According to Eqs. (5) and (6), ω is set between 1.0 and 1.5, and Ω is set between -π and π so that the Johnson distribution roughly covers the above range of the skewness and the kurtosis.

Table 1 Skewness and kurtosis of several well-known distributions.

	skewness	kurtosis
Johnson distribution	0-inf	0-inf
Normal distribution	0	0
Erlang distribution	0-2	0-6
Laplace distribution	0	3
Exponential distribution	2	6

In order to set the above range of ω and Ω by a NN, ω, Ω, $\bar{x}$ and $\sigma(>0)$ are used as outputs of the NN, instead of estimating the initial Johnson distribution parameters γ, ξ, δ, and λ). Once the four parameters of ω, Ω, $\bar{x}$ and σ are obtained, the initial parameters of Johnson distribution are easily determined using Eqs. (3) to (6).

C. NN structure and data preparation

The proposed NN should estimate four parameters (ω, Ω, $\bar{x}$ and σ) by minimizing the objective function. Considering the strong capability of function fitting of a deep NN[18], the fully connected feedforward NN (FFNN) with two hidden-layers is applied. The parameters of FFNN are summarized in Table 2. The number of nodes and layers hardly affect the estimation performance, so the small network is created. Adam[19] is applied as a training algorithm. Please see Sec. IV A and B for the selection of inputs, and the NN structures are the same except the number of inputs.

Table 2 FFNN parameters.

Layers	**Number of nodes**	**Activation function**
1st layer	256	ReLU[20]
2nd layer	256	ReLU

Output	4	Linear

While the range of outputs in FFNN is unlimited, each NN output should have the limited range shown above. Therefore, the following conversions are made to estimate four parameters (ω, Ω, $\bar{x}$ and σ) using the unlimited NN outputs (o_1, o_2, o_3, and o_4).

$$\omega = 1 + \frac{0.5}{1+e^{-o_1}} \tag{8}$$

$$\Omega = \pi \tanh(o_2) \tag{9}$$

$$\bar{x} = o_3 \tag{10}$$

$$\sigma = \log(1 + \exp(o_4)) \tag{11}$$

In this way, the NN is able to estimate the parameters of Johnson distribution with limited range of the skewness and kurtosis. The schematic image of the training process is summarized in Fig. 2.

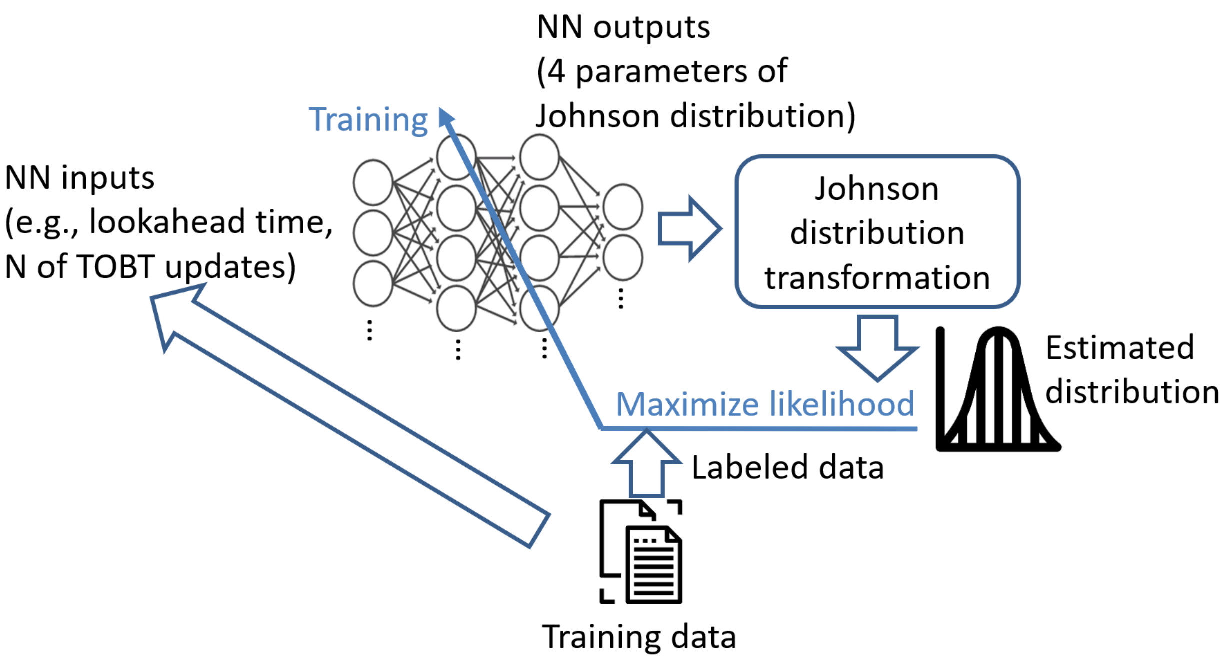

Fig. 2 The summary of the training process of the proposed method.

