

Machine Learning Techniques for Taxi-out Time Prediction with a Macroscopic Network Topology

Jianan Yin^{1,2,*}, Yuxin Hu³, Yuanyuan Ma³, Yan Xu⁴, Ke Han², Dan Chen¹

¹National Key Laboratory of Air Traffic Flow Management, Nanjing University of Aeronautics and Astronautics, Nanjing, China

²Department of Civil and Environmental Engineering, Imperial College London, London, United Kingdom

³Department of Air Traffic Management, The 28th Research Institute of China Electronics Technology Group Corporation, Nanjing, China

⁴Department of Physics - Aeronautics Division, Technical University of Catalonia, Catalonia, Spain

*Corresponding author: j.yin@nuaa.edu.cn

Abstract—Accurate prediction of taxi-out time is essential for enhancing airport performance and flight efficiency. In this paper, we apply machine learning techniques to predict the taxi-out time of departure aircraft at Shanghai Pudong International Airport. The exploration of historical data reveals several relevant influencing factors of taxi-out time as well as their correlations. We formulate an extensive system of predictors for our machine learning approach, based on a macroscopic network topology from an aggregate view. The predictors can be divided into 4 categories; namely surface instantaneous flow indices (SIFIs), surface cumulative flow indices (SCFIs), aircraft queue length indices (AQLIs) and slot resource demand indices (SRDIs). Three machine learning methods: linear regression (LR), support vector machines (SVM) and random forest (RF) are formulated using one-day and one-month training samples, and applied to new test dataset to validate the prediction performance. Computational results show that the training RF model using one-month sample significantly outperform other models in terms of prediction accuracy. The proposed methodology can bring significant benefits to analyzing airport ground movement performance and support the activities of airport decision making.

Keywords—air transport, taxi-out time, machine learning, prediction, macroscopic network topology

I. INTRODUCTION

Airport ground movements play an important role in the whole process of flight operations, and have been recognized as one of the key bottlenecks in global air transport system [1]. With the growth of taxi network structure and air traffic volume, airport ground movements experienced by air traffic have become more and more complex, with problems of surface conflicts, push-back delays and taxi uncertainties [2]. Taxi time is a major performance indicators to assess surface situation and flight efficiency at busy airports. Extended taxi times, especially for the taxi-out times of departures, which include large queuing times before entering the runway threshold, are direct symptoms of inefficient air traffic management, and are often associated with increased costs, high risks as well as negative environmental impacts. However, the modelling and analysis for accurate taxi-out time prediction is a challenging undertaking for air transport stakeholders because of the dynamic nature and significant uncertainties associated with flight operations.

Previous studies related to aircraft taxi-out time prediction include both simulation models and analytical models. The simulation models calculate the taxi-out times using the modules of airport structure, conflict detection and resolution [3-4]. By simulating the ground movements of all the arrival and departure aircraft, the taxi-out time, i.e. the travel time spent by a flight to move between gate and runway, can be got from the system outputs. The analytical models mainly focus on linear regressions, and some of those attempt to apply other machine learning techniques [5]. For the linear regression models, many studies identify main factors that affect taxi-out time and establish prediction models by taking into account some significant factors such as the take-off queue size and the number of taxiing aircraft on surface [6-7]. Through the data transformation, e.g., logarithmic transformation, the curvilinear regression is also applied to formulate the quadratic, cubic, compound, growth and exponential models to predict the taxi-out time [8]. For the other machine learning models, algorithms of reinforcement learning, support vector machines, k-nearest neighbors, random forest, and neural networks have been attempted to predict the taxi-out time. The system state, surface spot, runway, gate, departure fix and weight class, are selected as the features of machine learning methods [9-12]. Then, the performances of machine learning algorithms are analyzed and compared based on the computational results from the training and test experiments.

Research to date focuses on the taxi-out time prediction using input information primarily related to departure movements, while ignoring the impact of arrivals on the departure taxi processes. In reality, of course, these two ground movements are closely coupled and interdependent with each other. Although some studies investigate the impact of arrivals on departure taxi operations, the relationships of an extensive list of more influencing factors of taxi-out time have not yet been fully considered [13]. Additionally, among the numerous studies attempting to predict taxi-out times, few managed to conduct a comprehensive comparison of different models for the prediction. In light of the above motivation, this paper seeks to address the problem of taxi-out time prediction with a macroscopic network topology, using machine learning techniques with a set of predictors related to departure as well as arrival movements. The goal is to improve the accuracy of aircraft taxi-out time prediction and enhance the efficiency and predictability of airport operations.

II. METHODOLOGY

A. Traffic Data Analysis

In this paper, the Shanghai Pudong International Airport (ZSPD) is used for taxi-out time prediction research. It is well known that ZSPD is one of the major hub airports in China and around the world. This section describes the dataset and analyzes the distribution of taxi-out time in the entirety of the operational month. Then, aggregate statistical characteristics of air traffic operations are investigated by correlation analysis.

1) Datasets

The datasets used in this research come from Air Traffic Management Bureau (ATMB), Civil Aviation Administration of China (CAAC). Figure 1 shows the airport ground layout at ZSPD. ZSPD has 3 runways (consistent with the dataset date) numbered 16/34, 17L/35R, 17R/35L and 193 gates. Two main terminal buildings for passengers are located between runway 16/34 and 17L/35R. The airport ground movements of arrivals and departures are frequently interacted with each other during the taxi-out and taxi-in processes.

