A STOCHASTIC DYNAMIC PROGRAMMING APPROACH TO TAXI-OUT PREDICTION USING REINFORCEMENT LEARNING

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Abstract

This research is driven by the critical need for a technological breakthrough in taxi-out prediction, and intelligence-based decision making capabilities for an airport operating system. With the advent of sophisticated automation, the use of information-driven intelligent decision support system (IIDSS) to control service operations such as airport has become a necessity to ensure efficiency and throughput. However, airlines, airports, and air traffic controller (ATC), still lack the use of intelligent systems that can assist them in delay prediction, schedule adjustments, and optimal decision making in the face of uncertainties. As per U.S. Govt. Joint Program Development Office's roadmap, new technology is needed to accurately predict delays and efficiently utilize the existing capacity to support the Next Generation Air Transportation System (NGATS). Hence, new research is needed to accurately predict taxi-out times which in turn can assist in making schedule adjustments to reduce congestions and delays, and provide a means for better utilization of ground staff of the airlines. We propose a novel reinforcement learning (RL) based stochastic approximation scheme for predicting taxi-out times that was tested on data from Detroit Metropolitan Wayne County International Airport (DTW). Initial results show that the average prediction error for >80% of the flights are <3 min.

Introduction

Flight delays are one of the most pressing problems that have far reaching effects on both the society and nation's economy. The United States National Airspace System (NAS) is one of the most complex networked systems ever built, and has several components to it. The major components include the administration, control centers, airports, airlines, aircrafts, and passengers. The complexity of NAS poses many challenges for its efficient management and control. One of the challenges includes reducing flight delays. Delays propagate throughout the system and it increases with time over the length of the day. This is known as the cascading effect and it means that there are fewer delays in the morning than in the evenings. Delays result in losses for the airlines via cancellations, increased passenger complaints, and difficulty in managing the airline and airport operations since both gate operations and air traffic controllers (ATC) could simply be overwhelmed at certain peak hours by too many take-offs and landing aircrafts. Delays are caused by several factors. Some of these include increases in demand, near capacity operation of the major hubs (leads to congestion), weather, and air traffic management programs such as the ground delay program (GDP). GDP is said to be in effect, when an aircraft is held at the gate of the origin airport due to delays experienced at the destination airport. Hence, it is necessary for all stakeholders (the Federal Aviation Administration (FAA), airlines, Passengers (PAX), and the ATC) to stay informed, understand the causes, and find solutions to predict and mitigate the delays. The delay phenomenon is continuously evolving, and is both stochastic and elastic. The stochastic nature is due to the uncertainties that lie at the local level (such as the local control tower, arrival/departures movements on ground, human causes), system level (such as GDP), and in the environment (weather). The elastic behavior is due to the fact that delay could be adjusted (positively or negatively) by flying speed, taking alternate routes, turnaround time on the ground, position in the departure clearance queue especially during busy hours of the airport. Thus, total delay of a flight segment from its origin to destination comprises of turn-around time delay, gate-out delay, taxi-out delay, airborne delay, taxi-in delay, and gate-in delay. Among these delay elements, historical data indicates that, taxi-out time contributes to over 60% of the total delay. Hence, it is imperative to minimize taxi-out delay, which we believe has a significant impact on the efficiency of airport operations and on the performance of the entire NAS.

In order to minimize taxi-out delay, it is necessary to accurately predict taxi-out under dynamic airport conditions. This information in turn will allow the airlines to better schedule and dynamically adjust departures, which minimizes congestions, and the control towers will benefit from smoother airport operations by avoiding situations when demand (departure rates) nears or exceeds airport capacity. There is also a great potential for increased and efficient utilization of the airport capacity, which is one of the key focus items of NGATS, as per the report from Joint

Program and Development Office (JPDO) [1]. This will also lead to significant improvement in the capabilities for Flow Contingency Management and Tactical Trajectory Management, and will benefit the implementation of an holistic Total Airport Management (TAM) system [11]. As an example of a future concept of automating airport control towers and Terminal Radar Control (TRACON) operations, it will be necessary to predict airport dynamics such as taxi-out times, and feedback this information for aiding artificial intelligence-based decision making at airport operational level. Improved taxi-out time prediction can be used by airline operating centers (AOC), and airline station operations to increase utilization of ground personnel and resources.

