

Application of Reinforcement Learning Algorithms for Predicting Taxi-out Times

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Abstract—Accurate estimation of taxi-out time in the presence of uncertainties in the National Airspace System (NAS) is essential for the development of a more efficient air traffic management system. The dynamic nature of operations in the NAS indicates that traditional regression methods characterized by constant parameters would be inadequate to capture variations in taxi-out time across a day. In this paper, we describe how to build a taxi-out time estimation model using Reinforcement Learning, and identify factors that influence taxi-out time through the day. Taxi-out time predictions for a flight are made 15 minutes in advance of scheduled gate pushback time. Results from a case study of Detroit International Airport (DTW), Tampa International Airport (TPA), and John F. Kennedy International Airport (JFK) are presented and analyzed.

Keywords—taxi-out time estimation; reinforcement learning; air transportation system

I. INTRODUCTION

Taxi-out delay accounts for a significant portion of the total delay experienced by a flight. Accurate predictions of taxi-out time prior to scheduled gate departure will assist in adopting proactive rather than reactive strategies to the problem of congestion on the surface and subsequently in the entire National Air Space System (NAS). Air traffic controllers are often overwhelmed by the increase in the number of arrivals and departures during peak hours of operation. A recent article published in Aviation Week [1] indicates that the percentage of on-time departures at JFK was about 65% (both in July 2007 and July 2008). Benefits of minimizing taxi-out delays include congestion mitigation by avoiding near-capacity operations, emissions compliance through optimal adjustment of departure schedules, reduction in fuel costs by avoiding returns to the gate for refueling, and efficient utilization of resources such as ground personnel, and gates. In addition, accurate taxi-out time predictions will be conducive in determining if a flight can meet its estimated departure clearance time, allowing for more efficient traffic flow management procedures.

Traditional models to estimate taxi-out time, such as regression are characterized by constant parameters, and due to the complex nature of airport operations, it is difficult to obtain differential equation based mathematical models and closed form solutions that completely describe the dynamics at the airport. In the context of the Next Generation Air

Transportation System (NGATS), the Federal Aviation Administration (FAA) is looking towards a modernized Air Traffic Control (ATC) system, with increased levels of automation. Such a system would need to be supported by taxi-out time predictions in real-time, as the airport system and the rest of the NAS evolves. The taxi-out time estimation algorithm proposed in this work is a data-driven approach that adapts to changing airport dynamics, and is a step towards meeting this need for real-time predictability. The method is based on a reinforcement learning scheme, and has its roots in stochastic dynamic programming.

This paper is organized as follows. Section II presents a brief literature review of current methodologies for taxi-out time estimation. Section III describes the reinforcement learning methodology for taxi-out time prediction. Section IV presents observations and results from testing the RL methodology to predict taxi-out times at DTW, TPA and, JFK airports. Conclusions are presented in Section V.

II. LITERATURE REVIEW

A detailed understanding of the departure process at an airport in the National Airspace System (NAS) can be obtained from the report by Idris and Hansman [2]. The authors conducted a field study of Boston Logan International Airport. The overall objective was to identify flow constraints and inefficiencies in the airport departure process and to gain insight into the underlying causes of, and interactions amongst, these flow constraints. The airport departure process was identified as a complex interactive queuing system with controlled blocking; the control actions being issued by air traffic controllers. Aircraft queues were considered as manifestations of flow constraints and were hence used to analyze potential constraints caused by contention for airport resources (terminal airspace, runways, taxiways, ramp, gates, air traffic controllers, communication channels). Their conclusions suggest that efficiency of the departure flow process must be improved by adopting proactive, as opposed to currently employed reactive methods. Based on previous work the authors suggest that it is possible to reduce taxi-out times (and thus incur environmental benefits) by regulating flow while keeping throughput the same. It is suggested that appropriate take-off orders be computed in the presence of downstream restrictions.

Dareing and Hoitomt [3] put forth an interesting discussion on potential benefits that can be derived from specifically assigning accountability (to the FAA, and airlines) for various causes of inefficiency. Alternative ways to measure delays are also suggested.