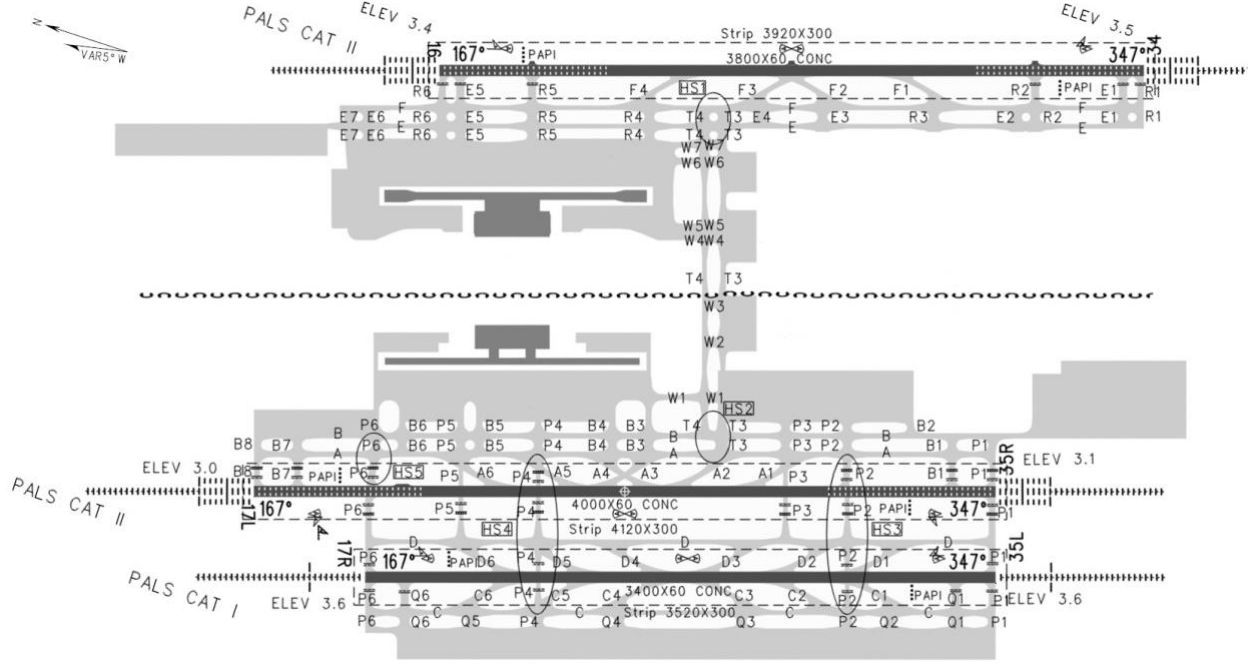


Figure 1. Airport ground layout at ZSPD

Figure 2 illustrates the distribution of taxi-out time of all the departures in each day in October, 2014 at ZSPD, based on the five number summary: minimum, first quartile, median, third quartile, and maximum in each target day. It can be seen that there is a small difference about the average value of taxi-

out time in each day, but the fluctuations exist and are different from each other. Without loss of generality, we randomly select the day Oct. 2 as the test dataset, by training the sample from one day (Oct. 1) and one month (Sep. 1~30).

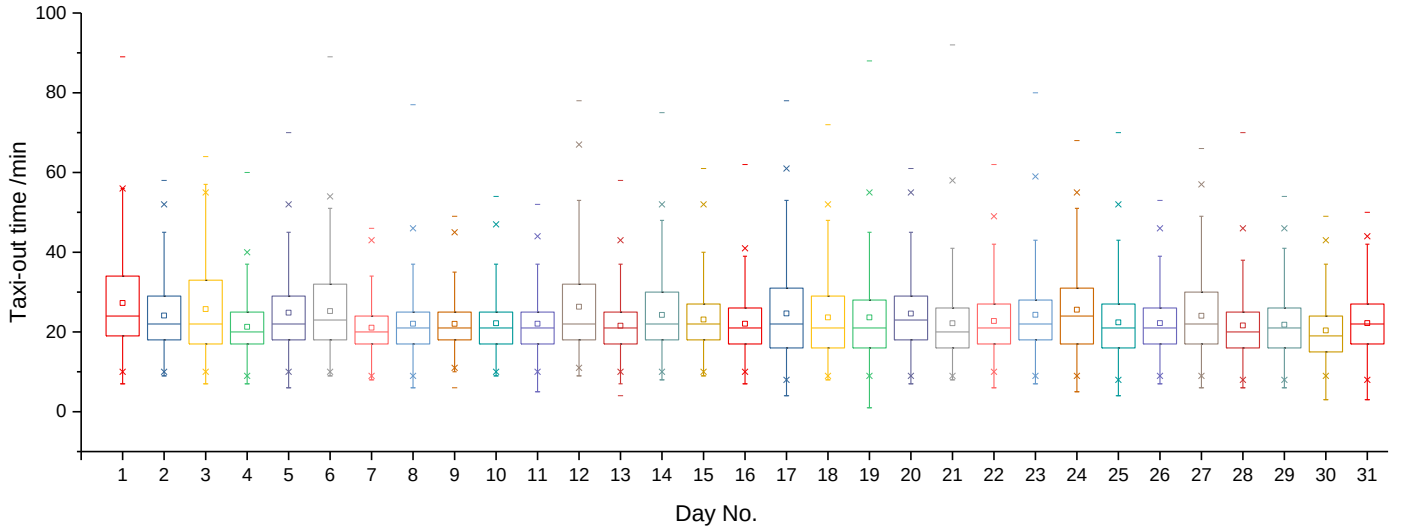


Figure 2. Taxi-out time distribution in each day in October 2014 at ZSPD

2) Aggregate Statistic Characteristics

The current studies reveal the fact that the size of take-off queue is the most significant factor of aircraft taxi-out time, and the arrival movements also have some impact on taxi-out process [6-7, 13]. We investigate the correlations between taxi-out time and the factors of surface flow and runway queue from the aggregate level. Note that the surface flow and runway queue factors include both arrival and departure operations. This is different from most of the existing studies which only focusing on the departure factors, but ignoring the arrival factors, when predicting the taxi-out time. Figure 3 shows the aggregate statistic characteristics of some relevant factors of taxi-out time.

