International Journal of Engineering Research in Computer Science and Engineering Engineering (IJERCSE) Vol 2, Issue 3, March 2015

Securing Data in Cloud Using Session Key

[1] Miss. Dolly Patel, [2]Miss. Farheen Khan, [3]Miss. Ashwini Malode, [4]Miss. Komal Bhatia
Guided by Prof. Sujit A. Ahirrao Department of CSE, BE Students, Sandip foundation, Nashik, 422001, India
[1] 3211maahi@gmail.com, [2]farheenk07@gmail.com, [3]ash.malode@gmail.com[4],kmbhatia13@gmail.com.

Abstract — **Cloud computing provides quick delivery of services and it provides benefits from low-cost and pay-by-use model. Cloud computing is very flexible it poses great threat to security of user data as user user fully trust o cloud services and data is transparent to the user. So there are many existing systems which provides security to the cloud and user data but there is no security mechanism for the data transmission or the data path. Therefore our system is focusing on the data transition path in which user can safely access and update the data on cloud. So our project provides session key for securing data transition path. The user will autonomously interact with the cloud without the external interface .We pay more attention on synchronizing and access rights to the user.**

Index Terms — Cloud computing,Security,Session Key.

I. INTRODUCTION

Air Transportation has been progressing at a very fast pace, which has brought great pressure on the airline industry to reduce the flight delays and keeping up the on time performance of flights. The delay phenomenon at the airport has been categorized so that the officials have an accountability of the delay reason. The various categories are Passenger and Baggage Delays, Weather delays, Air Traffic Flow Management Restrictions (ATFM), Engineering delays, delays due to Airport and Government Authorities, Crew movement, Reactionary delays, etc. Among these, most of the delays point to taxi-out time delays. For example, Reactionary delays are caused due one aircraft being delayed because of another aircraft. This other aircraft was late because of yet another aircraft, thus causing a reaction to each delay. The ATFM restrictions comprises of delays that are caused when there are aircrafts co-taxing for the runway, or when a flight is yet to land and the other aircrafts are waiting for its runway slot time. Accurate prediction of taxi-out time under uncertain airport conditions, allow the schedulers to allow the airlines to achieve a better schedule and dynamically adjust departures so as to avoid scenarios that nears or exceeds the capacity of the airport. According to the FAA more than 20% of total flight delays contribute to the taxi-out time delays. Predicting accurate taxi-out time has significant challenges because of the dynamic airport configurations and unexpected weather changes. An accurate prediction of the taxi-out time would lead to determine whether an aircraft meets its stipulated parking slot time, along its traffic flow.

At an airport, aircrafts compete for resources like the runways, taxiways, ramp and gates. A taxiway is a path on an airport that connects runways with ramps, terminals and gates. Taxi-out time is defined as the time between the chocks off (at the gate) and the wheels off (at the runway) of a flight departure. The Aviation System Performance Metrics (ASPM) falls under two categories: airport data and individual flight data. The Out Off On In timings from the individual flight data gives the details of an aircraft journey. A major function of Aircraft Communication Addressing and Reporting System (ACARS) is to automatically detect and report changes to the major flight phases (Out of the gate, Off the ground, On ground, and Into gate). Taxi-out time of a flight is calculated as follows:

Taxi-out time = Out Time – Off time … (1)

If an aircraft is scheduled to depart at 3:00 am, the brakes at the wheels of the aircraft are released at 3:00 am. The aircraft taxis from the ramp along the taxiway to the runway where it takes off at 3:12 am. Therefore, the taxi-out time taken is 12 minutes. If the aircraft wheels touch runway of the arrival station at 4:00 am, this time is noted as On Time. Again the aircraft taxis from the runway along the taxiway up to the ramp where the brakes are put on at 4:13 am. This time is noted as In Time. The block time of a flight is calculated as follows:

Block time = In time – Off time … (2)

