Intelligent Departure Metering Advisory Tool (I-MATE) for Airport Airside Congestion Management

Hasnain Ali*
Mechanical and Aerospace Engineering
Nanyang Technological University
Singapore, 637460
hasnain.ali@ntu.edu.sg

Sameer Alam
Mechanical and Aerospace Engineering
Nanyang Technological University
Singapore, 637460
sameer.alam@ntu.edu.sg

Abstract

Airport airside taxi delays significantly impact airlines, passengers, and the environment. Departure Metering (DM) is an effective approach to contain taxi delays by controlling departure pushback timings. In this work, we demonstrate the potential of Deep Reinforcement Learning (DRL) based DM method to reduce taxi delays by effectively transferring delays from taxiways to gates. This work casts the DM problem in a markov decision process framework to train a DM policy over simulations generated using historical airport surface movement data. We further develop an Intelligent Departure Metering Assistant Tool (I-MATE) that employs the trained DM policy to recommend pushback advisories to Air Traffic Controller (ATCO). We conducted validation experiments to assess the efficacy and acceptability of I-MATE in assisting ATCOs to manage airside traffic. The results reveal a significant reduction in taxi delays (25.6%) with increased compliance with I-MATE recommendations, which may translate to improved efficiency, cost savings for airlines, and enhanced passenger experience. While increased compliance reduced taxi delays, a slight decrease in runway throughput (3.2%) was also observed. This suggests a potential trade-off between optimizing runway usage and minimizing delays. The study also reveals a spectrum of compliance among ATCOs, influenced by factors like experience and age. Qualitative feedback indicates high user satisfaction with I-MATE, suggesting its usefulness, reliability, and trustworthiness. This research underscores the value of AI-based decision support systems for air traffic control, thereby paving the way for further advancements in airside traffic management.

1 Introduction

Airport taxi delays cost millions in excess fuel burn, cause missed connections, and contribute to increased carbon emissions Ali et al. [2022b, 2019b,a]. Effectively addressing taxi delays necessitates the synchronization of stochastic and uncertain airside operations, encompassing aircraft pushbacks, taxiway movements, and runway take-offs. Airport Departure Metering (DM) offers a potential solution to reduce taxi delays by coordinating aircraft pushback timings. This approach aims to improve airside traffic flow, ensuring on-time takeoffs while preventing large queue formation on the airside Feron et al. [1997]. State-of-the-art DM tools employ model-based control policies that depend on simplified airside departure models Ali et al. [2020], Ali [2022], Ali et al. [2024b]. These models inherently involve simplifying assumptions, limiting their ability to capture the full complexity of real-world airside scenarios—leading to poor performance of DM tools under uncertainties Mori [2019], Badrinath et al. [2020]. Moreover, since the effects of pushback approvals are realized much

*Webpage:https://hasnainiitd.github.io/

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later (typically, after 10-15 minutes of aircraft taxiing to the runway), ATCOs find it challenging to consider uncertain runway traffic forecasts in their DM decisions effectively.

This study presents the Intelligent Departure Metering Advisory Tool (I-MATE), an AI-based DM assistant that recommends pushback timings to ATCOs to reduce taxi delays while maintaining runway throughput. I-MATE introduces a model-free and simulation-based learning of DM control policy by adopting a Deep Reinforcement Learning (DRL) approach. DRL has demonstrated remarkable potential in performing tasks that demand a careful balance between immediate actions and delayed rewards or outcomes Sutton and Barto [2018]. By iteratively learning from experience and adjusting policies (strategies) based on feedback, DRL systems can optimize decision-making processes in dynamic and uncertain settings. DRL formulates DM as a Markov Decision Process (MDP), yielding state, action, reward, and next-state sequences. Its goal is maximizing the discounted sum of future rewards Ali et al. [2021]. The simulated Singapore Changi Airport environment, which incorporates stochastic and uncertain spatial-temporal interactions between aircraft, is designed and implemented. For a detailed description of the implemented MDP design (see Figure 1), including states, actions, and rewards used for policy learning, please refer to the work Ali et al. [2022a]. This centralized DM agent, using "spot metering" at terminals, learns to optimize taxi-out times for simulated airside traffic scenarios, with minimal impact on runway throughput.