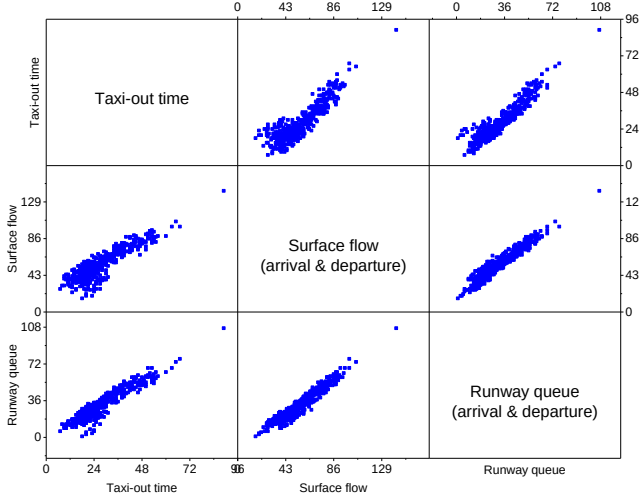


Figure 3. Analysis of some relevant factors of taxi-out time

As shown in Figure 3, there is a strong linear correlation between the taxi-out time and surface flow. This is due to the overlap between the taxi process of the reference aircraft and those of other aircraft, which leads to the competition for surface resources and resulting taxi delays. Similarly, the linear correlation between the taxi-out time and runway queue is also strong, with the reason that the runway queue, which counts the sum of aircraft that land on and take off during the taxi process of any reference aircraft, is an indicator of the runway saturation level and hence the level of congestion at the taxiway. In addition, The correlation between surface flow and runway queue is also significant. Considering the above positive results, we will introduce a more extensive system of factors to formulate the features of our machine learning methods in the following.

B. Macroscopic Network Topology

In order to calculate the features of our methods for taxi-out time prediction, we adopt a model of macroscopic network topology proposed in our previous work [14] to formulate the machine learning inputs. By this macroscopic network topology, it is expected that we can find a group of features, which will be used to determine the predictor variables for taxi-out time predictions later. Figure 4 illustrates our macroscopic network topology model of arrival and departure taxi operations in any spatial-temporal domain.

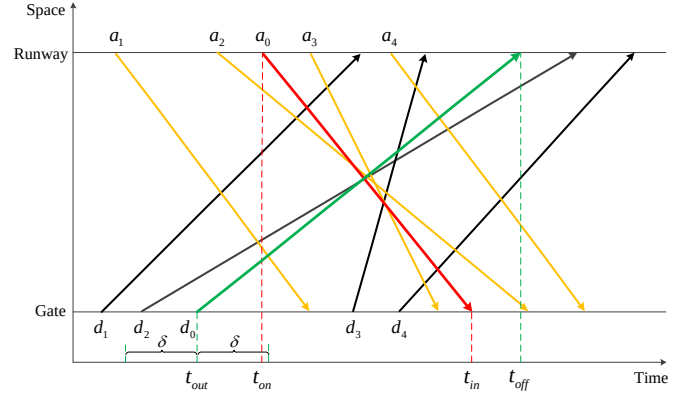


Figure 4. Macroscopic network topology of taxi process

In the real practice on airport surface, the processes of taxi-out and taxi-in are clearly coupled and interdependent on each other. Hence we consider the impact of arrival operations on taxi-out processes of departures. And then the spatial-temporal topology modelling is a general and universal framework to present the macroscopic resource flow at any airport systems. Note that the departures $d_1, \dots, d_4$ represent all the four different relationships with the reference departure aircraft d_0 : “Off-block Before, Take-off Before”, “Off-block Before, Take-off After”, “Off-block After, Take-off Before” and “Off-block After, Take-off After”. Similarly, the arrivals $a_1, \dots, a_4$ represent all the four different relationships with the reference arrival aircraft a_0 : “Landing Before, In-block Before”, “Landing Before, In-block After”, “Landing After, In-block Before” and “Landing After, In-block After”. The notations t_{on}, t_{in} represent the landing time and in-block time of the reference arrival aircraft a_0 , and t_{out}, t_{off} represent the off-block time and take-off time of the reference departure aircraft d_0 . And δ represents the arrival and departure slot threshold.

C. Response and Predictor Variables

The response variable in the machine learning context is the output data, referring to the aircraft taxi-out time indicator (ATTI). Take the reference departure aircraft d_0 in Figure 4 as an example, the ATTI is the difference between the take-off time t_{off} and the off-block time t_{out} .

The predictor variables are the input data that is mapped to the response variable through the machine learning models. Based on the macroscopic network topology presented in Figure 4, we formulate a system of machine learning predictors. The system of predictors can be divided into 4 categories and 8 indices, surface instantaneous flow indices (SIFIs), surface cumulative flow indices (SCFIs), aircraft queue length indices (AQLIs) and slot resource demand indices (SRDIs). Each category of predictors are calculated from two statistic perspectives focusing the departure aircraft (with prefix “D-”) and arrival aircraft (with prefix “A-”). Table 1 illustrates the quantities of the system of predictors used in our machine learning algorithms, with d_0 being the reference departure aircraft in Figure 4 for analysis.

