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Taxi-out time prediction at Mohammed V Casablanca Airport

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ABSTRACT

Airports are vital for global connectivity. However, the increasing volume of air travel has presented significant challenges in airport managing. Accurate predictions of taxi-out times (TXOT) offer potential to enhance airport performance, minimize delays, optimize airline schedules, and enhance customer satisfaction. This paper focuses on developing a machine learning model to forecast taxi-out times at Mohammed V Airport. Historical taxiing data from various airports will be analyzed to predict taxi-out times based on diverse runway-stand combinations and congestion levels. we used neural network (NN), support vector machines (SVM), and regression tree (RT) in order to create a real-time model that forecasts TXOT and congestion levels for different runway-stand combinations. The result showed that the NN model outperformed other forecasting models when their performances are compared using the mean absolute percentage error, root mean square error as accuracy measures.

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1. INTRODUCTION

Airports play a pivotal role in the global transportation network, connecting people and goods to destinations worldwide. They serve as gateways to the world, facilitating international and domestic travel and trade. However, with the increasing volume of air travel and the growth of the aviation industry, managing congestion and ensuring safety have become major challenges for airport operators because the congestion can lead to delays, frustrated passengers, and even safety hazards, while safety concerns can put people and property at risk [1], [2].

The taxi-out times (TXOT) is the time that an aircraft spends on the ground from pushback to take-off, is a critical factor in airport operations. Predicting taxi-out times accurately can have a significant impact on airport efficiency, reducing delays, and improving overall performance. Precise forecasting not only aids airlines in fine-tuning their schedules but also in minimizing fuel usage and enhancing customer satisfaction. Numerous airports and airline operators have adopted taxi-out time prediction systems, leveraging real-time data and predictive analytics to gauge the duration required for an aircraft to taxi from the gate to the runway. The importance of taxi-out time predictions is only likely to increase as air traffic continues to grow, making efficient and safe airport operations even more critical [3].

The aims of this study are to develop an accurate machine learning model to predict taxi-out times at Mohammed V (MED V) International Airports. TXOT refers to the time between an aircraft off block time and start taking off from the runway to do this, we will first analyze and examine historical taxiing data in many international airports to better understand and predict TXOT for different runway-stand combinations and levels of congestion. Next, we will pinpoint crucial processes that stand to gain from predictions driven by data-driven machine learning. Third, we will determine the most effective machine learning method based on performance measures in order to propose a model that will allow us to identify the key factors that impact TXOT.

2. LITERATURE REVIEW

Previous studies reported in the literature have tried to predict the actual TXOT. We divided the previous studies in two dataset, the first one concerns statistical detection methods such as queuing models [4], statistical regression approaches [5], fuzzy rule-based systems [6]. The second one focus on feasible machine learning methods to deliver available time to fly, eliminate collision, to predict aircraft performance on taxiway and predict TXOT. Such as neural networks (NNs), multiple linear regression, stochastic gradient boosting and principal component regression [7]. Table 1 is a presentation of methods applied to several international airports worldwide.

Table 1. Take-off and taxi-out variables

Variable	Designation
Date	Flight date
Aircraft type	There are three types of aircraft 1: super heavy, 2: medium, 3: heavy
AOBT	Actual off block time
START_ROUL	Start Rolling
JOINHP	Waiting point P before runway
CL_ALIGN	Alignment Order
START_ALIGN	Start alignment
END_ALIGN	End alignment
CL_DECOLL	Take-off order
ATOT	Actual take off time
DEPASSQ1	Time when the aircraft pass the waiting point Q1 of the runway
DEPASSM1	Time when the aircraft pass the waiting point M1 of the runway
DRWYT	End take-off time
QFU	Runway orientation (waiting point before runway) 1: S1, 2: R1
DSTND	Departure stand