IV. Applications

A. NN test construction with a simple distribution

This section evaluates the performance of the proposed method. First, it is confirmed that the proposed method works in practice by using the known distribution, i.e., the parameters of the density function are estimated by the proposed method using the generated data samples based on the known distribution. In order to show the capability of modeling the complex function with the proposed method, the known distribution assumes to follow a normal distribution with two inputs (x_1, x_2), with the average of $2{x_1}^2 - x_2$ and the SD of $\exp(x_1 x_2)$). The both inputs are set uniformly between -1 and 1. Once two inputs are determined, the output y is generated to follow the intended normal distribution. 1000 data samples (two inputs and one output) are prepared. 500 data samples are used for model construction (375 for training and 125 for validation), and the rest of 500 data samples are used to test the result. Due to the nonlinearity of the known distribution, the successful modeling will show a good capability of the proposed distribution modeling method. Using these data sets, the four parameters of Johnson distribution are estimated using a NN.

Fig. 3 shows the estimation result of key parameters ($\bar{x}$ and σ) based on the generated inputs, the estimated parameters in each data sample are shown in the figure. Since the distribution is estimated with a limited number of data samples, it is difficult to estimate the parameters with high accuracy. However, the NN in general successfully estimates the parameters of normal distribution. The result shows that the proposed NN approach succeeds in estimating the distribution parameters using the data samples.

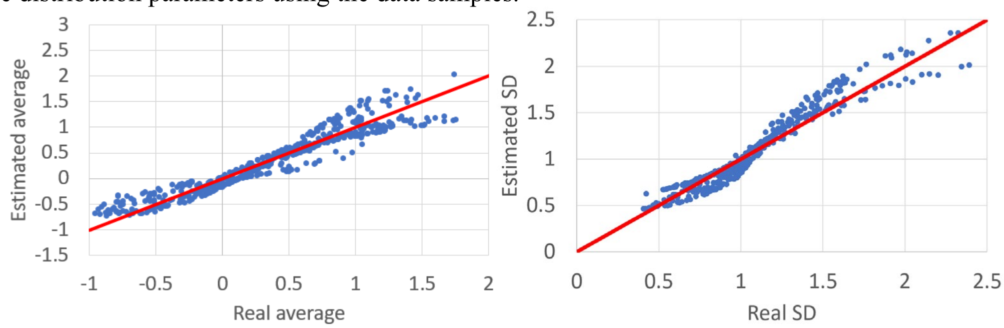

Fig. 3 NN estimation results.

B. NN construction for TOBT prediction

Next, the proposed NN distribution modeling method is applied to predict the distribution of TOBT, i.e. four parameters of Johnson distribution. The important information to determine the TOBT distribution is already explained in Sec. II.C. Here, the following 8 variables are used for the NN inputs.

1) Time lag between the current time and the latest reported TOBT
2) Number of TOBT updates
3) Time lag between the latest TOBT update time and the current time
4) Time lag between the latest reported TOBT and the first reported TOBT
5) Time lag between the first reported TOBT and SOBT
6)-8) One-hot encoding (airline 1, airline 2, or others)

As for the inputs 6)-8), the TOBT update strategy may differ among aircraft operators. However, sufficient data are required to distinguish the TOBT update strategies among aircraft operators. Therefore, the aircraft operators are grouped into three: two major aircraft operators (airline 1 and airline 2), which have enough flights each, and the rest. In other words, all airlines apart from Airline 1 and 2 are assumed to follow the same TOBT reporting strategy.

As for the data preparation, the input data are generated every minute between the first TOBT report time and AOBT. A total of 138,890 data are created with more than 3000 flights. Only the first 2/3 data are used for training and validation data. 80 % are used for training and 20 % are used for validation. The NN is trained by the training data only, and every step the objective function is calculated using validation data. The network which gives the minimum objective function of the validation data is used as an answer. The rest 1/3 of the data is used for test purpose in Section V.