Table 1 The quantities of all the machine learning predictors

Predictors		Relevant aircraft	Values
SIFIs	D-SIFI	$\{d_1, d_2\}$	2
	A-SIFI	$\{a_1\}$	1
SCFIs	D-SCFI	$\{d_1, d_2, d_3, d_4\}$	4
	A-SCFI	$\{a_0, a_1, a_2, a_3, a_4\}$	5
AQLIs	D-AQLI	$\{d_1, d_3\}$	2
	A-AQLI	$\{a_0, a_2, a_3, a_4\}$	4
SRDIs	D-SRDI	$\{d_2\}$	1
	A-SRDI	$\{a_0, a_2\}$	2

Taking Figure 4 as an example, the following details the definitions and calculation methods of predictors in Table 1. For any departure aircraft d_0 , the SIFIs include D-SIFI and A-SIFI, denoting the number of taxiing departures and arrivals, respectively, when d_0 is being pushed back from the gate. The SCFIs include D-SCFI and A-SCFI, referring to the number of departures and arrivals, respectively, whose taxiing period has overlap with the taxiing period of d_0 . The AQLIs include D-AQLI and A-AQLI, denoting the number of take-offs and landings, respectively, on the runway during the entire taxi process of d_0 . The SRDIs include D-SRDI and A-SRDI, denoting the number of push-backs and landings, respectively, in the departure slot $[t_0 - \delta, t_0 + \delta]$ where t_0 is the off-block time of d_0 , and δ is the statistic threshold coefficient introduced in Figure 4. In general, the value of δ can be set between 10 min and 30 min.

D. Machine Learning Algorithms

Machine learning explores the study and construction of algorithms that can learn from and make predictions on data, by building a model from sample inputs through a training process [15]. Such algorithms can overcome the strictly static program instructions by making data-driven predictions or decisions. In this paper, our machine learning algorithms use statistical and analytical techniques from the aggregate perspective to get the ability to learn and predict the change of aircraft taxi-out time with air traffic data. Figure 5 illustrates the general procedure of making taxi-out time predictions with machine learning algorithms.

The key aspects and the corresponding steps in the process of machine learning are as follows:

(1) Data: set a good dataset of air traffic operations that allow us to use taxi-out time prediction models; preprocess the data; divide the data into training data and test data.

(2) Training: train the algorithms with training data until the correct models with minimum errors are obtained.

(3) Test: make new predictions on the test data with the training machine learning models.

(4) Analysis: analyze the taxi-out time results; compare the prediction performance of different models.

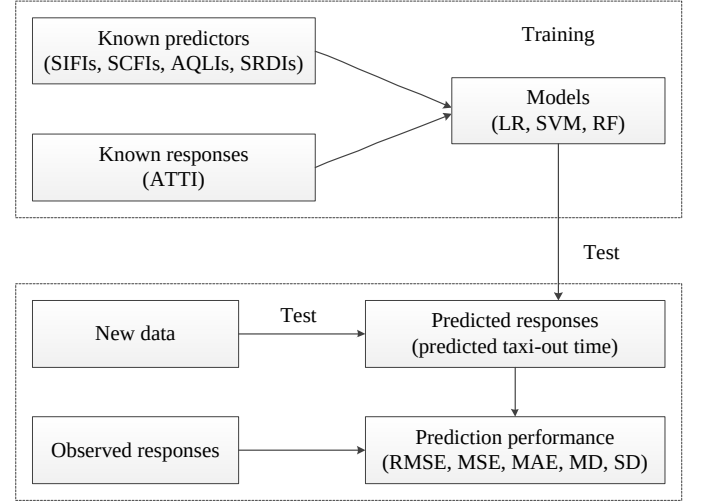


Figure 5. General procedure of making taxi-out time predictions with machine learning

We present three different algorithms for the task of taxi-out prediction; i.e. linear regression (LR), support vector machines (SVM) and random forest (RF). The LR algorithm is a classical method based on the statistical relationships among ATTI and SIFIs, SCFIs, AQLIs, SRDIs. The SVM algorithm predict the taxi data by mapping them from the input space into a higher dimensional feature space via a kernel function. The RF algorithm is designed by constructing a multitude of decision trees and assigning the class of taxi data based on the mode of the classes of individual trees. In order to obtain the best prediction performance, some key parameters used in the above algorithms are dynamically adjusted. For example, after a group of computational experiments, we find that the prediction performance of SVM algorithm reaches the best when using the cubic function as kernel function for regression, rather than the functions of Gaussian, linear and quadratic. In the RF algorithm, we set the minimum leaf size to 4. The maximum surrogates per node is set to 5.

Finally, the aforementioned LR, SVM and RF algorithms are compared with several performance metrics: R-Squared, root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), mean difference (MD), and standard deviation (SD). The above performance metrics are calculated by the following equations:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - o_i)^2} \quad (1)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (p_i - o_i)^2 \quad (2)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |p_i - o_i| \quad (3)$$

$$MD = \frac{1}{N} \sum_{i=1}^N (p_i - o_i) \quad (4)$$

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - o_i - MD)^2} \quad (5)$$

Where N is the total number of departures; p_i and o_i are the predicted and observed taxi-out time of aircraft i respectively.