In Boston Logan Airport the researches proposed a model performance evaluation using the surface detection of the equipment, and also with comparing real data with predictions to improve the accuracy of TXOT estimation by detecting the main cause that influences rolling time, and it was about the queue length [8], [9]. Shumsky tried the construction of a probability model to predict taxi-out congestion during take-off in the first part. In the second part they tried the construction of a queueing management model using the services provided on runways [10]. Jordan *et al.* [11] used simple linear and log-linear functional forms in regression to determine the factors effect on taxi time. The predictive capacity of the models was verified on an independent dataset in order to identify and validate the relation between airport efficiency and aggregated factors related to traffic movement surfaces in Dallas/Fort Worth International Airport [11], [12]. Levy and Legge [13] proposes a statistical basic approach to predict TXOT at Atlanta Hartsfield Jackson Airport using airport surface detection equipment, model X (ASDE-X) in the model construction [13], [14]. Khanmohammadi *et al.* [15] exploit an artificial neural network (ANN) to predict TXOT at the airport, using independent variables such as weather conditions, runway configuration, and passenger numbers. The main challenge of this approach is managing nominal variables [15]. Zhang and Wang descript of predicting TXOT method based on unimpeded TXOT variable calculating, and then simulating the data using supervised learning methods [16], [17]. Chatterji and Zheng [18] used an artificial neural network to predict TXOT with surface management system absence that allows the scheduled take off times prediction in Dallas/Fort Worth Airport. They created a linear model with the same set of metrics as independent variables and the aircraft's time depart from the terminal as dependent variable [18]. Other research proposed a reinforcement learning model for predicting TXOT with an estimation based on a probabilistic workspace. The performance of predicting taxi time before take-off was examined on data available on aviation system performance measures for Detroit International, Washington Reagan National, Tampa International Airport (TPA), and John F. Kennedy International Airports [19]–[22]. In order to identify the factors affecting the variability of taxi times for arrivals and departures. Other work has proposed a model that combines layout and historical information on airport taxi times using multiple linear regression analysis, [5], [23]. Yin *et al.* [24], [25] proposed a model that use three regression methods (linear regression, support vector machine, and random forest) for predicting taxi-out time, compare the methods using performance indicators mean squared error (MSE) and change the types of variables from a one-day simulation to a month-long dataset. To predict the delay (defined as the waiting time at the parking area or runway) of each departure, Atkin *et al.* [26] sed two steps. The feasibility of departure time assignment must be taken into account in the departure sequence. The characteristics of the real-world problem and the differences between it and similar problems are analyzed in depth. The differences include a nonlinear objective function with a non-convex component; the integration of two sequence-dependent separation problems; a separation that vary over time; and slot extension. Each of these factors contributed to the design of the resolution algorithm [26]. Herrema *et al.* [27] introduced three methods for predicting taxi times: lasso, multilayer perceptron, and neural networks. They proposed a novel machine learning approach that integrates viable machine learning techniques to forecast abnormal runway occupancy times using distinct radar data [27].

3. METHOD

3.1. Aerodrome operation steps

The paragraph describes a model that simulates aircraft traffic within an airport, specifically focusing on the movement of planes from the departure airport's pre-departure queue until they reach the designated parking area at the arrival airport. The model takes into account the various stages of queuing that occur during this process [28]. Figure 1 and Figure 2, which are referenced in the paragraph, provide visual representations of these queuing processes, offering a clearer understanding of how aircraft flow through the system:

a. At the departure stand (pre-departure queuing to optimize network performance).
b. At the departure runway (take-off queuing).
c. In the arrival terminal airspace (arrival queuing in the arrival sequencing and metering area).