C. TOBT prediction results

Figures 4 and 5 show the TOBT prediction results. The horizontal axis indicates the time in second from midnight. There are 5 black lines in the figure, which show 2.5, 25, 50, 75, and 97.5 percentile of the predicted TOBT, respectively. The range of 2.5 percentile and 97.5 percentile indicates the 95 % confidence interval predicted by the NN.

Fig. 4 shows the prediction result when the TOBT is updated once. TOBT is reported at t = 41709 s, and the reported TOBT is 44100 s, which is equal to SOBT. In most cases, the first reported TOBT is equal to SOBT. This first TOBT is reported about 40 minutes before the reported TOBT. The TOBT is updated at t = 43600 s, and the updated TOBT is 45000 s, 900 s (15 minutes) later than the first reported TOBT. Finally, the aircraft starts pushback at t=44786 s (= AOBT). The 95 % confidence interval gradually gets smaller as time proceeds, but it gets wider again at the TOBT update. After that, the 95 % confidence interval gets smaller again with time. It should be noted that only 97.5 percentile is set far from other 4 percentile lines. This infers that the predicted distribution has a long positive tail.

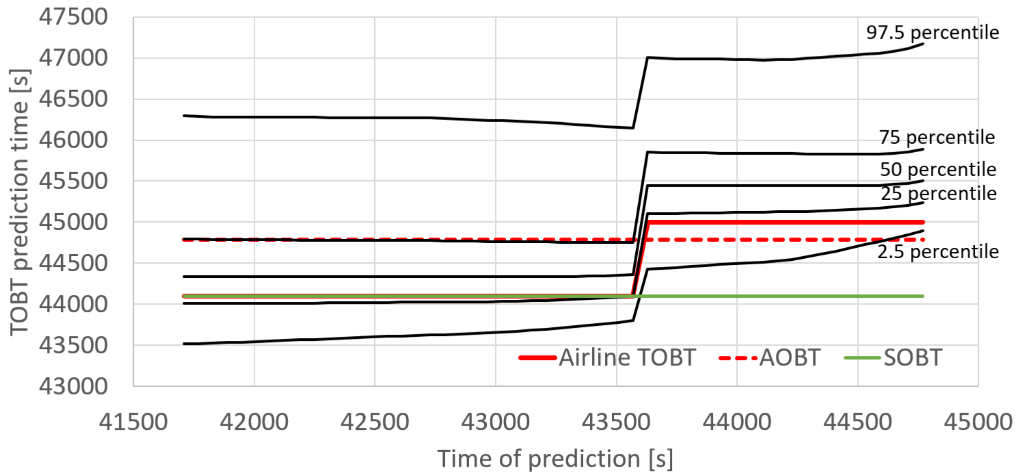

Fig. 4 An example of TOBT prediction result when TOBT is updated once.

There are some aircraft which updates TOBT many times and the AOBT is totally different from the first reported TOBT, and the example is shown in Fig. 5. The first reported TOBT is 33900 which is 5 minutes earlier than SOBT, but TOBT is updated many times, and AOBT is finally 39401 s, about 1.5 hour later than the first reported TOBT. Since the such large TOBT prediction error is not expected at the beginning, AOBT is out of the 95 % confidence interval at the early stage. As the TOBT is updated again and again, the 95% confidence interval gets wider. When the TOBT is updated many times, the TOBT becomes more unreliable, which is learned from the data.

The reason for such a long delay cannot be identified, but the following is a possible scenario. The short delay was expected at the beginning due to some small trouble (e.g., engine restart), but it was not solved (e.g., more serious engine troubles), and TOBT was delayed repeatedly. The person in charge of the flight tried to inform ATC of the latest information as much as possible, so TOBT was frequently updated.