III. RESULTS

In this section, we conduct the taxi-out time prediction based on the LR, SVM and RF algorithms. Then the prediction results will be compared with the actual observed values, and several metrics of error will be comprehensively analyzed.

A. Training models

The training models of LR, SVM and RF are calculated under the following two cases:

Case a: one-day training sample, Oct. 1, 2014;

Case b: one-month training sample, Sep. 1~30, 2014.

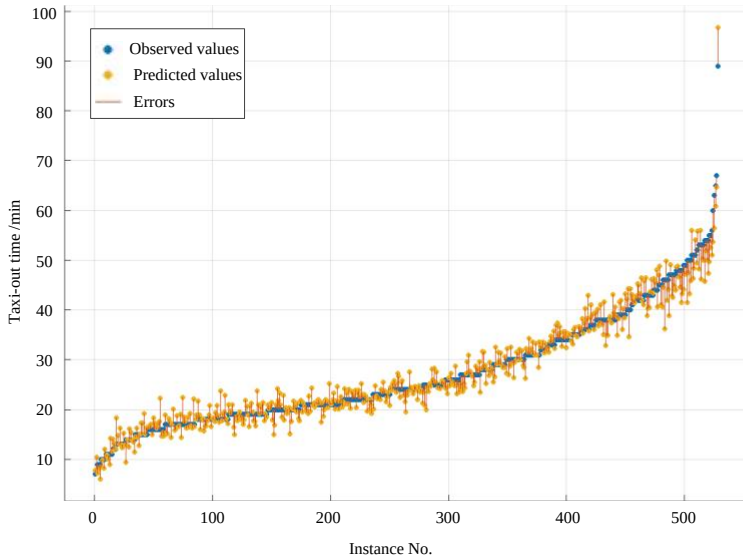
We take the taxi data from *Case a* and *Case b* to validate the training performance. According to the computational results from LR, SVM and RF models, Table 2 illustrates the

comparison of training performance with the metrics of R-Squared, and RMSE, MSE, MAE, MD, SD in minutes, under the two cases of using one-day and one-month samples.

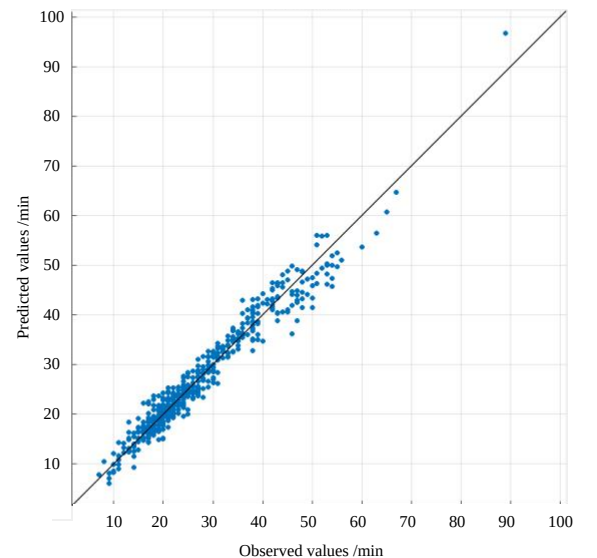
Table 2 Comparison of training performance metrics using one-day and one-month samples

Metrics	LR		SVM		RF	
	Case a	Case b	Case a	Case b	Case a	Case b
R-Squared	0.95	0.89	0.96	0.92	0.88	0.86
RMSE	2.42	3.07	2.27	2.63	3.89	3.43
MSE	5.87	9.40	5.14	6.90	15.15	11.76
MAE	1.85	2.22	1.68	1.91	2.81	2.56
MD	7.40 E-14	-2.32 E-13	1.14 E-2	-1.55 E-1	2.52 E-15	-1.01 E-17
SD	2.36	3.06	1.68	2.60	2.21	2.11

It can be seen that the training performances of LR and SVM models under *Case a* are better than those under *Case b*. But the training performance of RF model under *Case a* is worse than that under *Case b*, except the R-Squared value. In both *Case a* and *Case b*, the SVM model has the largest R-Squared value over the LR and RF models. For all the machine learning models, the mean taxi-out time differences between predicted values and observed values under *Case a* and *Case b* are close to zero. Among the three machine learning models, the SVM model shows the best training performance, and the LR model has a relatively good performance. But the RF model has the largest errors of RMSE, MSE, MAE, especially with a large error of MSE. Take the results under *Case a* as an visual example, Figure 6 ~ Figure 8 show the training performance of LR, SVM and RF models respectively.