Previous studies related to departure flow planning include both simulation models and analytical formulations. The DEPARTS [4] model developed as a prototype for Atlanta International Airport (ATL), by Mitre Corporation, attempts to reduce taxi times by generating optimal runway assignments, departure sequencing and departure fix loading. The input to this decision support tool is a near-real time airport information system and specifically takes advantage of the independent parallel runway operations for arrivals and departures at ATL, and the availability of flight status data (through the Airport Resource Management Tool (ARMT) from the Atlanta Surface Movement Advisor (SMA), the ATL Automated Radar Terminal System (ARTS), and manual scanning of bar coded flight strips at the ATL air traffic control tower. ARMT also captures traffic flow management constraints, airport configuration, and the current weather conditions. Results of their analysis indicate that benefits derived from DEPARTS increase during days with higher actual taxi times, and also that pushback predictability could influence all phases of flight and traffic flow management.

A simulation based study of queueing dynamics and “traffic rules” is reported in [5]. The authors conclude that flow-rate restrictions significantly impact departure traffic. The impact of downstream restrictions is measured by considering aggregate metrics such as airport throughput, departure congestion, and average taxi-out delay.

A “mesoscopic” airport queueing model is developed in [6]. The Airline Service Quality Performance (ASQP) data collected by the Department of Transportation, and that from the Preferential Runway Assignment system (PRAS) database were used for the purpose of model validation. The model is used to evaluate preliminary control strategies, and the impact of these schemes on operating costs, environmental costs, and overall delay is presented.

In [7] a queueing model for taxi-time prediction is developed. The authors identify takeoff queue size to be an important factor affecting taxi-out time. An estimate of the takeoff queue size experienced by an aircraft is obtained by predicting the amount of passing that it may experience on the airport surface during its taxi-out, and by considering the number of takeoffs between its pushback time and its takeoff time. However, this requires prior knowledge of actual takeoff times of flights and hence may be unsuitable for planning purposes. The model is valid for a specific runway configuration since the runway configuration at the future time of taxi-time prediction is unknown. Suggested extensions to the model include a runway configuration predictor. A queueing model based on simulation to test different emissions scenarios related to duration of taxi-out was developed in [8]. Some of the scenarios that are considered are redistribution of flights evenly across the day, and variation in number of departures under current capacity. The study showed that lower taxi-out times (and thus lower emissions) are experienced by airlines

that use less congested airports and don’t rely on hub-and-spoke systems. Many statistical models that consider the probability distribution of departure delays and aircraft takeoff time in order to predict taxi-time have evolved in recent years [9,10]. Other research that develops a departure planning tool for departure time prediction is available in [11-15].

A Bayesian networks approach to predict different segments of flight delay including taxi-out delay has been presented in [16]. An algorithm to reduce departure time estimation error (up to 15%) is available in [17], which calculates the ground time error and adds it to the estimated ground time at a given departure time. A genetic algorithm based approach to estimating flight departure delay is presented in [18]. Other research that has focused on departure processes and departure runway balancing are available in [19-20].

Direct predictions attempting to minimize taxi-out delays using accurate surface surveillance data have been presented to literature [21,22]. Signor and Levy [23] discuss the implications of accurate OOOI (Gate Out, Runway Off, Runway On, Gate In) data for efficient resource utilization. A pair-wise comparison between Aircraft Situation Data to Industry (ASDI), OOOI data provided by Northwest Airlines (NWA) (Flight Event Data Source: FEDS), and Multi-dependent static surveillance (MDS) data was conducted. It was found that potentially, the surface surveillance radar track data provide independent and most accurate OOOI event times that is also more generally accessible in comparison to proprietary data (from airlines for example). In addition, a bivariate quadratic polynomial regression equation was developed for taxi-out time forecasting. The data used was from the Sensis Corporation’s Airport Surface Detection Equipment – Model X (ASDE-X) system at Detroit International Airport (DTW). It is concluded that a standard error of 2 minutes can be achieved for departures up to 10 minutes prior to the aircraft leaving the ramp area.

A methodology to estimate total and excess taxi-times from the ASDE-X system has been developed at Sensis Corporation [24]. Data is currently available for 13 major airports in the United States. Metrics related to environmental factors, such as total and excess fuel burn, fuel cost, and emissions are also estimated. Details of the algorithms used to extract OOOI events and excess taxi times from the surveillance data are presented. Estimated metrics may be reported on a per-airport, per-aircraft, or per-carrier basis.