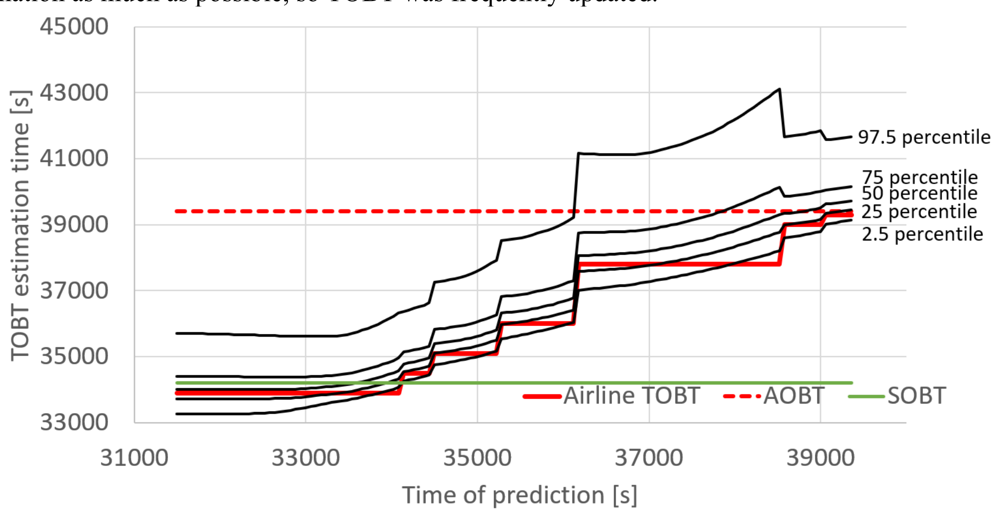

Fig. 5 An example of TOBT prediction result when TOBT is updated many times.

The error statistics are also shown here to compare the estimation performance between the reported TOBT and the one by the proposed method. Since the proposed method estimates TOBT as a distribution, not a single point of TOBT, 50 percentile value of the estimated distribution is assumed to be the estimated TOBT. The two lookahead times (40 minutes before the reported TOBT, and 5 minutes before the reported TOBT) are considered, and the result is shown in Table 3. In both lookahead times, the average error is close to zero for the proposed method, while a large average error existed for the reported TOBT. As indicated before, the reported TOBT tends to be set earlier, so the proposed method corrects the bias. However, the SD is almost the same between the reported TOBT and the proposed method. The proposed method is developed in order to estimate the TOBT as a distribution, not to improve the TOBT accuracy itself. Therefore, no difference of the SD is to be expected.

Table 3 Error statistics of AOBT – TOBT using test data sets.

Lookahead time	Data source	Average [minutes]	SD [minutes]
40 minutes	Reported TOBT	2.75	11.04
	Proposed method	–0.26	10.99
5 minutes	Reported TOBT	5.05	9.38
	Proposed method	0.45	9.22

D. Impact of inputs to TOBT distribution prediction

This NN uses 8 inputs as shown in Sec. IV B. Here, we investigate which input impacts the results the greatest. Although the NN is said to be a black box, there are recently several methods to explain the importance of the inputs. This time, SHAP (SHapley Additive exPlanations) is used to analyze the importance of the inputs [2]. SHAP value can be calculated as the importance of each input to each output in each dataset. The average SHAP values can be regarded as the average importance of each input to each output.

Fig. 6 shows the normalized SHAP value of each input to predicted average and predicted SD, where the largest SHAP value is set to 1 to each output. The figure shows that the lookahead time gives the largest impact on both the average and SD. As for other features, the larger impact is given to SD than average. The single point prediction corresponds to the prediction of average only, so such features will hardly affect the single point prediction. However, when TOBT is predicted as a distribution, such features affect the result, and the proposed method can predict the reliability of TOBT at each given time.

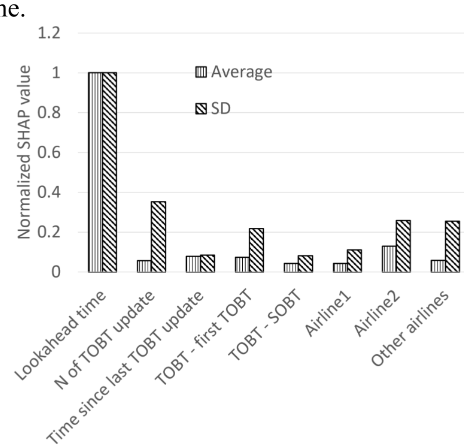

Fig. 6 Normalized SHAP values.