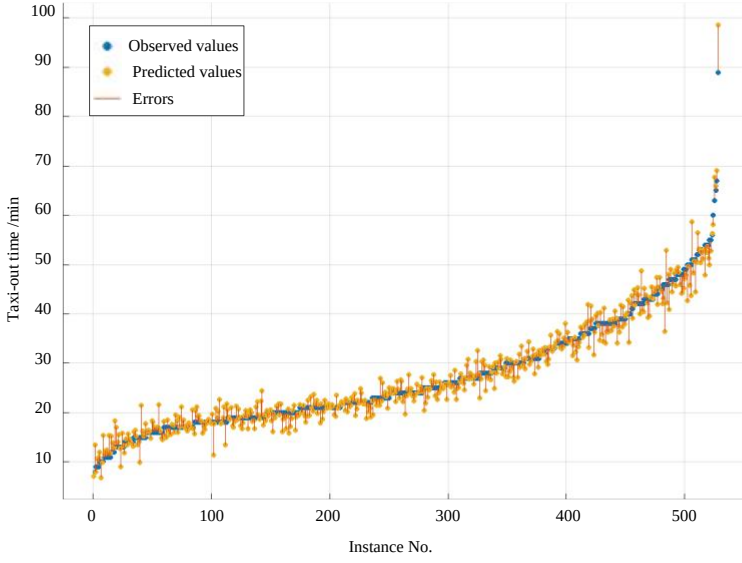


(a) Prediction performance

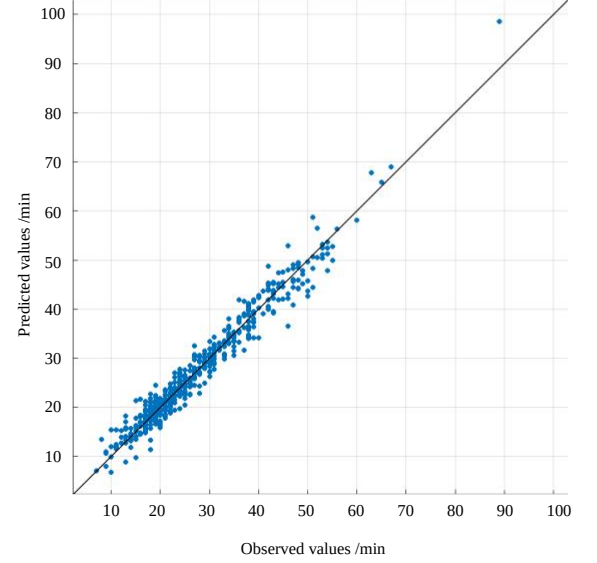


(b) Predicted vs. observed values

Figure 6. Training performance of the LR model

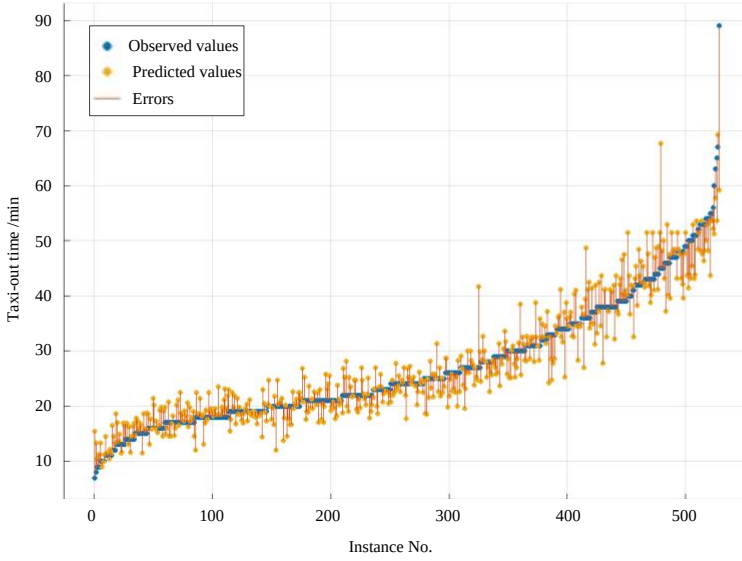


(a) Prediction performance

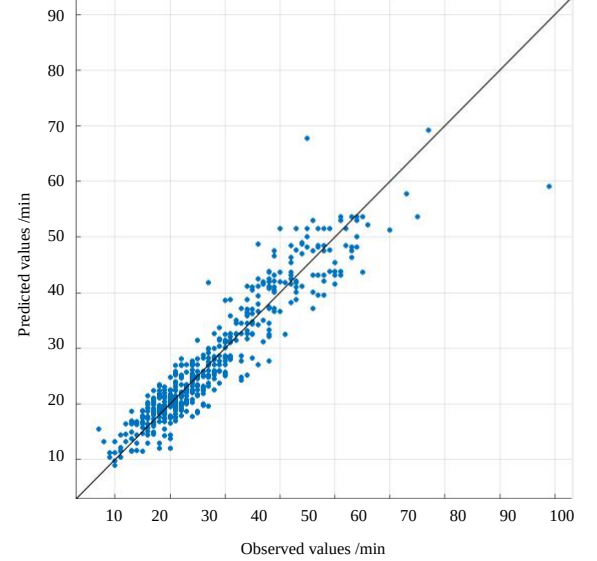


(b) Predicted vs. observed values

Figure 7. Training performance of the SVM model



(a) Prediction performance



(b) Predicted vs. observed values

Figure 8. Training performance of the RF model

Considering the fact presented in Table 2 that *Case a* has higher training performances from LR and SVM models, compared with *Case b*. Without loss of generality, Figure 6 ~ Figure 8 only illustrate the comparisons between predicted values and observed values from the LR, SVM and RF models under *Case a*. The results under *Case b* are similar to the visualization in Figure 6 ~ Figure 8. It can be easily seen from Figure 6(a) ~ Figure 8(a) that the training performances of LR and SVR models are significantly better than that of the RF model. In order to obtain the best training performance, we also try reset the parameters of the RF model, e.g., the minimum leaf size, and the maximum surrogates per node, but the training performance is still not improved.

Figure 6(b) ~ Figure 8(b) show that the points are distributed around the line $y = x$, this means that the errors (i.e., the difference between predicted values and observed values) with positive and negative fluctuations would tend to cancel each other. This can also be validated by Table 2 that the mean taxi-out time differences between predicted values and observed values are close to zero.

Note that a model with a high training performance may not have a high prediction performance, we will conduct a comprehensive comparison of prediction performance under *Case a* and *Case b* in the following part.