The primary objective of this research is to accurately predict ground delays (taxi-out time) at major airports, in the presence of weather and other unexpected events, by developing and validating a artificial intelligence based RL model (a strand of Approximate Dynamic programming, ADP). The taxi-out prediction problem is cast in the framework of probabilistic dynamic decision making and is built on the mathematical foundations of dynamic programming, and machine learning. The methodology is tested using data from the Aviation System Performance Metrics (ASPM) data base maintained by Federal Aviation Administration (FAA). In particular the study was conducted on ASPM data for Detroit Metropolitan Wayne County Airport (DTW). In the next section we review some of the related literature in the area of taxi-out prediction and artificial intelligence based prediction and control methods.

Motivation and Related Literature

Many recent studies have proposed different methods to predict and then use the prediction to minimize taxi-out times. One such study is to predict gate push back times using Departure Enhanced Planning And Runway/Taxiway-Assignment System (DEPARTS) [2], in which the objective for near-term departure scheduling is to minimize the average taxi-out time over the next 10 to 30 minutes, to get flights into the air from the airport as early as possible without causing downstream traffic congestion in the terminal or en route airspace. DEPARTS uses a near-real time airport information management system to provide its key inputs, which it collects from the airport's surface movement advisor (SMT), and recommends optimal runway assignment, taxi clearance and takeoff clearance times for individual departures. The sensitivity of taxi-out delays to gate push back times was also studied using DEPARTS model. Other research that develops a departure planning tool for departure time prediction is available in [3]-[7], [12], [14]. Direct prediction of taxi-out times has been presented to literature. Such direct predictions attempts to minimize taxi-out delays have been done using accurate surface surveillance data [8] [9]. One such work is presented in [10] which uses surface surveillance data develops a bivariate quadratic polynomial regression equation to predict taxi time. In this work data from Aircraft Situation Data to Industry (ASDI) and that provided by Northwest Airlines for DTW (Flight Event Data Store, FEDS) were compared with surface surveillance data to extract gate OUT, wheels OFF, wheels ON, and gate In (OOOI) data for prediction purposes. Algorithms such as space time network search which uses Dijkstra's algorithm and event based A* algorithm and co-evolution based genetic algorithm have been compared for taxi-time prediction in [15]. Cheng *et al.* [18] studied aircraft taxi performance for enhancing airport surface traffic control in which they consider the surface-traffic problem at major airports and envisions a collaborative traffic and aircraft control environment where a surface traffic automation system will help coordinate surface traffic movements. Specifically, this paper studies the performance potential of high precision taxi toward the realization of such an environment. A state-of-the-art nonlinear control system based on feedback linearization is designed for a detailed B-737 aircraft taxi model. Other research that has focused on departure processes and departure runway balancing are available in [13] and [19]. Many statistical models have evolved in recent years which considers the probability distribution of departure delays and aircraft take-off time for taxi-time prediction purposes [17] [20]. For example, queuing models have been developed for taxi time prediction as in [16]. A Bayesian networks approach to predict different segments of flight delay including taxi-out delay has been presented in [21].

With the advent of sophisticated automation techniques and the need to automate airport functions for efficient surface flow movements, the use of information-driven intelligent decision support system (IIDSS) to predict and control airport operations has become a necessity. However, industry still lacks the use of intelligent reconfigurable systems that can autonomously sense the state of the airport and respond with dynamic actions continuously. Thus, in many cases decisions are still dependent on human intervention, which are based on local considerations, which are often not optimal. One of the primary reasons for this deficiency is the lack of comprehensive tools for achieving 'automation in decision making' and validated procedures that can simultaneously look at the whole system dynamics, account for uncertainties, and suggest optimal decisions, which can be used by airline and traffic controllers to improve the quality of airport operations. As a first step in the direction of developing such an IIDSS for the entire airport, this paper presents a novel method that uses artificial intelligence to predict taxi-out time, which can be fed back for making optimal schedule adjustments to minimize taxi-delays and congestions. This approach overcomes many limitations of regression model based approaches with constant parameters that are not suitable in the presence of adverse events such as weather that affect airport operations. Another limitation arises due to the complex nature of airport operations and the uncertainties involved, which often make it difficult to obtain mathematical models to describe the complete airport dynamics. In such situations model-free learning based techniques can perform better that model based approaches. A unique feature of this model free approach is its adaptive nature to changing dynamics of the airport.