V. Benefit of TOBT distribution prediction to TSAT assignment

A. Brief summary of TSAT assignment

The benefit to predict TOBT as a distribution is to estimate the expected waiting queue length of departure aircraft at the runway. Such information can improve the performance of TSAT operation. TSAT operation is a ground air traffic control operation. When many departure aircraft leave the gate at the same time, the departure aircraft make a queue just before the runway, because the runway operation can handle a single aircraft at a time and the required separation between the consecutive departure aircraft must be established. Since departure aircraft on the ground consume the fuel while waiting in a departure queue, TSAT operation let departure aircraft wait at the gate with engines off and minimize the stay in the departure queue. In the TSAT operation, the pushback time to each departure aircraft must be assigned. This time is also called TSAT. The graphical image of TSAT assignment is shown in Fig. 7. TOBT is the predicted pushback time, which is predicted in the previous section. The estimated take-off time (ETOT) can be calculated as the sum of TOBT and the estimated taxi time. However, only a single aircraft can take off at a time, so the TTOT (target take-off time) is the predicted take-off time considering the departure queue. When assigning TSAT, the calculation starts from TTOT. If no uncertainty exists, TTOT–taxi (called ideal TSAT) becomes the optimal pushback time to minimize the taxi time. If all aircraft leave the gate at ideal TSAT, all aircraft ideally will not wait at a departure queue at all. However, the real-world exists various uncertainties, which do not allow aircraft to follow the predicted schedule. The assignment of TSAT delays the pushback time, so TSAT potentially delays the take-off time, but never expedites the take-off time. The world major airport has a runway capacity problem and the take-off delay reduces the runway capacity, which will not be acceptable. Therefore, TSAT must be assigned as long as the take-off delay caused by TSAT operation is negligible. To do so, the buffer is often set to absorb the uncertainty, and TSAT is finally calculated as ideal TSAT – buffer. The difference of TOBT and TSAT is the expected reduction of taxi time. Therefore, TSAT assignment problem corresponds to the buffer assignment problem to each departure aircraft. The idea in this paper is that the buffer can be reduced by predicting TOBT as a distribution while keeping the same level of take-off delay.

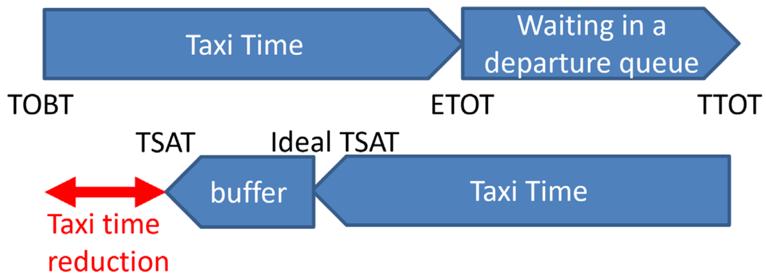

Fig. 7 The graphical image of TSAT assignment.

The benefit of predicting TOBT as a distribution is explained using the following example. Assume that there are two aircraft with TOBT being 08:30. If EXOT is assumed to be 10 minutes, ETOT of both aircraft will be 08:40. The question is how many aircraft will wait in the runway queue at each time step. If TOBT is predicted as a single point in time, both aircraft will arrive at the runway at 08:40. Therefore, no aircraft is expected to reach the runway prior to 08:40, as both two aircraft are expected to reach the runway at 08:40. However, in reality, no aircraft may reach the runway at 08:40 if the pushback time of both aircraft is delayed. On the other hand, if TOBT is predicted as a distribution, the probability to reach the runway at $t = t_{RWY}$ is easily obtained as $F(t_{RWY})$ in Eq. (2). In this example, the probability to reach the runway by 08:40 is roughly about 50 %, because the probability to reach the runway before and after the target time is equal. Therefore, the expected number of aircraft at the runway at 08:40 is about 0.5+0.5=1.0, while it is 2.0 by single point prediction. This is the difference between the single point prediction and the distribution prediction.

As for the performance of TSAT operation, both TSAT assignment algorithm and TOBT prediction method are important, but the discussion of TSAT assignment algorithm is out of the scope of the current paper. Therefore, the TSAT assignment algorithm in this paper is the one the author previously developed, and the difference of TOBT prediction method is investigated. The details of the TSAT assignment algorithm used in this study can be found in Ref. [22]. In this algorithm, the buffer is set by controlling the expected number of aircraft waiting at the runway. There is a parameter *c*, which is the minimum number of aircraft which should wait at the runway. When *c* is set large, TSAT is assigned only when many aircraft are expected to wait at the runway, so the waiting time is not saved much and the take-off delay is expected to be small. In the past research, a single TOBT estimation was used, so the expected number of aircraft waiting at the runway was always counted as an integer. However, if the TOBT is estimated as a distribution, the expected number of aircraft waiting at the runway becomes a decimal value, which improves the predictability of runway situation.