B. Prediction Performance

Based on the training models of LR, SVM and RF presented in Table 2 and Figure 6 ~ Figure 8, we take the taxi data on Oct. 2, 2014 to validate the prediction performance of our machine learning models. Table 3 illustrates the comparison of prediction performance with the metrics of RMSE, MSE, MAE, MD and SD in minutes, under the two cases of using one-day and one-month samples.

Table 3 Comparison of prediction performance metrics using one-day and one-month samples

Metrics	LR		SVM		RF	
	Case <i>a</i>	Case <i>b</i>	Case <i>a</i>	Case <i>b</i>	Case <i>a</i>	Case <i>b</i>
RMSE	2.47	2.60	4.44	2.25	3.92	1.92
MSE	6.09	6.76	19.68	5.07	15.36	3.70
MAE	1.79	1.91	2.54	1.56	2.82	1.32
MD	-0.35	0.11	-1.02	-0.21	-1.26	-0.08
SD	2.44	2.60	4.32	2.24	3.71	1.92

It can be seen that the prediction performances of SVM and RF models under *Case b* are better than those under *Case a*. But the prediction performance of LR model under *Case b* is worse than that under *Case a*. When using one-day sample to get the training models, the LR model has the best prediction performance over the SVM and RF models. But the results when using one-month sample are different from the one-day sample, than means the RF model has the best prediction performance over the LR and SVM models.

Table 4 illustrates the comparison of accuracies within different error ranges of $\pm 5, \pm 4, \pm 3, \pm 2, \pm 1$ in minutes, under the two cases of using one-day and one-month samples. When using either LR, SVM or RF model under *Case b*, more than 95% of departures can be found within the ± 5 -minute taxi-out time prediction error range. Similar to the results in Table 3, the accuracy of all the error ranges for the SVM and RF models under *Case b* are better than those under *Case a*.

Table 4 Comparison of accuracy within different error ranges using one-day and one-month samples

Error range	LR		SVM		RF	
	Case <i>a</i>	Case <i>b</i>	Case <i>a</i>	Case <i>b</i>	Case <i>a</i>	Case <i>b</i>
$[-5, 5]$	97.2 %	95.4 %	90.7 %	96.8 %	84.2 %	98.1 %
$[-4, 4]$	94.2 %	91.4 %	86.2 %	95.1 %	77.1 %	95.8 %
$[-3, 3]$	83.4 %	80.9 %	76.0 %	86.9 %	64.6 %	91.8 %
$[-2, 2]$	65.8 %	62.9 %	63.7 %	74.6 %	51.5 %	81.4 %
$[-1, 1]$	36.8 %	35.7 %	35.4 %	44.8 %	29.6 %	53.2 %

According to the results from Table 3 and Table 4, we can easily find a fact that the RF model under *Case b* has the best prediction performance over the LR and SVM models, although the training performance of RF model under *Case b* is a little worse than the other two models in terms of most of the performance metrics shown in Table 2. In both *Case a* and *Case b*, the last column results in Table 3 is the smallest among all the columns. The RF model from the training process under *Case b* has the smallest mean difference of taxi-out time between predicted values and observed values, with the smallest fluctuations of standard deviation of error. Therefore, we select the RF model under *Case b* as the final model to predict the taxi-out time at ZSPD.

In order to visualize the prediction performance, we describe all the results of the taxi-out time prediction made by the LR, SVM and RF models. Figure 9 show the prediction performance of LR, SVM and RF models respectively under *Case b*, and the comparisons between predicted values and observed (i.e., true) values.

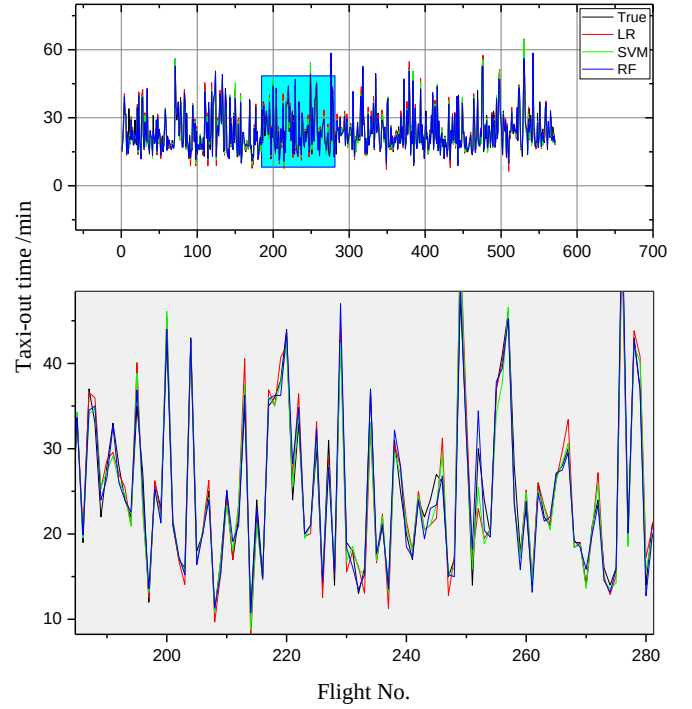


Figure 9. Comparison of the prediction results under different machine learning models

For the 571 departure aircraft in the test dataset, most of the predicted taxi-out time are very close to the true values, with small fluctuations for each departure aircraft. Especially for the RF model, over 50% of departures can be found within the ± 1 -minute taxi-out time prediction error range. More than 95% of departures fall into the window of ± 4 -minute. Additionally, more than 98% of departures fall into the window of ± 5 -minute. Obviously, our machine learning models formulated in this paper have a good performance for the taxi-out time prediction, especially for the RF model under *Case b*. And it can be expected that the prediction accuracy of our machine learning models in this paper can be furtherly improved as the size of the training dataset increases.