Learning-based model-free prediction and control systems, though has been in existence, its potential has not been fully explored. The word model-free is often a misnomer since it is understood as a lack of mathematical construction. Typically, these systems use some form of artificial intelligence such as neural networks, fuzzy-logic rules, and machine learning and have very strong mathematical foundations underlying their construction. These intelligent controllers have been tested on robots and hierarchical manufacturing systems as well. Some of these systems, particularly neural networks and fuzzy-logic rules, though are claimed to be model-free, do contain certain hidden or implicit models, and make certain strong modeling assumptions when it comes to proving the stability of the controller. Hence, data-driven machine-learning-based controllers (presented below) are preferred, and they have been shown to be more effective than neural networks and fuzzy-logic based controllers. However, their wide spread use in the industry has been limited due to the lack of comprehensive studies, implementation procedures, and validation tests. The above types of learning-based prediction and control can be further classified based on three major learning paradigms. These are supervised learning, unsupervised learning and reinforcement learning (a strand of ADP).

Neural network based prediction and control schemes use supervised or unsupervised learning. In a supervised learning, the learner is fed with training data of the form (x_i, y_i) where each input x_i is usually an n-dimensional vector and the output y_i is a scalar. It is assumed that the inputs are from a fixed probability distribution. The aim is to estimate a function f in $y_i=f(x_i)$ so that the y_i can be predicted for new values of x_i. For a successful implementation of neural network using supervised learning, the training data samples must be of good quality without noise. The learning of the weights on the network arcs during training is usually done using the backpropagation algorithm. In unsupervised learning there is no a priori output. The network self organizes the inputs and detects their emergent properties. This is useful in clustering and data compression but not very useful in control where corrective actions based on outputs are desired. The model-free (information-driven) reinforcement learning-based (RL) control, a simulation-based optimization technique, is useful when examples of desired behavior is not available but it is possible to simulate the behavior according to some performance criteria. The main difference from supervised learning is that there is no fixed distribution from which input x is drawn. The learner chooses x values by interaction with the environment. The goal in RL is not to predict y but to find an x^* that optimizes an unknown reward function $R(x)$. The learning comes from long term memory. In what follows we describe the advantages of reinforcement learning-based control.

Why a Reinforcement Learning-Based Model-Free Prediction and Control?

These RL-based prediction and control methods are built on strong mathematical foundations of approximate dynamic programming (ADP) are an excellent way to obtain optimal or near-optimal control of many systems. They have certain unique advantages. One of the advantages is their adaptive nature and flexibility in choosing optimal or near-optimal control action from a large action space. Moreover, unlike traditional process controllers, they are capable of performing in the absence of process models and are suitable for large-scale complex systems. They can also be trained to possess auto-reconfigurability.

Machine learning based controllers use stochastic approximation (SA) methods, which have been proved to be effective for control of non-linear dynamic systems. In this method the controller is constructed using a function approximator (FA). However, it is not possible for a model-free framework to obtain the derivatives necessary to implement standard gradient-based search techniques (such as back-propagation) for estimating the unknown parameters of the FA. Usually such algorithms for control applications rely on well-known finite-difference stochastic approximations (FDSA) to the gradient. The FDSA approach, however, can be very costly in terms of the number of system measurements required, especially in high-dimensional problems for estimating the parameters of the FA vector. This led to the development of simultaneous perturbation stochastic approximation (SPSA) algorithms for FA, which is based only on measurements of the system that operates in closed-loop [23]. Among the several variants and applications of SPSA, the implementation of SPSA in simulation-based optimization using RL offers several advantages in solving many stochastic dynamic sequential decision-making problems of which the prediction and control problem is a subset. RL (a strand of ADP) is a method for solving Markov decision processes (MDP), which is rooted in the Bellman [24] equation, and uses the principle of stochastic approximation (e.g. Robbins-Monro method [25]). Howard first showed how the optimal policy for a MDP may be obtained by iteratively solving the linear system of Bellman equations. Convergent average reward RL algorithms can be found in [26].