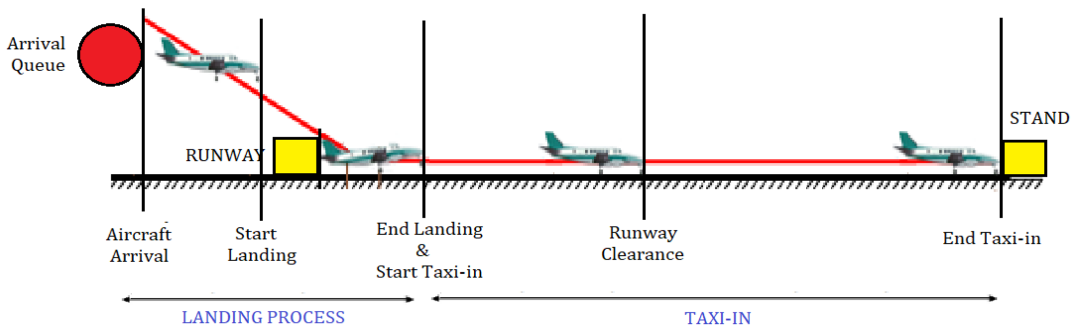


Figure 1. Landing process steps

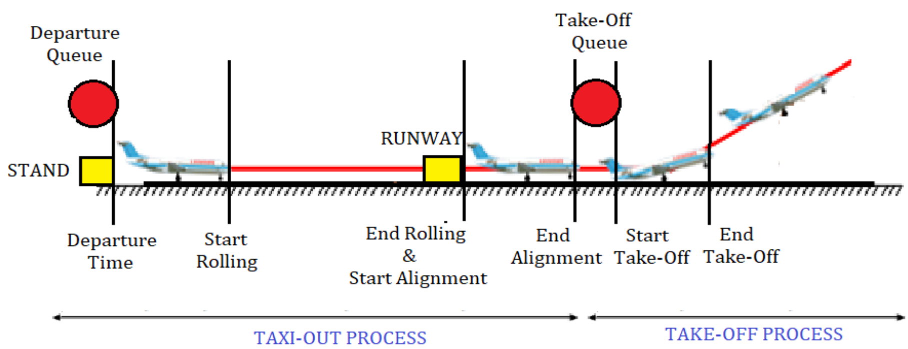


Figure 2. Take-off process steps

The landing and taxi-in processes are a discrete event model. They constitute various intervals of time, called events in systems modelling. As shown in the Figure 1, the aircraft arrival is anticipated with a queue arrival then it uses the runway to ensure landing. Afterwards, the aircraft needs to join the stand through the taxi-in process.

Figure 2 present that the taxi-out and take-off processes are also a discrete event model. The first one consists of taking a place in the departure queue, starting to roll after the off-block order and then standing at the runway, and finally rolling. The second process consists of respecting the take-off queue and then taking-off.

3.2. TXOT variables

In order to utilize machine learning (ML) techniques, the TXOT response must first be obtained. The TXOT indicator serves the purpose of accurately predicting the average waiting time for outgoing flights during congested periods at the airport. Taking into account the provided timestamp data, TXOT is characterized as the time interval between the actual off-block time (AOBT) at a designated stand and the actual take-off time (ATOT) on a specific runway.

Operational taxi data for aircraft are derived from recorded runway scheduler data supplied by MED V Airport. The dataset utilized in our simulation comprises taxi-in and taxi-out information collected over a period of 20 days, encompassing peak hours. Table 1 present the data related to take-off and taxi-out operations and Table 2 lists the input (potential) prediction variables related to the target variable AcTXOT that have been identified [17].

Table 2. Calculated prediction variables

Variable	Designation
AcTXOT	Actual taxi out time
Unimpeded TXOT	Unimpeded taxi out time
Add TXOT/vol	Additional taxi out time per flight
Add TXOT/airport	Additional taxi out time per airport
Congestion level	The level off traffic encountered by a departing flight Throughout the aircraft taxi-out stage
Saturation level	The maximum traffic level served under non-congested traffic conditions.

4. RESULTS AND DISCUSSION

4.1. Data preparation

The data preparation phase is composed of various tasks which are able to transform the initial raw aircraft operational taxi data into a final dataset. This includes merging and cleaning the taxi data. Additionally, the process involves selecting the relevant features that are crucial for accurately describing the variability in the dataset. The goal of feature selection can be categorized into three main areas: enhancing the prediction accuracy of the predictors, enabling faster computational performance and more efficient predictors, and gaining a deeper insight into the underlying process that produced the data.

The source of the datasets utilized in this study is the Network Management Directorate Operations/Airports (NMDO) of the Civil Aviation Administration of Morocco (CMN), which were collected during August 2019. The data pertains to taxi-out records from a span of 20 days. However, certain flights lacked information regarding actual out or off times, leading to the absence of taxi time values. Consequently, these flights were omitted from the departure flight data analysis. Following this filtration process, a total of 340 departures were included in the study. Table 1 demonstrates the various variables that were assessed for every departure in order to make predictions regarding taxi time. Therefore, it is crucial to identify which features should be chosen from the vast amount of traffic data using methods for feature selection [29].