B. Simulation conditions

The simulation conditions are used as appeared in Ref. [1] in Sec. IV D. The stochastic airport simulation model is used to consider the uncertainty in the airport operation, and the model was validated in the author's past study [23]. The unimpeded taxi-out time is assumed to be a function of the taxi-out distance, and the nominal taxi-out time and uncertainty are modeled from the real-data. The nominal take-off separation and its associated uncertainty are also obtained from the real-data. In the simulation, AOBT is determined based on the real data, and the unimpeded taxi-out time is calculated obtained above including the uncertainty. The departure aircraft are ordered by the time when the aircraft reaches the runway (AOBT + unimpeded taxi-out time), and finally the ATOT is determined considering the take-off separation obtained above. If TSAT is assigned, AOBT is changed to whichever later between AOBT and TSAT.

As for the simulation scenario, the large traffic is assumed, and two days of traffic are merged into a single day. The actual TOBT history is used in the simulation, so TSAT performance is evaluated based on actual TOBT report history. Since the evaluation should be done with the data not used in NN development, the training and validation data are set to Day1-20 of a month (which corresponds to the use of 2/3 data in Sec. IV.B). Day21-30 of a month is used for the simulation, whose TOBT data is used for neither training nor validation.

Therefore, 5 cases of two-days traffic simulation are conducted (Day21/22, Day23/24, Day25/26, Day27/28, Day29/30). Since the simulation considers the uncertainty of unimpeded taxi time and take-off separation, 20 times simulations are conducted in each case. In total, 100 times simulations are conducted.

For the comparison purpose, three TOBT prediction methods are used. The first method is a single point TOBT prediction. The second method is that TOBT is assumed to follow a normal distribution with the SD of 6 minutes. This method does not use a NN prediction, but assumes TOBT as a distribution. The third method is to assume Johnson distribution, and the parameter of the distribution is estimated by NN. As a benchmark, the calculation result without setting TSAT is also obtained, and the average waiting time saved and the average take-off delay of three methods from the benchmark are calculated.

C. Overall simulation results

The TSAT performance among prediction methods is shown in Fig. 8. The performance is better when the waiting time saved (= taxi-out time saving) is large and the delay (= take-off time delay) is small. The simplest way shown in the black line is the single point TOBT prediction, i.e., only the latest TOBT is used to calculate TSAT. c is an important parameter, and no waiting time in a departure queue is expected when c = 0 in ideal situation (all uncertainties are estimated in advance). However, in reality, the uncertainty exists, and the expected number of aircraft in the departure queue is different from the actual number. This discrepancy causes the take-off delay. Increase in c can reduce the take-off delay, and the increase of c corresponds to the increase of the buffer in Fig. 7. The appropriate range of c must be set by uncertainty that is not considered in TSAT assignment and the obtained result. Therefore, in this example, c is set between 2 and 10.

The delay is small when the waiting time saved is small, but the delay increases as the waiting time saved increases. "*c*=2" indicates that there should be minimum 2 aircraft waiting in a departure queue, but the large delay is caused in this setting. This is because TOBT has a large prediction error and the actual departure queue length becomes often zero. Therefore, even if c is set to 10, the take-off delay does not become zero.

To verify the benefits of using TOBT as a distribution, TOBT is assumed to follow the normal distribution with the SD of 6 minutes, which is shown in the black dotted line. Here, c is set between 1 and 7. Compared to the single point prediction of TOBT, the delay is halved just by predicting the TOBT as the normal distribution with a constant SD. The range of parameter c becomes small compared to the single point prediction while the waiting time saved by TSAT is within similar range, which infers that the distribution prediction can estimate the departure queue length more accurately. This demonstrates the potential of TOBT distribution application compared to a single point prediction. However, the take-off delay still remains 2-3 minutes even if c is set 7.

The red dotted line indicates the case where the Johnson distribution is assumed and its parameters are estimated by NN. c is set between 0 and 3, but the delay is still small (6-7 minutes) even when c is set to 0. This means that further taxi time reduction is impossible considering the current TOBT prediction accuracy. When c is set 2 or 3, the take-off delay is almost negligible (less than 1 minute) while about 500 minutes taxi time is saved. Compared to the single point prediction, the associated delay is reduced by more than 90 % while keeping the same waiting time saving.