In what follows we demonstrate the reinforcement learning (RL) based taxi-out prediction methodology.

RL Based Prediction Methodology

The RL based functional block diagram for taxi-out prediction is shown in Figure 1. The system state $X = (x1,x2,x3,x4)$ is defined as the number of flights in the departure queue waiting for take off *(x1)*, number of departing flights taxiing *(x2)*, number of arriving flights that are taxiing *(x3)* and the average taxi time in the last 30 minutes from current time *(x4)*. A flight is said to be waiting in the departure queue if it has exceeded the nominal taxi time and has still not departed. The purpose of the RL estimator is to predict taxi out time given the dynamic system state. The dynamic system state evolution is modeled as a Markov chain and the prediction process is modeled as a Markov decision process. The MDP process is solved using RL based stochastic approximation schemes. The input to RL is the system state and the output of the learning process is a reward function $R(X,P)$ where P is the predicted taxi out values. The utility function (reward) $R(X,P)$ is updated based on the difference between the actual an predicted taxi-out values. Mathematical details of the RL based prediction methodology are available in [22] and is not presented here for the sake of brevity.

As seen from Figure 1, the scheduled arrivals and departures up to *t+45* minutes was used to obtain the system state X where t is the current time. 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 30 minutes from its scheduled departure time. 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, its taxi-out time will be predicted at least 15 times. To calculate average taxi-out times before current time t, actual flight data between t and *t-30* are used.

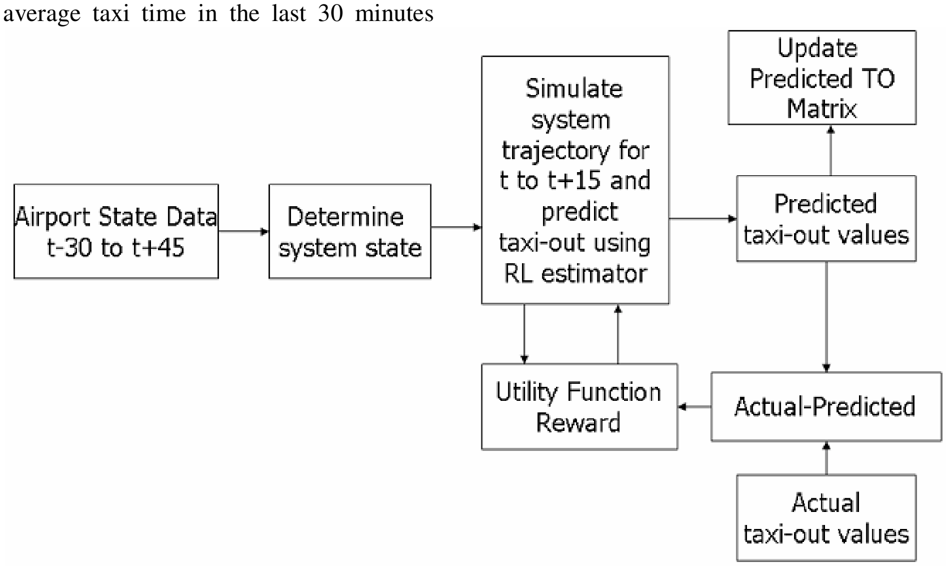

Figure 1: RL Based Functional Block Diagram for Taxi-Out Prediction

Data Source

OOOI data for DTW airport was extracted from the Aviation System Performance Metrics (**ASPM**) data base maintained by Federal Aviation Administration (FAA). The data from 1st May 2006 to 26th July 2006 was used to train the RL based Taxi-out time predictor. Testing was done on data from July 27th to July 31st 2006 and on Jan 2006 data.

The following were extracted from the ASPM database for each individual flight: flight number, actual on time (ACTONTM), actual in time (ACTINTM), actual out time (ACTOUTTM), actual off time (ACTOFFTM), scheduled out time (SCHOUTTM), actual taxi out time (ACTTO), actual taxi in time (ACTTI), nominal taxi in time (NOMTI), and nominal taxi out time (NOMTO).

Model Evaluation

A common model valuation metric is the mean square error (MSE) between the actual and predicted taxi-out values. Also mean, median and standard deviation of the actual and predicted taxi-out times were compared. The RL based estimator was coded using Matlab software.