To enhance the predictive ability of the predictors, feature selection algorithms are utilized, which lead to more efficient and economical predictors, as well as a deeper comprehension of the underlying data-generating process [30]. Typically, the Relief method is employed as a feature selection technique, which is applied during a pre-processing step prior to the learning of the model [31]. In order to identify the appropriate features to be chosen from the vast amount of traffic data, we employed a certain method, the results of which are presented in Figure 3. This figure illustrates the four crucial features that impact the TXOT prediction, namely congestion level, UTXOT, saturation level, and aircraft type.

4.2. Experimental setup

We introduce three distinct algorithms to predict taxi-out time: neural network (NN), support vector machines (SVM), and regression tree (RT). In our work, the cross-validation method was used to train our models. Specifically, 85% of the data was allocated as input for SVM, ANN and RT models (training data) while the remaining 15% are intended to test the model (testing data). To ensure optimal accuracy in predicting the TXOT problem, we ran the SVM, ANN, and LR methods with specific parameters.

a. For SVM method we employed the RBF kernel function and set the parameters to $C=10$, $\varepsilon=0$ and $\gamma=0$. To estimate these parameters, we followed the practical method proposed in [32] and [33].

b. For ANN method, we trained a one feedforward network using the One Step Secant algorithm with four hidden layers consisting of 20 neurons each and set the number of epochs to 1,000.
c. For RT method, we established the minimum number of leaf node observations at 1 and expanded the maximum depth of the tree until all leaves were pure.

Finally, the algorithms are evaluated using various performance metrics, including R-squared, root mean square error (RMSE), MSE, mean absolute error (MAE), mean difference (MD), and standard deviation (Sd).