The block time of the flight is the time between the chocks on time and chocks off time which is 1 hour 25minutes. The flight time is calculated as follows:

Flight time = Out time – On time … (3)

The accurate taxi-out time prediction will lead in fulfilling the estimated block and flight time and thus maintaining the On Time Performance of flights. Apart from that, the airlines will be able to cater to the single largest operating cost, i.e. fuel cost. Also, during peak hours, the passengers, Air Traffic Control (ATC) authorities, ground operations and pilots have to have a Collaborative Decision Making (CDM) process that would facilitate a smooth departure of the flight. A control over the flight delays would also compensate to the unexpected weather conditions. Often, due to prolonged waiting after gate pushback, aircrafts would have to go back to the gate for refueling. Compliance regulations can be met by a good taxi-out time prediction.

In this paper, based on the factors affecting the taxi-out time, a Markovian Decision Process (MDP) model is analyzed. A Reinforcement Learning (RL) approach based on time which when applied on the MDP model would encourage exploration of a more accurate prediction of taxi-out times. RL is identified as a promising approach that performs well for the specific characteristics of the decision making process for prediction of taxi-out times. This approach is a modernized Air Traffic Control (ATC) system with increased automation. Predictions are in real-time, as the system evolves. Due to uncertainties involved in the departure, and the complex nature of airport operations, it is often difficult to obtain mathematical models to completely describe airport dynamics. But, this can be addressed using reinforcement learning as this method is adaptive to changing airport dynamics. This paper proposes an MDP model for an RL approach with Q learning and Temporal Difference Algorithm to reduce taxi-out time. RL learns by interacting with the environment alleviating need for good training data. A literature review is carried out in the next section. Section III supports the development of the proposed system. Finally in Section IV a conclusion is made.

II. LITERATURE SURVEY

The departure process at Boston Logan International Airport is studied from the report by Idris and Hansman [2]. The main motive was to identify the ATFM restriction delays and inefficiencies in the airport departure process and to investigate the root causes of these restrictions and inefficiencies. 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 by regulating the flow even when the throughput is kept same.

The IATA put forth a handbook consisting of IATA codes in order to specifically assign accountability for various delay reasons [3]. Prominent among them were 93 K delays, which are reactionary delays. The reactionary delays occur when one aircraft is delayed because of another aircraft due to various reasons, majorly, due to waiting for another aircraft to arrive or depart at the aerodrome.

In a queuing model for prediction of taxi-out times, a takeoff queue size estimate is obtained by predicting the amount of passing aircrafts that it may experience on the airport surface while it is taxiing out, and by considering the number of takeoffs between pushback time and its takeoff time. Other research that develops a departure planning tool for departure time prediction is available in [4-8].

A Bayesian networks approach to predict different segments of flight delay including taxi-out delay has been presented in [9]. An algorithm to reduce departure time estimation error (up to 15%) is available in [10], 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 [11].

Direct predictions attempting to minimize taxi-out delays using accurate surface surveillance data have been presented to literature [12] [13]. Signor and Levy [14] discuss the implications of accurate OOOI (Gate Out, Runway Off, Runway On, Gate In) data for efficient resource utilization.

III. PROPOSED WORK

Reinforcement Learning (RL) is a learning method where the problem of sequential prediction is well-suited to the stochastic dynamic programming formulation. RL is a model free approach that is adaptive to changing airport dynamics. It is suitable for large-scale optimization due to its simple recursive formulation. RL is a learning method based on a feedback (reward) coming from the environment. The idea is that the learner controller) interacts with the system by applying changes (actions) while their effect is monitored through the reaction of the

International Journal of Engineering Research in Computer Science and Engineering Engineering (IJERCSE) Vol 2, Issue 3, March 2015

environment. Based on this, a policy is generated which tries to maximize the received reward. [1]