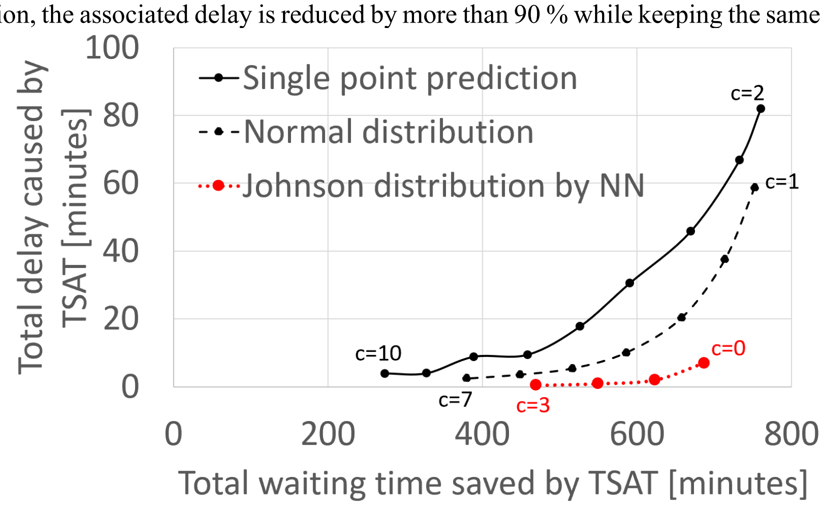

Fig. 8 The graphical image of TSAT assignment.

D. Difference among days

This subsection considers the difference of five days. Fig. 9 shows the TSAT performance on each day. For the comparison purpose, the results by a single point prediction and the proposed NN-based prediction are shown. The result shows that the waiting time saved highly depends on the day, but the delay caused by TSAT shows the similar trend; i.e., the proposed NN prediction method always shows the negligible take-off delay. The exception is Day27/28. The waiting time saved is very small, and the result hardly changes within the range of c. The waiting time saved seems to depend on the traffic pattern. If the departure queue is short enough throughout a day, TSAT will hardly reduce the taxi time, because TOBT includes uncertainty anyway.

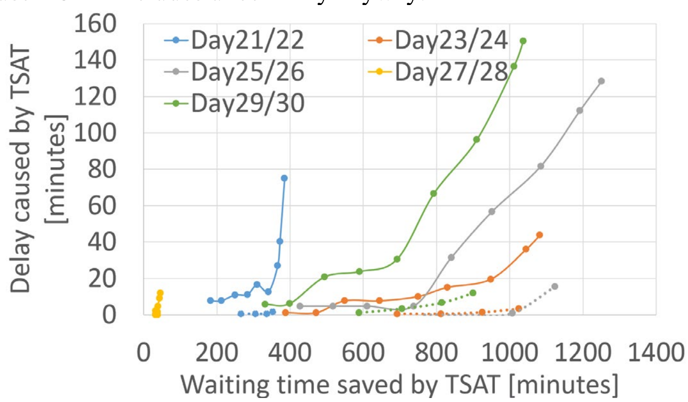

Fig. 9 Taxi-out time saving and delay by TSAT assignment. (solid line: single point prediction, dotted line: NN Johnson distribution prediction)

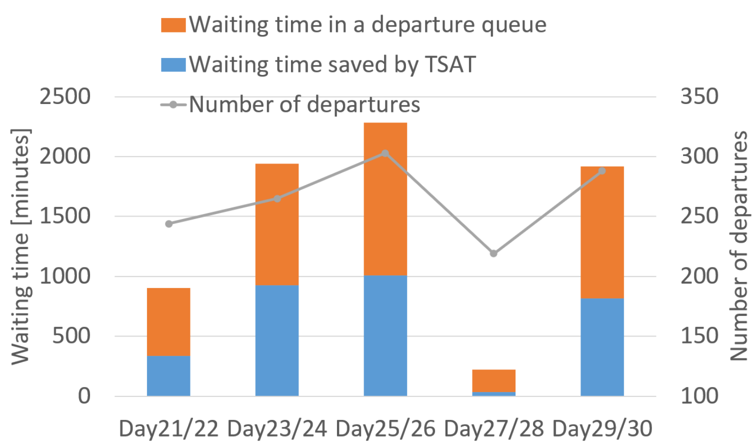

Fig. 10 Waiting time saved and waiting time in a departure queue on each day. (c=1, NN Johnson distribution prediction)