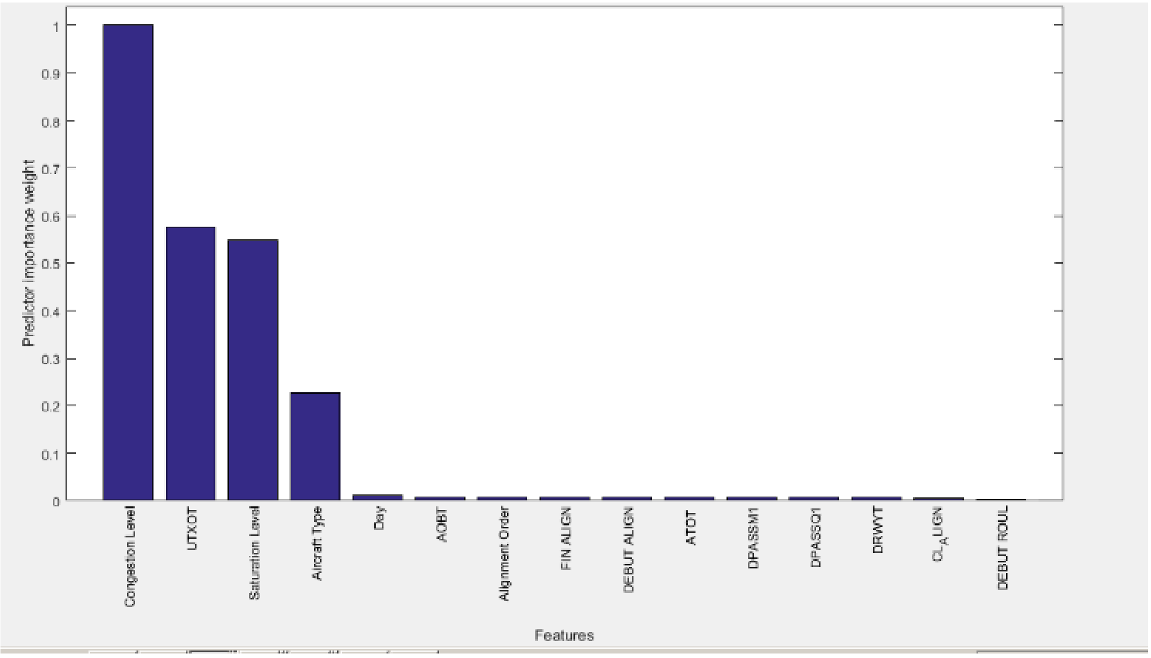


Figure 3. Normalized feature selection evaluation of feasibility

4.2. Prediction methods performance

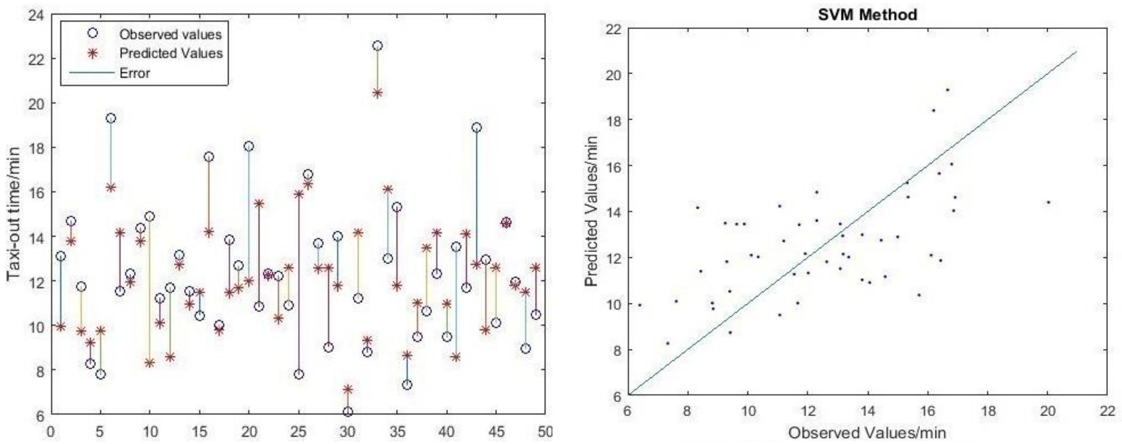
Various methods could be used to predict future scenarios, such as linear regression or machine learning. In our paper we use the tree methods independently, the NN the SVR and the RT. We confirmed the significance of the database size, considering that we had only 340 observations. The results shown in Table 3 reveled that the NN model outperformed the two ML models, displaying an unexpectedly high level of accuracy. This tool can prove valuable in limited data situation, particularly in the airports sector. Furthermore, the integration of additional parameters or input factors can enhance the performance and accuracy of the results.

Table 3. Prediction methods performance

	SVM	NN	RT
RMSE	2.9012	2.6798	3.0318
MSE	8.4984	7.3100	9.2858
MAE	2.3020	2.1456	2.4252
MD	-0.2689	-0.0111	-0.0386
SD	2.8545	2.6423	2.9967
Time execution	0.0423	1.3629	4.69

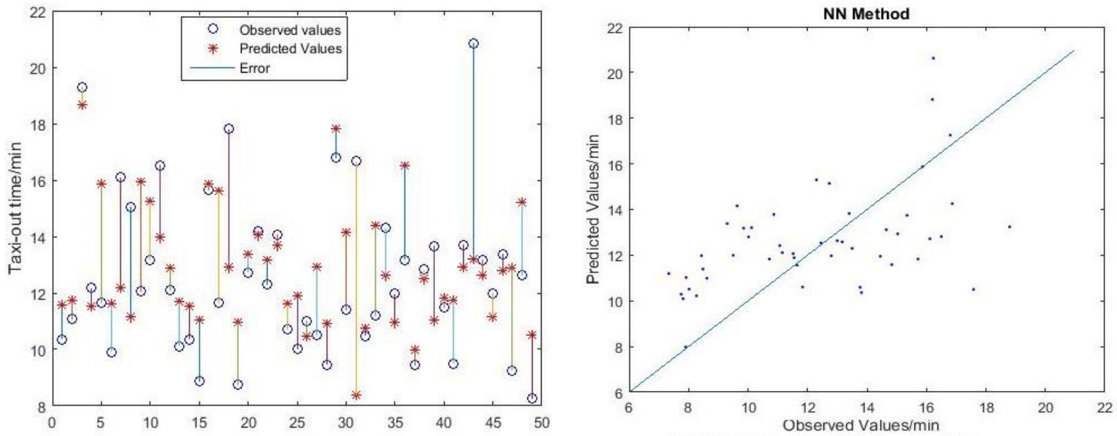
Figures 4 to 6 exclusively present the distribution of data predicted and observed values of the SVM, NN and RT models. Figures 4(a), Figure5(a), and Figure 6(a) demonstrate that the NN and SVM models exhibit notably superior training performance than the RT model.