The use of a temporal difference (TD) based algorithm provides stable behavior. *V'* (*s*) is the updated value of a state *s* based on the previous state value *V* (*s*), and the temporal difference of the previous value of state *s* and the following state s', added to the immediate return r. Parameters a and *γ* are the learning rate and the discount factor, respectively. [1]

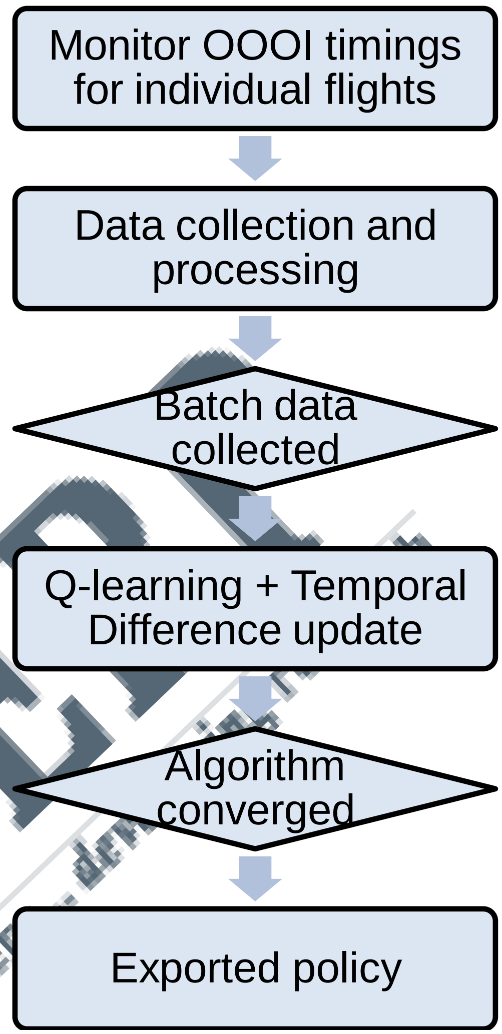
$$V'(s) = V(s) + a\left[r + \gamma V(s') - V(s)\right]$$

A Q-learning algorithm along with Temporal Difference algorithm is proposed. Q-learning algorithm is based on the TD update rule but instead of estimating the state value *V* (*s*), it estimates the state action value *Q* (*s*, *a*) based on the temporal difference of the current state action value and the maximum of the following state:

$$Q'(s,a) = Q(s,a) + a\left[r + \gamma \max_{a'} Q(s', a') - Q(s,a)\right]$$

In this paper, a *Q*-learning algorithm is applied within the learning framework, which uses the proposed MDP model. The algorithm estimates all the Q values of the state space based on a number of data sets fed offline. The data sets are in the form of episodes and for every episode the Q values are updated. In the end of every episode, a policy is extracted and updated by finding those actions that generated the biggest Q values. The same process goes until the algorithm has converged and the policy does not update any more. This is called experience reuse [1].

Fig.1 shows the experimental process flow chart. The individual flight data and operational data are first monitored and data is collected as experience sets, which relate the current state of the system with an action and the state after the change. The experience sets are collected in a database to compute the reward and for further analysis of the average taxi-out time. Once a complete batch of taxi-out time experiences has been collected, the batch Q-learning algorithm is applied until convergence has been achieved (Q-value change nearly 0). Then, a policy is extracted than can be used to recommend actions for known states when a new flight's taxi-out time needs to be predicted.



IV. CONCLUSION

In this paper, the first formal Markovian Decision Process (MDP) model and Reinforcement Learning (RL) approach have been reported for taxi-out time reduction. A formal MDP model was presented for the capture and analysis of the ramp-up process. The MDP states, action characteristics, and feedback reward were defined based on the technical characteristics of an aircraft departure process. An offline batch reinforcement learning algorithm has been developed, which utilizes the MDP to find the most optimal taxi-out time policy from a small number of previous taxi- out time experience cases. For reinforcement learning, a Q-learning algorithm along with a Temporal Difference gives a stable behavior to the stochastic environment. The proposed method requires some initial data to export a good policy. It is better suited generally for either repetitive taxi-out times of similar or the same stations after a disturbance or change.