Fig. 10 shows the total waiting time on a departure queue and the waiting time saved by NN prediction method (c = 1) as well as traffic volume on each day. First of all, the waiting time on a departure queue is closely related to the number of departures. As the number of departures increases, the waiting time in a departure queue also increases. On Day25/26 when the longest waiting time is observed, the waiting time per aircraft is about 7.5 minutes. As seen in the figure, the waiting time in a departure queue on Day27/28 is much smaller than that on the other days. About 30 minutes saving is achieved while about 220 minutes waiting time in a departure queue is observed, so about 15 % waiting time reduction is achieved. On the other hand, on Day25/26, about half waiting time reduction is achieved. TOBT has error with the SD of about 6 minutes, so if the departure queue length is roughly less than this value, it is almost impossible to reduce the waiting queue length, otherwise take-off delay will be caused. Therefore, it makes sense that the longer the waiting time in a departure queue is, the larger the ratio of waiting time saved is. This also infers that TOBT prediction accuracy should be improved to reduce the waiting time further, especially when the waiting time in a departure queue is not long enough. The proposed NN distribution prediction method can improve the TSAT performance, but it does not improve the TOBT accuracy itself.

E. Sensitivity analysis

Further validation of the proposed method is done by sensitivity analysis. According to Fig. 6, the lookahead time is a main factor to affect the shape of the distribution, so two sensitivity cases are considered: 1) lookahead time of all aircraft are set −10 minutes, 2) +10 minutes. In addition, to validate the importance of the use of Johnson distribution, the following case is also considered: 3) the normal distribution is assumed and the average and SD are calculated by NN.

Fig. 11 shows the result. As for the cases 1) and 2), the result gets worse than the original result (red dotted line) as expected. However, both 1) and 2) results are much better than the result by Normal distribution with fixed SD. This means that the proposed method will work well even if the NN inputs include noise. On the other hand, the result of case 3) is similar or slightly better than the result by Normal distribution with fixed SD. The skewness information seems to be very important to assign TSAT, and the impact of updating the average and SD is limited as long as the Normal distribution is assumed.

According to the result, it is beneficial to predict TOBT as a distribution instead of a single point. It is also confirmed that the use of Johnson distribution is a key factor.

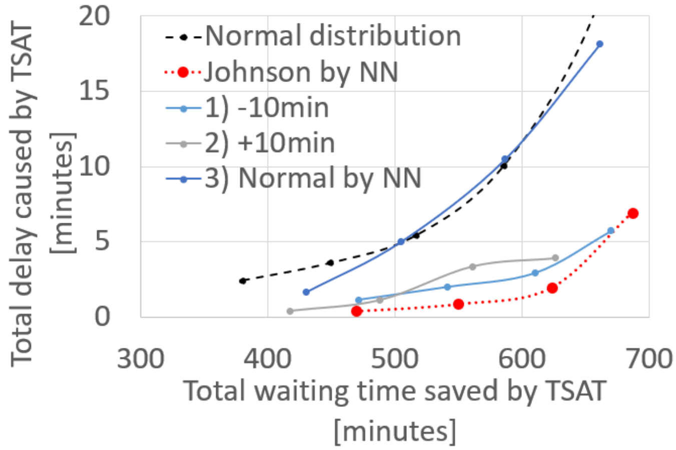

Fig. 11 Sensitivity analysis of the simulation result.

VI.Conclusion

In this research, the author proposed to predict TOBT as a distribution, and showed the benefit in TSAT assignment. While the existing studies use the latest reported TOBT, the proposed approach use the history of TOBT reports provided by aircraft operator. The Johnson-SU distribution was assumed to model TOBT distribution, and the distribution parameters were estimated. A NN is used to estimate the Johnson-SU distribution parameters by using the information of the history to TOBT reports. The proposed method was applied to a TSAT assignment problem, and the simulation result showed more than 90 % reduction of take-off delay while saving the taxi-out time compared to the single point TOBT prediction. This paper demonstrated a great potential to improve the airport operation. Although the departure traffic is considered in this paper, the proposed method will be extended to arrival traffic, which will boost the airport operational performance. In addition, this paper showed that a more accurate prediction of TOBT distribution improves the performance of TSAT operation. TOBT is currently reported as a single point by aircraft operators, but the aircraft operators may have information of possible uncertainty of TOBT. If such information is provided by the aircraft operators, further improvement of airport traffic situation including TSAT operation.

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