Figures 4(b), Figure 5(b), and Figure 6(b) reveals that the points are scattered around the y=x line, indicating that the errors, characterized by positive and negative fluctuations, tend to counterbalance each other. This observation is further supported by the values in Table 3, which indicate that the mean differences in the taxi-out times between predicted and observed values are almost zero.



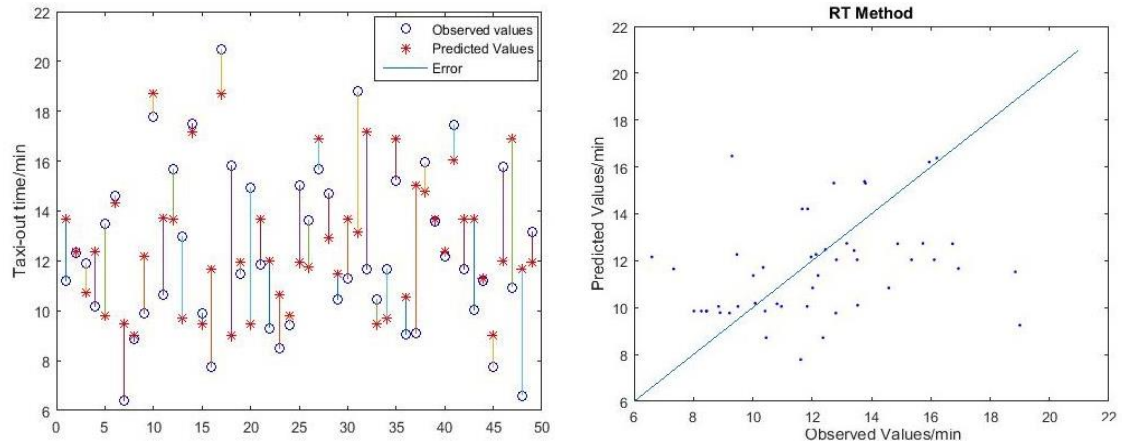
(a) (b)

Figure 4. Distribution of data predicted and observed values of the SVM model (a) TXOT mean square error and (b) TXOT predicted/observed values



(a) (b)

Figure 5. Distribution of data predicted and observed values of the NN model (a) TXOT mean square error and (b) TXOT predicted/observed values



(a) (b)

Figure 6. Distribution of data predicted and observed values of the RT model (a) TXOT mean square error and (b) TXOT predicted/observed values

5. CONCLUSION

This article focuses on utilizing machine learning techniques to predict the taxi-out time of Mohammed V air-port ft based on NN, RT, and SVM. The suggested methodology is integral to modeling and predicting airport surface operations, thereby facilitating the evaluation of airport efficiency. By employing advanced taxi performance indicators, optimal scheduling of take-off, landing, off-block, and in-block times can be achieved, leading to increased airport capacity and efficiency, along with reduced fuel consumption and emissions.

An exploration of historical data at ZSPD (ZS: airport country code; PD: Shanghai Pudong Airport) reveals interesting statistical characteristics of factors that influence the taxi-out time. The paper begins by introducing ML model for arrival and departure taxi operations. Furthermore, a set of indicators is formulated to serve as predictors in the machine learning algorithms. These indicators take into account how prediction variables influence taxi-out times. Subsequently, training experiments are conducted using one-day and one-month samples to develop three machine learning models: NN, SVM and RT. Based on these trained models, validation experiments are performed to compare the prediction performance of all machine learning models. The computational results demonstrate that the NN model trained with a one-month sample outperforms the other models in terms of prediction accuracy. Surprisingly, the paper demonstrates that a machine learning model with lower training performance can still demonstrate superior prediction performance.

This paper centers on the efficient machine learning method proposed for predicting the departure time of aircraft, taking into account the interactions between arrivals and departures. This method provides substantial benefits in airport ground movement performance analysis and has the potential to support airport decision-making processes, improving the overall efficiency and predictability of airport operations.