Results from Prediction Analysis

In this section we present some of the preliminary results obtained from using our RL based methodology for predicting taxi out time.

Figure 2 shows a plot of departure and arrival demand and actuals (ETMS values) plotted along with the airport arrival (AAR) and departure (ADR) rates per quarter (15 minute time intervals) for data collected on 1st May 2006. An obvious pattern is the increase and decrease in arrival and departures that are almost staggered. A peak (dip) in departure is in a different quarter in comparison to the nearest arrival peak (dip). The difference between the departure peak (dip) and the nearest arrival peak (dip) is only 1-2 quarters.

The airport operated above its ADR and ARR many times in a day as shown by the ETMS values which have exceeded the ADR and ARR limits. Interestingly, the ETMS values follow the same pattern as the demand curves. This shows that the ATC has tried to meet the demand (arrival and departure) and at times have operated above the ADR and ARR to meet this demand. It was also noted that some days in May had high average taxi out time and some had low. However, the ADR and ARR were the same for such days. Hence, ADR and ARR was not used as a factor for prediction purposes. This means our TO calculations are based on schedules that are already affected by ADR and ARR.

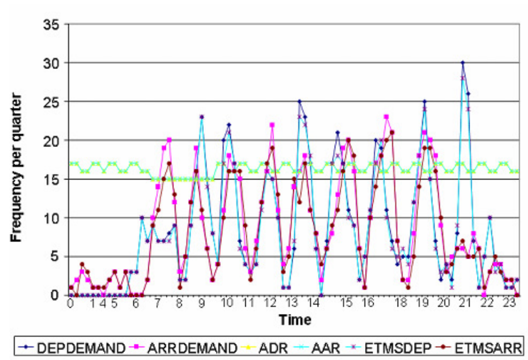

Figure 2: Arrival And Departure Demand Per Quarter

From Figure 3, It is interesting to observe that there is strong correlation between taxi-out time and factors that influence it. These factors include

- Number in departure queue (A flight is considered in queue if its real time TO has exceeded its unimpeded TO and the flight has still not taken off with respect to current time.)
- Number of departing flights that are taxiing queue (A departing flight is considered taxiing if its real time TO has not exceeded its unimpeded TO and the flight has still not taken off with respect to current time.)
- Number of arriving flights that are taxiing (An arriving flight is considered taxiing if its real time TI is before current time but Gate in has not occurred.)

As an example, take a flight at 8 AM GATE OUT (see bottom picture in Figure 3). You will notice that the Taxi out is decreasing (indicated as L) for flights between 8 and 8: 30 AM. You will notice that the factors above are also decreasing (at a low value) in the top picture of Figure 3 for the same time period. Also the ETMS departure and arrival is also at a low from Figure 2 for the same time period. They are all correlated.

Similarly from Figure 2 ETMS departure and arrival are at a low at around 9:45, 11:30, 13:00, 2:45, 4:45, 18:00, 20:30, 22:00 hours. The H and L of Figure 3 match one-on-one to this pattern.

Also, it can be observed that the red line lags behind the blue in Figure 3 (top picture). This shows the queue builds as number of taxiing flights increase beyond a threshold. Clearly the above factors influence taxi out time and are used in system state. It also shows that it's necessary to consider the behavior of the above factors over a time period (say 30 min) from the scheduled gate out time to make an accurate prediction of taxi out time based on predicted airport dynamics. It will be incorrect to predict taxi out by looking at the ground condition only at the instant of departure.

As mentioned earlier for a 15 min interval there will be 15 predictions for each flight, unless the flight leaves earlier than the scheduled time. These 15 predicted values can be combined into a single value by averaging or weighted averaging. This weighted value will be compared with actual taxi out time to obtain mean square error.