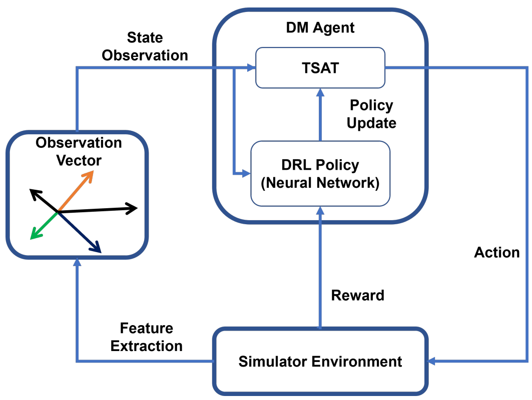

Figure 1: Proposed framework for DRL approach to the DM problem. State observation features extracted from the simulation environment serve as inputs to the training of the DRL based DM policy. The policy generates Target Startup Approval Time (TSAT) actions, either holding or releasing departure aircraft, which impact the environment state. A centralised DM agent is trained based on step and cumulative reward signals to co-ordinate aircraft pushback decisions for minimizing taxi delays.

This study also assesses the efficacy and acceptability of I-MATE in assisting ATCOs to manage airside traffic. To the best of our understanding, this is the first study that evaluates the efficacy of an AI assistant tool in assisting ATCOs to manage airside traffic. Metrics such as taxi delay reduction, runway throughput, and subjective feedback on acceptability and situational awareness will be evaluated. Furthermore, the study will evaluate adherence to I-MATE recommendations and examine the impact of various factors, including experience and age, on decision-making processes among ATCOs. Qualitative feedback from ATCOs will also be collected to assess the acceptability of I-MATE, providing insights into potential areas for improvement Ali et al. [2024a].

2 Intelligent Departure Metering Advisory Tool

I-MATE is designed to assist ATCOs in managing airside traffic through an intuitive, interactive interface that balances data clarity with efficient workflows (refer to the Figure 2). Key features include real-time updates, visualizations of taxi delays and runway throughput, and proactive conflict alerts to enhance situational awareness and decision-making. The interface supports pushback approvals, route visualization, and interactive controls, allowing ATCOs to efficiently respond to changing traffic conditions. The ability to record and analyze ATCO interactions with I-MATE is crucial for ongoing improvement. I-MATE's interface facilitates this by capturing data on recommendations provided, actions taken, and response times. This data can then be used to refine I-MATE's recommendations, user experience, and overall effectiveness over time.

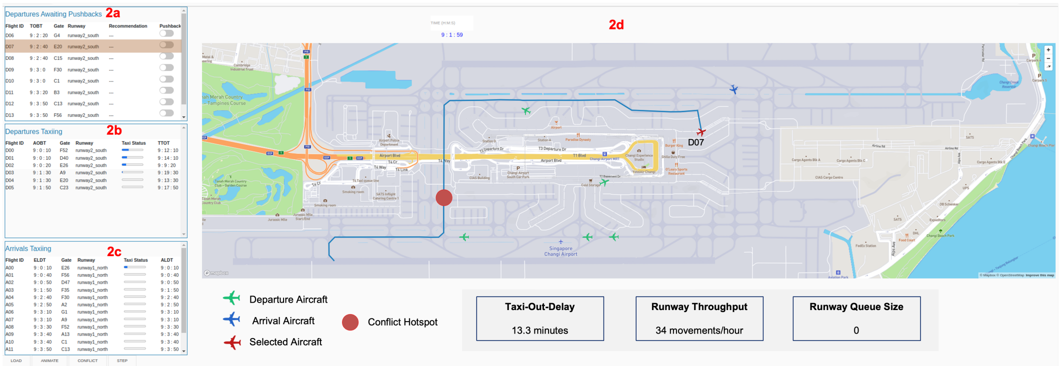

Figure 2: Interactive interface design of I-MATE. Figure 2a represents planned departure information alongside pushback recommendations and controls. Figure 2b represents taxiing information of departures after pushback. Figure 2c represents planned and taxiing information for arrivals. Figure 2d represents the traffic state with additional traffic statistics on the airside map.

3 Validation Scope and Objective

Each Air Traffic Controller (ATCO) is presented with multiple airside traffic scenarios where they approve pushback requests for departures from their respective gates. The primary goal is to optimize runway throughput by enabling the quickest possible departures while minimizing taxi-out delays. The validation of I-MATE is conducted using two key metrics: **Taxi-out-Delay** and **Runway Throughput**.