REFERENCES

[1] PRC, "PRR 2021 performance review report an assessment of air traffic management in Europe performance review commission," *Performance Review Report*, 2022. Accessed Jun. 9, 2023. [Online]. Available: www.eurocontrol.int/sites/default/files/2023-03/eurocontrol-draft-performance-review-report-2022.pdf

[2] PRC, "PRR 2018 performance review report," *Performance Review Report*, 2019. Accessed Jun. 9, 2023. [Online]. Available: https://www.eurocontrol.int/publication/performance-review-report-prr-2018

[3] G. Lian, Y. Zhang, J. Desai, Z. Xing, and X. Luo, "Predicting taxi-out time at congested airports with optimization-based support vector regression methods," *Mathematical Problems in Engineering*, vol. 2018, 2018, doi: 10.1155/2018/7509508.

[4] N. Pujet, B. Delcaire, and E. Feron, "Input-output modeling and control of the departure process of congested airports," *1999 Guidance, Navigation, and Control Conference and Exhibit*, vol. 8, no. 1, pp. 1835–1852, 1999, doi: 10.2514/atcq.8.1.1.

[5] 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*, vol. 64, no. 9, pp. 1347–1360, Sep. 2013, doi: 10.1057/jors.2012.123.

[6] J. Chen, S. Ravizza, J. A. D. Atkin, and P. Stewart, "On the utilisation of fuzzy rule-based systems for taxi time estimations at airports," *OpenAccess Series in Informatics*, vol. 20, pp. 134–145, 2011, doi: 10.4230/OASIcs.ATMOS.2011.134.

[7] Z. Bursac, C. H. Gauss, D. K. Williams, and D. W. Hosmer, "Purposeful selection of variables in logistic regression," *Source Code for Biology and Medicine*, vol. 3, pp. 1–8, 2008, doi: 10.1186/1751-0473-3-17.

[8] H. Idris, J.-P. Clarke, R. Bhuva, and L. Kang, "Queuing model for taxi-out time estimation," *Air Traffic Control Quarterly*, vol. 10, no. 1, pp. 1–22, Jan. 2002, doi: 10.2514/atcq.10.1.1.

[9] I. Simaiakis and H. Balakrishnan, "Queuing models of airport departure processes for emissions reduction," AIAA Guidance, Navigation, and Control Conference and Exhibit, Aug. 2009, doi: 10.2514/6.2009-5650.

[10] R. A. Shumsky, "Dynamic statistical models for the prediction of aircraft take-off times," PhD Dissertation, Massachusetts Institute of Technology, Sloan School of Management, pp. 1–214, 1995.

[11] R. Jordan, M. A. Ishutkina, and T. G. Reynolds, "A statistical learning approach to the modeling of aircraft taxi time," *29th Digital Avionics Systems Conference*, Salt Lake City, UT, USA, 2010, pp. 1.B.1-1-1.B.1-10, doi: 10.1109/DASC.2010.5655532.

[12] M. Kistler and G. Gupta, "Relationship between airport efficiency and surface traffic," in *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, Sep. 2009, pp. 1–13, doi: 10.2514/6.2009-7078.

[13] B. Levy and J. Legge, "Departure taxi time predictions using ASDE-X surveillance data," in *the 26th Congress of ICAS and 8th AIAA ATIO*, Sep. 2008, pp. 1–7, doi: 10.2514/6.2008-8958.

[14] A. Srivastava, "Improving departure taxi time predictions using ASDE-X surveillance data," in *2011 IEEE/AIAA 30th Digital Avionics Systems Conference*, Oct. 2011, pp. 2B5-1-2B5-14, doi: 10.1109/DASC.2011.6095989.

[15] S. Khanmohammadi, S. Tutun, and Y. Kucuk, "A new multilevel input layer artificial neural network for predicting flight delays at JFK airport," *Procedia Computer Science*, vol. 95, pp. 237–244, 2016, doi: 10.1016/j.procs.2016.09.321.

[16] EUROCONTROL, "Additional taxi-out time performance indicator document," 00-04 edition, European Organization for Safety of Air Navigation, 2015.

[17] Y. Zhang and Q. Wang, "Methods for determining unimpeded aircraft taxiing time and evaluating airport taxiing performance," *Chinese Journal of Aeronautics*, vol. 30, no. 2, pp. 523–537, 2017, doi: 10.1016/j.cja.2017.01.002.