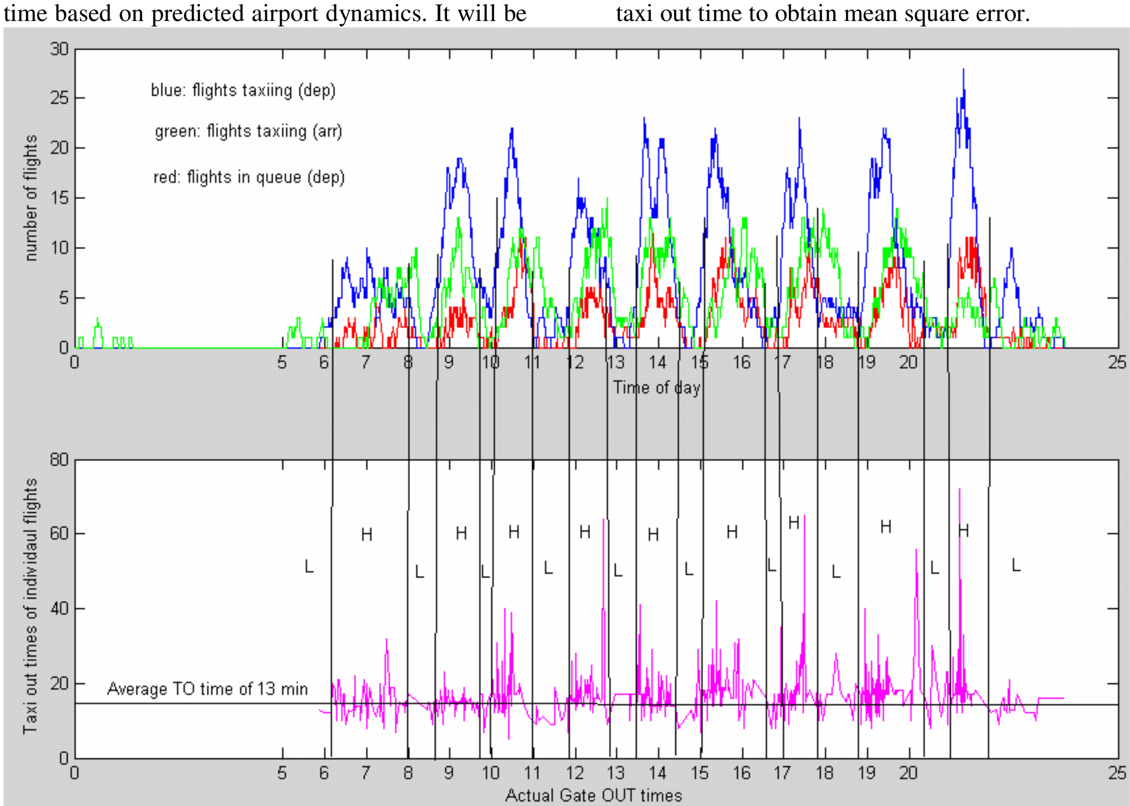

Figure 3: Plot of # of taxiing flights, queue length, and actual taxi out times for May 1st 2006.

Due to lack of gate and runway allocation information from ASPM database, if 2 runways are for departures, then a queue size of 15 would mean about 7-8 flights in each runway. It is assumed that runways are used equally. It is also assumed that the nominal TO time is an indicator of the nearness of the runway from the gate. Accuracy of predications will be improved if exact gate and runway allocations are obtained. Also size of aircraft was not considered in the prediction algorithm.

Figure 4 shows the histogram of actual and predicted taxi out time for July 28^{th} 2006. It can be observed that the spread of the predicted values are less than the actual. This also observed from the standard deviation values of actual and predicted taxi out times in Table 1.

Date: July 2006	27	28	29	30	31
Mean actual taxi out time	19.59	16.27	15.93	17.70	17.04
Std. dev. actual taxi out time	6.89	5.08	4.90	5.83	5.12
Mean predicted taxi out time	17.07	16.80	16.22	17.27	17.13
Std. dev. predicted taxi out time	3.04	2.50	2.59	3.04	2.77
Median actual taxi out time	18.00	16.20	15.00	16.80	16.20
Median predicted taxi out time	17.00	16.88	16.20	17.45	17.15
% flights with MSE <3.0	73.00	82.00	82.00	78.00	79.00
MSE	3.04	2.83	2.90	3.19	2.92

Table 1: Taxi out prediction metrics for July 27-31 2006

In general it was observed that the prediction was not accurate for flights with high taxi out times of >25 minutes. These account for about 10-15% of flights in a day. Also, from Table 1, if the MSE were to be restricted to <3 min, only about 80% of the flights would satisfy this criteria. It is to be noted that all flights (commercial, cargo) were considered, and an outlier analysis was also not done. Hence, there is a scope for improvement in prediction accuracy with more learning data and eliminating flights with >35 minutes taxi out times during the learning phase.