IV. CONCLUSIONS

This paper focuses on the machine learning techniques for predicting the taxi-out time of departure aircraft based on a macroscopic network topology from an aggregate view. The proposed methodology is a crucial way to model and predict airport surface operations, and also support to assess the efficiency of airport operations. Advanced taxi performance indicators can be used to schedule optimal take-off, landing, off-block and in-block times, which can increase the capacity and efficiency of airports, with the additional benefits of reduced fuel burn and emissions.

The exploration of historic data at ZSPD reveals some interesting statistical characteristics of relevant factors influencing the taxi-out time. This paper first introduces a macroscopic network topology model of arrival and departure taxi operations. Then a system of indicators are formulated as the predictors used in our machine learning algorithms. These indicators consider the impact of all the arrival and departure on the taxi-out times. Finally, we conduct training experiments to get three machine learning models of LR, SVM and RF using one-day and one-month samples, respectively. Based on the formulated training models, the validation experiments are conducted to compare the prediction performance of all the machine learning models. Computational results show that the training RF model using one-month sample significantly outperform other models in terms of prediction accuracy. An interesting fact we find in this paper is that a machine learning model with a lower training performance may still have a higher prediction performance.

The significance of this paper is an efficient machine learning method to predict the taxi-out time of departure aircraft considering the interactions between arrivals and departures. The method proposed brings significant benefits to analyze the performance of airport ground movements. It has the potential to support airport decision making and enhance the efficiency and predictability of airport operations.

ACKNOWLEDGEMENT

This work is supported by the China Postdoctoral Science Foundation (Grant No. 2017M611809), Jiangsu Planned Projects for Postdoctoral Research Funds (Grant No. 1701099C) and National Natural Science Foundation of China (Grant Nos. 61573181, 61671237 and U1633126).

REFERENCES

- [1] A. G. Marin, "Airport management: taxi planning," *Annals of Operations Research*, 2006, 143(1), pp. 191-202.
- [2] J. A. D. Atkin, E. K. Burke, and S. Ravizza, "The airport ground movement problem: Past and current research and future directions," *Proceedings of the 4th International Conference on Research in Air Transportation (ICRAT)*, 2012.
- [3] J. N. Yin, M. H. Hu, and Z. Zhao, "Simulation model and algorithm of multi runway airport gate assignment," *Journal of Traffic and Transportation Engineering*, 2010, 10(5), pp. 71-76.
- [4] H. Lee, and H. Balakrishnan, "Fast-time simulations of Detroit Airport operations for evaluating performance in the presence of uncertainties," *Proceedings of the 31st Digital Avionics Systems Conference (DASC)*, 2012.
- [5] S. Ravizza, J. Chen, J. A. Atkin, P. Stewart, and E. K. Burke, "Aircraft taxi time prediction: comparisons and insights," *Applied Soft Computing*, 2014, 14, pp. 397-406.
- [6] H. Idris, J. P. Clarke, R. Bhuva, and L. Kang, "Queuing model for taxi-out Time Estimation," *Air Traffic Control Quarterly*, 2001, 10(1), pp. 1-22.
- [7] S. Ravizza, J. A. D. Atkin, M. H. Maathuis, and E. K. Burke, "A combined statistical approach and ground movement model for improving taxi time estimations at airports," *Journal of the Operational Research Society*, 2013, 64(9), pp. 1347-1360.
- [8] J. N. Yin, M. H. Hu, Y. Y. Ma, K. Han and D. Chen, "Spatial-temporal topology and performance analysis of airport taxi network," *Proceedings of the 97th Transportation Research Board Annual Meeting*, 2018.
- [9] F. Herrema, R. Curran, H. Visser, D. Huet, and R. Lacote, "Taxi-out time prediction model at Charles de Gaulle Airport," *Journal of Aerospace Information Systems*, 2018, 15(3), pp. 120-130.
- [10] H. Lee, W. Malik, and Y. C. Jung, "Taxi-out time prediction for departures at Charlotte airport using machine learning techniques," *Proceedings of the 16th AIAA Aviation Technology, Integration, and Operations Conference*, 2016.
- [11] H. Lee, W. Malik, B. Zhang, B. Nagarajan, and Y. C. Jung, "Taxi time prediction at Charlotte Airport using fast-time simulation and machine learning techniques," *Proceedings of the 15th AIAA Aviation Technology, Integration, and Operations Conference*, 2015.
- [12] P. Balakrishna, R. Ganesan, and L. Sherry, "Accuracy of reinforcement learning algorithms for predicting aircraft taxi times: A case-study of Tampa Bay departures," *Transportation Research Part C: Emerging Technologies*, 2010, 18(6), pp. 950-962.
- [13] R. Clewlow, I. Simaiakis, and H. Balakrishnan, "Impact of arrivals on departure taxi operations at airports," *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, 2010.
- [14] J. N. Yin, M. H. Hu, Y. Y. Ma, K. Han, and D. Chen, "Airport taxi situation awareness with a macroscopic distribution network analysis," *Networks and Spatial Economics*, 2018. <https://doi.org/10.1007/s11067-018-9402-5>.
- [15] M. I. Jordan, and T. M. Mitchell, "Machine learning: Trends, perspectives, and prospects," *Science*, 2015, 349(6245), pp. 255-260.