[18] G. Chatterji and Y. Zheng, "Wheels-off time prediction using surface traffic metrics," in *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Sep. 2012, pp. 1–14, doi: 10.2514/6.2012-5699.

[19] P. Balakrishna, R. Ganesan, and L. Sherry, "Application of reinforcement learning algorithms for predicting taxi-out times," in *Proceedings of the 8th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2009*, 2009, pp. 255–261.

[20] P. Balakrishna, R. Ganesan, L. Sherry, and B. S. Levy, "Estimating taxi-out times with a reinforcement learning algorithm," *2008 IEEE/AIAA 27th Digital Avionics Systems Conference*, St. Paul, MN, USA, 2008, pp. 3.D.3-1-3.D.3-12, doi: 10.1109/DASC.2008.4702812.

[21] P. Balakrishna, R. Ganesan, and L. Sherry, "Airport taxi-out prediction using approximate dynamic programming: intelligence-based paradigm," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2052, no. 1, pp. 54–61, Jan. 2008, doi: 10.3141/2052-07.

[22] P. Balakrishna, R. Ganesan, and L. Sherry, "Accuracy of reinforcement learning algorithms for predicting aircraft taxi-out times: a case-study of Tampa Bay departures," *Transportation Research Part C: Emerging Technologies*, vol. 18, no. 6, pp. 950–962, 2010, doi: 10.1016/j.trc.2010.03.003.

[23] S. Ravizza, J. Chen, J. A. D. Atkin, P. Stewart, and E. K. Burke, "Aircraft taxi time prediction: comparisons and insights," *Applied Soft Computing*, vol. 14, pp. 397–406, Jan. 2014, doi: 10.1016/j.asoc.2013.10.004.

[24] J. Yin, M. Hu, Y. Ma, K. Han, and D. Chen, "Airport taxi situation awareness with a macroscopic distribution network analysis," *Networks and Spatial Economics*, vol. 19, no. 3, pp. 669–695, Sep. 2019, doi: 10.1007/s11067-018-9402-5.

[25] J. Yin, Y. Hu, Y. Ma, Y. Xu, K. Han, and D. Chen, "Machine learning techniques for taxi-out time prediction with a macroscopic network topology," *AIAA/IEEE Digital Avionics Systems Conference - Proceedings*, pp. 2–9, 2018, doi: 10.1109/DASC.2018.8569664.

[26] J. A. D. Atkin, G. De Maere, E. K. Burke, and J. S. Greenwood, "Addressing the pushback time allocation problem at Heathrow airport," *Transportation Science*, vol. 47, no. 4, pp. 584–602, Nov. 2013, doi: 10.1287/trsc.1120.0446.

[27] 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*, vol. 15, no. 3, pp. 120–130, 2018, doi: 10.2514/1.I010502.

[28] E. Silva, "Aerodrome operational management," *Aerodrome Certification Workshop, Kiev, Ukraine*. 2019.

[29] B. Mohammed *et al.*, "Edge computing intelligence using robust feature selection for network traffic classification in internet-of-things," *IEEE Access*, vol. 8, pp. 224059–224070, 2020, doi: 10.1109/ACCESS.2020.3037492.

[30] K. P. Singh, N. Basant, and S. Gupta, "Support vector machines in water quality management," *Analytica Chimica Acta*, vol. 703, no. 2, pp. 152–162, 2011, doi: 10.1016/j.aca.2011.07.027.

[31] R. Zhang, F. Nie, X. Li, and X. Wei, "Feature selection with multi-view data: a survey," *Information Fusion*, vol. 50, pp. 158–167, Oct. 2019, doi: 10.1016/j.inffus.2018.11.019.

[32] G. E. P. Box and G. C. Tiao, "Intervention analysis with applications to economic and environmental problems," *Journal of the American Statistical Association*, vol. 70, no. 349, pp. 70–79, 1975, doi: 10.1080/01621459.1975.10480264.

[33] D. K. Simonton, "Creative productivity, age, and stress: a biographical time-series analysis of 10 classical composers.," *Journal of Personality and Social Psychology*, vol. 35, no. 11, pp. 791–804, 1977, doi: 10.1037/0022-3514.35.11.791.

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