Modeling flight delay propagation in airport and airspace network

Qinggang Wu, Minghua Hu, Xiaozhen Ma, Yanjun Wang, Wei Cong, Daniel Delahaye

Modeling flight delay propagation in airport and airspace network

Qinggang Wu, Minghua Hu, Xiaozhen Ma, Yanjun Wang*
College of Civil Aviation
Nanjing University of Aeronautics and Astronautics
Nanjing, China
{qgwu, minghuahu, xzma, ywang}@nuaa.edu.cn

Wei Cong
Data analytic group
VariFlight company
Nanjing, China
congwei@variflight.com

Daniel Delahaye
OPTIM-Team/ENAC-LAB
Ecole Nationale de l'Aviation Civile
Toulouse, France
daniel@recherche.enac.fr

Abstract*—An Airport-Sector Network Delays model is developed in this paper for flight delay estimation within air transport network. This model takes both airports and airspace capacities into account by iterating among its three main components: a queuing engine, which treats each airport in the network as a queuing system and is used to compute delays at individual airport, a Link Transmission Model, which computes delays at individual sector and transmits all air delays into ground delays, and a delay propagation algorithm that updates flight itineraries and demand rates at each airport on the basis of the local delays computed by the queuing engine and flow control delays computed by the Link Transmission Model. The model has been implemented to a network consisting of the 21 busiest airports in China and 2962 links that represent to 151 enroute control sectors in mainland China, and its performance is evaluated by comparing with the actual delay data and results of Airport Network Delays model. It is found that the proposed model is well-suited for simulating delays in air transport system where either airports or airspace could be the bottleneck of the system.

Keywords—airport and airspace network; flight delays; delay propagation

I. INTRODUCTION

Minimizing flight delay is one of the major challenges in the air transportation industry today. Flight delay is usually defined as the difference between scheduled and actual arrival time. A complete flight consists of several segments: pushing back from origin airport gate, taxiing out to the runway, taking off, climbing, cruising through several sectors, landing, and finally taxiing to the arrival gate. At the gate, the aircraft waits for turn-around, after which it will continue to its next flight leg. Thus, the determination of delay is not easy since it can be caused by many factors during the whole operation such as airport capacity, severe weather conditions, sector capacity, maintenance, etc.

This paper presents a new model, Airport-Sector Network Delays model (ASND), which is a combination of Airport Network Delays (AND) model and Link Transmission Model (LTM) [1,2]. The model can approximately compute flight delays at each individual airport and sector in a network. More important, the model can help us to understand how flight delays that occur in a network will impact the performance of the whole system. Three biggest contributors to flight delays in China [3], predecessor flight delays, airport capacity constraints, and sector capacity constraints, are taken into account in this model.

Early research work focuses on flight delays in a single airport [4], while it may neglect the impact of predecessor flights from upstream airports. To minimize the effect of upstream flight delays, airlines normally insert some "buffer" in their flight schedule. For instance, when an aircraft is scheduled to be on the ground for turn-around process (after it arrives at gate/apron, there will be a series of process including unloading passengers/goods, refueling, cleaning, boarding etc.) at the airport for 45 minutes, it may actually require only 35 minutes to complete all the turn-around process, thus providing 10 minutes buffer. However, these buffers are unable to absorb longer delays that typically occur on a daily basis, thus leading to the propagation of delay in the network. In order to explore how flight delays propagate within a large network system, Nikolas Pyrgiotis et al. developed an analytical queuing-based network decomposition model [1]. The AND model operates by iterating between its two main components: a queuing engine (QE), which treats each airport in the network as a queuing system and is used to compute delays at individual airport, and a delay propagation algorithm (DPA) that updates flight itineraries and demand rates at each airport on the basis of the local delays computed by the QE. AND is well-suited for simulating delays in the United States as it has been validated by operating within a large network consisting of the 34 busiest commercial airports in the continental United States and comparing the system-wide results from AND with real observations of delays [1].

However, AND model does not consider sector capacity or compute flight delays caused by airspace constraints. In the United States it is a justified assumption: it has been reported that nearly 84% of air traffic delays are generated by airports in 2001 and 95% in 2005 [5,6]. Instead, in China, airspace capacity is a main factor that causes flight delays

[7]. In general, limited available airspace capacity is responsible for up to 20% of the total delays in 2005. By 2015, this proportion has increased to nearly 30% [8]. The main reason could be that air traffic volumes continuously grow at 10% per year, while available airspace for civil aviation is limited. The imbalance between airspace capacity and traffic becomes more and more serious. Therefore, airspace capacity must be taken into account when modeling flight delays propagation in China.

P.K.Menon's Eulerian model seems to be an effective tool to model realistic airspace involving multiple traffic stream [9]. Unfortunately, although it can simulate and adjust traffic in airspace, it can hardly perform the adjustment strategies on individual flight. Taking this into account, the combination of Menon's model and AND is extremely difficult. We then turn to the Eulerian-Lagrangian large-capacity cell transmission model(CTM(L)) for air traffic flow developed by Sun et al. [10], which is control volume based(Eulerian) and takes the origin-destination information of the aircraft(Lagrangian) into account. CTM(L) has three progressive levels. The primary level is link level, which can be viewed as the connection between the entry point and exit point in a specific sector. The number of cells in one link is scaled by a unit time. The secondary level is sector level model, and since there is no interconnection between different links in one sector, the link level model can be spontaneously extended to obtain the sector level model by gathering all links in the same sector. After merge/diverge nodes are added into the network, the tertiary level, multicommodity network level model is created by putting all sector level models together. Then high-altitude routes can be combined by several links from different sectors. The overall number of cells accounting for the length of a route is obtained by averaging flight time of historical trajectories. Since CTM(L) is based on the origin-destination information of flights, every individual flight can be distinguished when operating in the airspace, which prompts us with the possibility of a combination of CTM(L) with AND. Since almost all links have length that are longer than 1-minute interval in CTM(L) model and at the next time instant, only a portion of the aircraft in an upstream link will fly to the downstream link, Cao et al. then use links instead of cells as the most basic element to develop a new model named Link Transmission Model(LTM) [2]. By reducing the number of state variables to one tenth of CTM(L), LTM is about six times faster than CTM(L) while computing [11]. In addition, compared with CTM(L), another advantage of the LTM is that LTM is able to simulate and predict ground delays, by using a special link, defined as the first link of each path to represent the airport. But ground delays simulated by LTM are all caused by sector capacity. Although these delays occur on the ground, they are all transmitted from the air delays. LTM does not model the airport capacity and the influence among airports.