The various literature sources reinforce the need for dynamic predictive models that will assist in building a decision support tool to aid ground and local controllers in improving the airport operational efficiency by mitigating surface congestion.

III. RL METHODOLOGY

The sequential decision making process to predict taxi-out time can be perceived as a stochastic control problem.

In this research, a machine learning approach is used for the task of taxi-out time $a \in A$ prediction of a flight, where A denotes the prediction space. The evolution of airport system state $x \in X$ is modeled as a Markov chain, where X denotes

the system state space. The state variables for the taxi-time prediction problem were determined by studying the available data, and through empirical analysis. The choice of state variables is detailed in section IV.

The decision to predict the taxi-out time based on the system state is modeled as a Markov decision process (MDP). For the purpose of solving the MDP, it is necessary to discretize X and A . Due to the large number of state and action combinations (x,a) , the Markov decision model is solved using a machine learning (reinforcement learning (RL), in particular) approach.

The purpose of the RL estimator is to predict taxi-out time given the dynamic system state. The input to RL is the system state and the output of the learning process is a reward function $R(x,a)$ (R-values) where $a \in A$ is the predicted taxi-out values. The utility function (reward) $R(x,a)$ is updated based on the difference between the actual and predicted taxi-out values $r(x,a,j)$. We define reward $r(x,a,j)$ for taking action a in state x at any time t that results in a transition to state j , as the absolute value of error $r(x,a,j) = |Actual\ Taxi-out - predicted\ Taxi-out|$ resulting from the action. The transition probability in a MDP can be represented as $p(x,a,j)$, for transition from state x to state j under action a . Then the prediction system can be stated as follows. For any given $x \in X$ at time t there is a prediction a such that the expected value of error (*Actual – predicted Taxi-out*) is zero. Theoretically, the action space for the predicted taxi-out could have a wide range of numbers. However, in practice, for a non-diverging process, the action space is quite small, which can be discretized to a finite number of actions.

For practical implementation since transition probabilities $p(x,a,j)$ are not known, we use the reinforcement learning version of the Bellman's optimality equation [25] to update $R(x,a)$ as follows, in which time t is replaced with the iteration number n .

$$R^{n+1}(x,a) = (1-\alpha)R^n(x,a) + \alpha[r(x,a,j) + \beta \min_{b \in A} R^n(j,b)]$$

$$x, j \in X \quad a \in A$$

where α is a learning parameter that is decayed over time, and β is the discount parameter ($0 < \beta < 1$). The α value is decayed as follows [26].

$$\alpha^n = \frac{\alpha_0}{1+u}$$

$$u = \frac{(n)^2}{K+n-1}$$

where K is a large number, and α_0 is the starting value of α .

Several measures of performance such as discounted reward, average reward, and total reward can be used to solve a MDP. At the beginning of the learning process, the R-values are initialized to zeros. When the process enters a state for the first time, the action is chosen randomly since the R-values for all actions are zero initially. In order to allow for effective learning in the early learning stages, instead of the greedy

action (action with lowest R-value) the decision maker, with probability P_n , chooses from other actions. The choice among the other actions is made by generating a random number from a uniform distribution. The above procedure is commonly referred to in RL literature as exploration. Learning ensues after exploration has ended during which the taxi-out times are learnt for different airport system states. The RL based functional block diagram is shown in Fig. 1. Theoretical details of the RL algorithm can be obtained from [25-29].

A. Obtaining Predicted Taxi-Out Time

Once learning is completed, the R-values (reward) provide the optimal prediction choice for each state. At any time t as the process enters a state x , the action a corresponding to the lowest non-zero R-value indicates the predicted taxi-out time a . In what follows we present the steps of the RL algorithm in the implementation phase. The RL estimator was coded in MATLAB®.