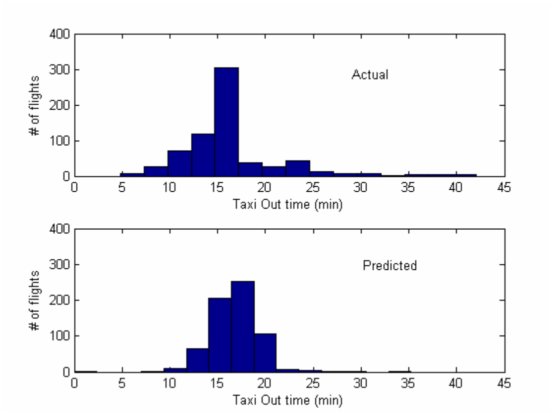

Figure 4: Histogram for actual and predicted Taxi out time for July 28th 2006.

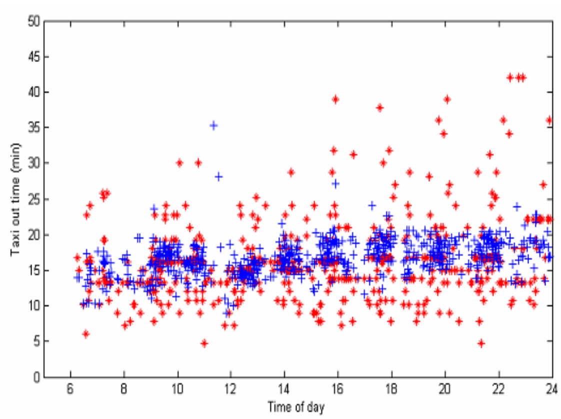

Figure 5: Actual (red) and predicted (blue) Taxi Out Time for July 28th 2006

Figures 5 and 6 shows actual and predicted taxi out times for July 28th and 27th 2006, respectively. It can be observed that there are many flights exceeding 25 minutes of actual taxi out time and July 27th has a higher average taxi out time than July 28th. This is also indicated in Table 1. Correspondingly the prediction of taxi out times for July 27th is less accurate than July 26th for flights having >25 min actual taxi out time.

A similar prediction was done for flights in the month of January 2006 and similar results were obtained. It is to be noted that the above findings are preliminary results from our ongoing research. Further analysis to capture seasonal trends and incorporation of runway and gate assignments could improve prediction accuracy. Also study of other majors hubs are part of ongoing research.

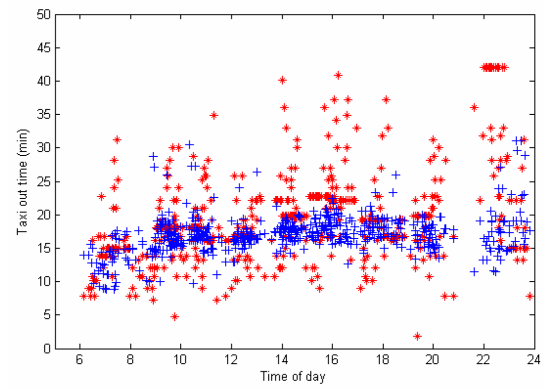

Figure 6: Actual (red) and predicted (blue) Taxi Out Time for July 27th 2006

Conclusions

This paper presents a new artificial intelligence based taxi out time prediction technique that adapts to changing airport dynamics. The method is based on the theory of stochastic dynamic programming and is solved using reinforcement learning techniques. Initial results presented show high correlation of taxi out time with queue time, and number of arriving and departing flights that are taxiing. Using data from ASPM database, approximately 80% of the flights were predicted with a MSE of less than 3 min. The predicted standard deviation is also less than 3 min for all flights in a given day. It is expected that both control tower operations and airline scheduling can benefit from this prediction by adjusting schedules to minimize congestion and delays, and by better utilization of ground personnel and resources. Accurate taxi out predication that results in minimized delays and better scheduling can also impact 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 (CDM) that envisions automation of several airport operations.

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Disclaimers

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