V. REFERENCES

[1] Stefanos Doltsinis, Pedro Ferreira, and Niels Lohse, *"An MDP Model-Based Reinforcement Learning Approach for Production Station Ramp-Up Optimization: Q-Learning Analysis"*, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, VOL. 44, NO. 9, SEPTEMBER 2014

[2] Idris, Husni, John R. Hansman, *"Observation and Analysis of Departure Operations at Boston Logan International Airport",* Ph.D.Thesis, Massachusetts Institute of Technology, Cambridge, MA, url: http://hdl.handle.net/1721.1/8862,2001

[3]http://www.b737mrg.net/downloads/b737mrg_delaycodes.pdf

[4] Barrer, J.N., G.F. Swetnam, W.E. Weiss, *"The Feasibility Study of using Computer Optimization for Airport Surface Traffic Management"*, The MITRE Corporation, MTR89W00010, 1989

[5] Idris, H.R., B. Delcaire, I. Anagnostakis, W.D. Hall, N. Pujet, E. Feron, R.J. Hansman, J.P. Clarke, and A.R. Odoni, *"Identification of Flow Constraints and Control Points in Departure Operations at Airport System.",* Proceedings AIAA Guidance, Navigation and Control Conference, AIAA 98-4291, Boston, MA,1998

[6] Anagnostakis, I., H.R. Idris, J.P. Clarke, E. Feron, R J. Hansman, A R. Odoni, and W.D. Hall, *"A Conceptual Design of a Departure Planner Decision Aid"*, Presented at the 3rd USA/Europe Air Traffic Management R&D Seminar, Naples, Italy,2000

[7] Shumsky, R.A., *"Real Time Forecasts of Aircraft Departure Queues"*, Air Traffic Control Quarterly, Vol. 5(4), 1997

[8] Lindsay, K., D. Greenbaum, C. Wanke, *"Pre-departure Uncertainty and Prediction Performance in Collaborative Routing Coordination Tools"*, Journal of Guidance, Control, and Dynamics, Vol. 28(6), 2005

[9] Laskey, K.B., N. Xu, C-.H. Chen, *"Propagation of Delays in the National Airspace System",* Technical Report, url:http://ite.gmu.edu/~klaskey/papers/UAI2006_Delay.pdf, 2006

[10] Futer, A., *"Improving ETMS Ground Time Predictions"*, 25th Digital Avionics Systems Conference, 2006 IEEE/AIAA, pp.1-12, 2006

[11] Tu, Y., M.O. Ball and W. Jank, *"Estimating Flight Departure Delay Distributions -- a Statistical Approach with Long-Term Trend and Short-Term Pattern"*, Technical Report, U. of Maryland, 2005

[12] Clow, M., K. Howard, B. Midwood, and R. Oiesen, 2004, *"Analysis of the Benefits of Surface Data for ETMS"*, Volpe National Transportation Systems Center, VNTSC-ATMS-04-01, 2004

[13] Welch, J., S. Bussolari, S. Atkins, *"Using Surface Surveillance to Help Reduce Taxi Delays"*, AIAA Guidance, Navigation & Control Conference, AIAA-2001-4360, Montreal, Quebec, 2001

[14] Signor, D.B., and B.S. Levy, *"Accurate OOOI Data: Implications for Efficient Resource Utilization"*, Sensis Corporation 25th Digital Avionics Systems Conference, 2006

[15] Poornima Balakrishna, Rajesh Ganesan, Lance Sherry, *"Estimating Taxi-out times with a reinforcement learning algorithm",* Center for Air Transportation Systems Research, George Mason University, Fairfax, VA Benjamin S. Levy, Sensis Corporation, East Syracuse, NY, 2008