Taxi-out delay is calculated as the difference between the actual taxi-out time and the unimpeded taxi-out time, where the unimpeded time is determined based on the taxi path length (l_i) and maximum allowable taxi speed (v_i^{max}) of each aircraft using the formula:

$$TOT_i^{unimpeded} = \frac{l_i}{v_i^{max}} \tag{1}$$

The average taxi-out delay (TOT^{delay}) across all departures is given by:

$$TOT^{delay} = \frac{\sum_i (TOT_i^{actual} - TOT_i^{unimpeded})}{k} \tag{2}$$

where k is the number of departures in the scenario. Runway throughput (R), representing the maximum number of aircraft taking off from a runway per hour, is computed by:

$$R = \frac{k}{T} \tag{3}$$

with T being the total scenario time to serve k departures.

The experiment includes three traffic scenarios, each lasting up to 20 minutes with 10 departures and 10 arrivals using runway configuration 02L/02C. The first scenario is a familiarization exercise to help ATCOs get accustomed to I-MATE. The subsequent two scenarios are used to evaluate I-MATE's performance based on the defined metrics. These scenarios are designed to have similar spatial and temporal characteristics by distributing taxi routes across terminals and runways to achieve an average unimpeded taxi-out time of around 10 minutes, while scheduling aircraft movements to occur within the first 10 minutes of the simulation.

(a) Deviation of pushback approvals. (b) Reduction in runway throughput. (c) Reduction in taxi-out delays.

Figure 3: Impact of ATCO compliance with I-MATE recommendations on pushback approvals (left), runway throughput (center), and taxi-out delays (right).

4 Results and Inference

This study reveals a nuanced picture of human behavior in following advisories provided by decision support systems. As shown in Figure 3, there is variability in ATCOs' compliance with pushback recommendations, with some ATCOs adhering closely (e.g., ATCOs D and G), while others show partial or minimal compliance (e.g., ATCO C). This variance suggests that factors such as experience, workload, and situational awareness influence decision-making.

Higher compliance with I-MATE recommendations in the second scenario resulted in a notable reduction in average taxi-out delays, decreasing from 16.4 to 12.2 minutes (a 25.6% improvement). Conversely, this increased adherence led to a slight decrease in runway throughput, from 37 to 35.8 take-offs per hour (a 3.2% reduction). This trade-off indicates that while ATCOs focused on minimizing taxi delays, it came at the cost of a minor decrease in departure efficiency, likely due to a more conservative gate release strategy. Overall, the benefits in reduced taxi delays outweigh the marginal impact on runway throughput, demonstrating the effectiveness of decision support advisories in optimizing ground operations.

5 Conclusion

This study investigated the application of decision-making (DM) systems to reduce taxi delays by optimizing departure pushback timings, utilizing an Intelligent Departure Metering Advisory Tool (I-MATE). The I-MATE framework, grounded in a Markov Decision Process (MDP) and trained via Deep Reinforcement Learning (DRL) on historical airside data simulations, demonstrated its effectiveness in providing pushback advisories and managing airside traffic. Validation experiments with Air Traffic Controllers (ATCOs) in simulated scenarios affirmed I-MATE's utility, revealing significant reductions in taxi delays (25.6%) with a slight decrease in runway throughput (3.2%).

Qualitative feedback from ATCOs confirmed the system's high reliability, accuracy, and trustworthiness. However, some ATCOs expressed the need for improved visual alerts, indicating areas for refinement in user interface design. The varying compliance rates among ATCOs suggest that factors such as training, experience, and cognitive preferences influence their interaction with decision support systems. Despite this, I-MATE's role in improving operational efficiency and reducing congestion-related delays was clear, making a positive impact on airside safety and airline costs.

The study highlights the need for balanced decision-making strategies, as optimizing runway throughput and minimizing taxi delays involve trade-offs. Future work could focus on refining I-MATE's algorithms to better balance these objectives and personalize recommendations based on individual ATCO preferences and cognitive styles. Additionally, conducting real-world validation studies to assess the long-term operational and economic impacts of such systems could further enhance their performance. By addressing these aspects, we can continually improve decision support systems like I-MATE, contributing to a safer, more efficient, and sustainable air traffic management system.

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