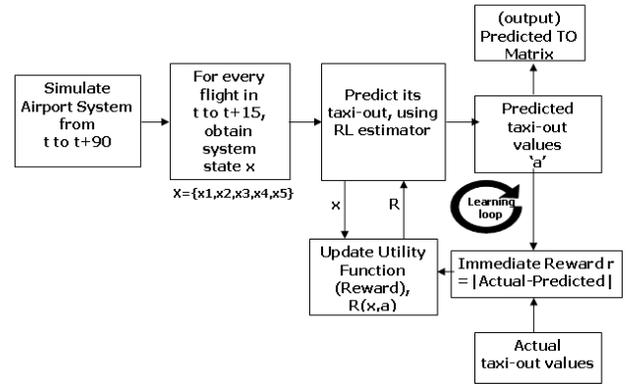


Figure 1. RL Functional Block Diagram

B. Steps for Implementing RL Methodology

Step 1: Once the states, actions, and the reward scheme are set up, the next step is to simulate the airport's $t+90$ minutes look-ahead window. Assume 15 minute decision (prediction) epochs *i.e.* prediction was done for flights in a moving window of length t to $t+15$ minutes. This means that for each departing flight in the 15 minute interval from current time, the airport dynamics was simulated for at least 75 minutes from its scheduled departure time.

Step 2: Simulate the first 15 minute window. For each flight in the window obtain the system state x . To calculate average taxi-out times before current time t , actual flight data between t and $t-30$ are used. Initialize $R(x,a)$ to zeros.

Step 3: If exploration has decayed go to step 4, else choose arbitrary actions (predictions from set A). The window is then moved in 1 minute increments and all flights in the window are predicted again. This means that every flight, unless it leaves before scheduled time, has its taxi-out time predicted at least 15 times. Simulate the new window of 15 minutes. Find the next state j for each flight. Compute $r(x,a,j)$. Update reward $R(x,a)$ using the fundamental Robbin-Monro's stochastic

approximation scheme [30] that is used to solve Bellman's optimality equation [25] provided earlier.

Step 4: If learning phase is in progress, choose greedy action a from set A (action corresponding to the lowest non-zero R-value). The $t+15$ minute window is then moved in 1 minute increment and all flights in the new window are predicted again. Find the next state j for each flight. Compute $r(x,a,j)$. Update $R(x,a)$.

Step 5: Continue learning by simulating every 15 minute interval, until all the flights in the 90 minute window have been completed. Next, move the window of width 90 minutes by a fixed time increment (say 15 minutes) and repeat learning by going to Step 2.

Step 6: Continue learning with several months of ASPM data until a stopping, or a near-optimal criterion is reached such as $|R^{n+1}(x,a) - R^n(x,a)| \leq \epsilon$ where ϵ is a very small positive number.

Step 7: Once learning is complete, the optimal prediction a for a given state x is the one that corresponds to the minimum non-zero R-value for that state.

C. Data Source

In this research OOOI (Out, Off, On, In) data for each flight departing or arriving at an airport is obtained from the Aviation System Performance Metric (ASPM) database maintained by the Federal Aviation Administration (FAA). OOOI data provides the following information for each recorded flight – Scheduled pushback time from the gate, Actual pushback time from the gate, Actual Wheels Off time, Actual Wheels On time at the arrival airport, and Actual In time which is recorded when the aircraft reaches the gate after the taxi-in process. In addition, the ASPM database also provides an airline (not individual flight) specific seasonal average for the nominal or unimpeded taxi-out time and taxi-in time.

The different attempts to model the airport departure process use varying inputs with distinct levels of detail depending on availability and accessibility. In this context it is noted that the proposed use of ASPM data in this research work does not capture the dynamics of the departure process between the gate pushback and takeoff events. Also, it is possible that an aircraft pushes back from the gate and for varying reasons may have to return to the gate and pushback again. It is unclear as to whether the actual pushback time reported by the airlines indicates the first pushback or the second pushback. The Bureau of Transportation Statistics (BTS) recently issued a directive [31] requiring all airlines reporting data to ensure that the first pushback time be recorded as the actual gate-out time. This clearly influences the measured taxi-out time.

IV. OBSERVATIONS AND RESULTS

Analysis of the data suggests that for a specific aircraft that is scheduled to pushback, the congestion on the ground, which is captured by variables such as the number of flights in the runway queue (x_1), the number of departure aircraft co-taxiing (x_2), and the number of arrival aircraft co-taxiing (x_3) are the major factors that influence taxi-out time. It is assumed that a

flight is in the runway queue if it has completed its unimpeded taxi-out time, and has not yet taken-off. During the initial studies, the training and testing of the taxi-out time estimator was conducted using the state variables $X=\{x_1,x_2,x_3\}$. The range of discretization for these three state variables is determined by observing the actual taxi-out times at the airport across the day.

Many times, it was observed that the taxi-out times for two different flights with the same values of $\{x_1,x_2,x_3\}$ were very different. This indicated that the three variables relating to queue length, and number of arriving and departing flights alone was not sufficient to capture the airport departure dynamics. A plot of actual taxi-out times across a given day in 15 minute intervals showed that the taxi-out time changes gradually over the day. Further analysis suggested that the taxi-out time during a given quarter hour was found to depend on the taxi-out times of the previous two quarters. So in order to capture the cascading (spill-over) effect of taxi-out times over the day the average taxi-out time of the previous two quarters was considered as a factor influencing taxi-out time of the subsequent quarter (x_4). Along these lines, the time of day (x_5) was also included as a factor because taxi-out time has a nonstationary characteristic. Thus, there are five variables that comprised the state vector in this research.

Clearly, additional information such as the runway allotted to a flight, days with severe weather/de-icing, and gate information could be used to better describe the system state of a flight, which may lead to more accurate predictions. However, this information is not available in the ASPM database.

A comparison was made between the average actual taxi-out time per quarter and the average predicted taxi-out time per quarter across the entire day. See Fig.2. First all flights that were predicted to take off in a certain quarter are considered and their corresponding mean predicted taxi-out times are plotted. Then all flights that actually took off in that same quarter are extracted and their corresponding mean actual taxi-out times are plotted. It is to be noted that the flights that actually took off in the quarter being analyzed may not exactly match the set of flights that were predicted to take off in that same quarter. Information regarding downstream restrictions affecting individual flights is not available. Hence it is not possible to account for passing of aircrafts in the taxi-out time prediction model.

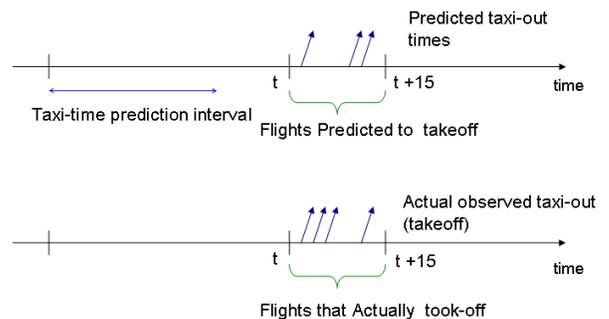


Figure 2. Comparison between predicted and actual taxi times

The accuracy of predicted average taxi-out time for a specified time interval of day, which indicates behavior of the airport, is estimated. An analysis of this type is extremely useful in predicting average airport taxi-out time trends approximately 30-60 minutes in advance of the given time of day (specifying the take off quarter).

Fig. 3 indicates the predication accuracy of the RL methodology at DTW airport when the average actual taxi-out time differed from the average predicted taxi-out time by +/- 3 minutes. The averages were taken in 15 minute intervals over the entire day.

Day (January 2006)	Prediction Accuracy of Average Taxi-Out times in 15 min intervals
	Prediction accuracy (in %) within ± 3 min (average predicted TO – average actual TO)
26th	97.1
27th	97.1
28th	97.1
29th	95.7
30th	97.1
31st	89.9

Figure 3. Prediction accuracy at DTW airport

Fig. 4 indicates the predication accuracy of the RL methodology at TPA airport when the average actual taxi-out time differed from the average predicted taxi-out time by +/- 3 minutes. The averages were taken in 15 minute intervals over the entire day.

Day (August 2007)	Prediction Accuracy of Average Taxi-Out times in 15 min intervals
	Prediction accuracy (in %) within ± 3 min (average predicted TO – average actual TO)
26th	95.7
27th	95.7
28th	92.8
29th	92.8
30th	95.7
31st	89.9

Figure 4. Prediction accuracy at TPA airport

Fig. 5 indicates the predication accuracy of the RL methodology at JFK airport when the average actual taxi-out time differed from the average predicted taxi-out time by +/- 5 minutes. The averages were taken in 15 minute intervals over the entire day.

Year 2007 Date	Time Period of Day	Dec 4th	Dec 5th	Dec 6th	Dec 7th	Nov 29th	Dec 9th
		Low		Medium		High	
Prediction accuracy within ± 5 min (%)	Before 4:00 P.M	70.00	67.50	72.50	77.50	100.00	95.00
	After 4:00 P.M	20.69	41.38	62.07	58.62	55.17	55.17
Average predicted TO- Average actual TO	Across Whole Day	49.28	56.52	68.12	69.57	81.16	78.26

Figure 5. Prediction accuracy at JFK airport

It can be observed from Fig. 5 that the prediction at JFK airport were not very consistent. The tabulated results suggest that consistently, prediction accuracy of the algorithm is higher for the period prior to 4:00 P.M. Upon comparing the mean and standard deviation of the taxi-out times at JFK across the days in Fig. 5, it was observed that the days with lower prediction accuracy had very high variance in taxi-out times. This illustrated in Fig 6. It is this variation in taxi-out times over the day that poses a challenge in the task of predicting taxi-out times in advance of scheduled departure from the gate.

Year 2007 Date	Dec 4th	Dec 5th	Dec 6th	Dec 7th	Nov 29th	Dec 9th
Mean of actual taxi-out time (min)	33.65	33.95	29.78	26.69	26.91	24.91
Mean of predicted taxi-out time (min)	35.81	36.80	30.88	27.34	26.91	25.21
Std. Dev. of actual taxi-out time (min)	16.19	14.95	12.21	10.35	10.78	8.84
Std. Dev. of predicted taxi-out time (min)	16.71	15.27	9.04	7.12	9.29	7.04
Median of actual taxi times (min)	28.20	31.80	28.20	25.20	24.00	24.00
Median of predicted taxi times (min)	31.20	34.30	32.00	27.36	25.64	24.00

Figure 6. Performance measures at JFK airport

V. CONCLUSIONS

Prediction of taxi-out time averages assists in near-time departure planning, where the objective is to minimize downstream congestion by getting flights into the air as early as possible. The prediction strategy discussed in this research enables one to predict average airport taxi-out time trends approximately 30-60 minutes in advance of the given time of day (specifying the take off quarter). The predicted average taxi-out times in 15 minutes intervals of the day were compared

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with the actual averages as observed at the airport. Compared to relatively well-behaved airports such as DTW and TPA that have been analyzed using the RL taxi-out time estimator, the departure behavior trend at JFK is comparatively more difficult to capture due to the overall high mean and variance and distinct peaking effects in the evening. Given the dynamically changing departure process predominant at JFK, we believe that traditional schemes for taxi-out time prediction such as those based on parametric regression cannot capture the trend in taxi-out times over the day. The learning based RL method tested in this research is a suitable approach that adapts to the stochastic nature of departure operations. The results presented above indicate that the RL estimator has good potential to capture the dynamics at even challenging airports such as JFK. In order to improve the prediction accuracy for JFK, further analysis of airport behavior and taxi-out time trends is part of our on-going research. Prediction accuracy on an individual flight basis is also being investigated. Comparisons with other existing taxi-out time prediction methods will also be undertaken.

It is expected that control tower operations, surface management systems, and airline scheduling can benefit from this prediction by adjusting schedules to minimize congestion, delays, and emissions, and also by better utilization of ground personnel and resources. Especially, with airport dynamics changing throughout the day in the face of uncertainties such as weather, prediction of airport taxi-out time averages combined with individual flight predictions, could help airlines manage decisions such as incurring delays at the gate as opposed to increasing emissions due to longer taxi times. Air Traffic Control would also benefit from this knowledge when making decisions regarding holding flights at the gate or ramp area due to increased congestion. This could improve the performance of air traffic flow management both on ground and in air across the entire NAS in the US and worldwide. It can be integrated to support the futuristic Total Airport Management concepts beyond Collaborative Decision Making [32] that envisions automation of several airport operations.

More detailed information on OOOI times and airport dynamics on an individual flight basis may be obtained with the development and deployment of surface surveillance systems. Future work in the development of surface surveillance systems includes analyzing the radar track information and overcoming challenges in extracting OOOI event times thereby increasing accuracy of the data [23]. Training the RL estimator with this more detailed information would potentially increase the accuracy of the taxi-out time predictions by more precisely capturing the state of the system, and through standardized and clearly defined OOOI event times.

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