As we can see, AND and LTM seem to be complementary. AND can calculate flight delays due to airport capacity constraints and flight schedule then provide transmission coefficients as parameters into LTM, while LTM can compute delays due to sector capacity constraints between each pair of airports in AND for individual flights. Thus, it is advantageous to combine AND and LTM together. In this paper, a new model is developed taking both airports and airspace capacity into account, the Airport-Sector Network Delays model(ASND). ASND operates by iterating among its three main components: a QE, which is the same as that in AND, a LTM, which computes delays at individual sector and transmits all air delays into ground delays following the control strategy of China, and a delay propagation algorithm (DPA) that updates flight itineraries and demand rates at each airport on the basis of the local delays computed by the QE and flow control delays computed by the LTM.

The main contributions of the present paper are several. First, a unique model is constructed by combining AND and LTM. In the model, both airport capacity and sector capacity are taken into account. Second, A network consisting of the 21 busiest airports in China and 2962 links that refer to 151 continental en route control sectors is constructed. ASND is successfully validated in that network by comparing with the results of AND and the empirical flight delays.

The rest of paper is organized as follows. Section Ⅱ introduces ASND model and main algorithms when running the model. Section Ⅲ describes the simulation and validation of ASND for 21 busiest airports and related sectors. The comparisons of ASND and AND for computing flight delays in two typical days are carried out. Section Ⅳ provides a summary of conclusions and future work with ASND model.

II. Model Description

ASND is generally used to simulate one-day operation of flights, beginning at a time when there are little air traffic activities within the whole network (for example, 6 a.m. in China). An entire day is subdivided into m sub-periods, $T_1, T_2, \cdots, T_m$ of equal length. Here, we use $m = 96$, with each sub-period is 15 min. The five main steps of ASND are described as follows.

Step 1. At first, QE is run for all airports respectively in all sub-periods Each airport is modeled as a queuing system and its runway system is modeled as a single server that serves both arrivals and departures. At each airport, demand rates can be obtained from flights itineraries and service rates can be obtained from the capacity of the runway system. Let $p_{a,j}(t)$ denote the state probability that there are j aircraft in airport a at time t.The expected waiting time in queue, $W_{a,q}(t)$, is determined as follows:

$$W_{a,q}(t) \approx \frac{L_{a,q}(t)}{\mu_a(t)} = \frac{\sum_{j=1}^{N}(j-1)p_{a,j}(t)}{\mu_a(t)} \tag{1}$$

where $L_{a,q}(t)$ is the expected number of aircraft in airport a at time t, N is a sufficiently integer that denotes the capacity of the queue, and $\mu_a(t)$ is the service rate in airport a at time t. The detail information for computing $p_{a,j}(t)$ can be found in [12].

Step 2. For flight f, we define the following variables.

$o(f)$: origin airport of f

$d(f)$: destination airport of f

$SD(f)$: scheduled departure time of f

$AD(f)$: adjusted departure time of f

$SA(f)$: scheduled arrival time of f

$AA(f)$: adjusted arrival time of f

$\mathrm{FT}_{o(f),d(f)}$: flying time between $o(f)$ and $d(f)$ of f

f': the predecessor flight to f, if there is one

$turn(f',f)$: turnaround time, which is the time between the scheduled arrival time of f' and the scheduled departure time of f

$minturn(f',f)$: a "minimum turnaround time" which is required to complete all the turn-around processes

Then the "buffer" time associated with f defined as $buffer(f)$, can be computed as follow:

$$buffer(f) = turn(f',f) - minturn(f',f) \tag{2}$$

We initially set $AD(f) = SD(f)$ and $AA(f) = SA(f)$ for all f. Then if there is a predecessor flight associated with f, DPA is performed to calculate the adjusted departure time of f as follow:

$$AD(f) = \max[SD(f), SD(f) + AA(f') + W_{d(f'),q}(AA(f') - SA(f') - \mathrm{buffer}(f)] \tag{3}$$

And the adjusted arrival time can be calculated for all flights as follows:

$$AA(f) = \max[SA(f), AD(f) + W_{o(f),q}\big(AD(f)\big) + FT_{o(f),d(f)}] \tag{4}$$

Step 3. Update demand rates of each airport by using the adjust departure and arrival times that are calculated above. Then, QE is performed to recalculate the expected waiting time after the time t_d, which is the earliest time that demand rate changes. The adjust departure and arrival time after t_d should also be update by using (3) and (4) since the expected waiting time may have changed. This step will repeat until no demand rates change during the whole day. So far we have run Pyrgiotis' AND completely. The flight delays obtained can be regarded as under un-capacitated sector capacity.

Step 4. Let k be the index of path, and s be the index of sector. We define l to be the index of link, which can be understood as the connection between the entry point and exit point inside a sector [10]. The length of a link is scaled by expected travel time of a flight through it. Then we define T_l^k to denote the length of link l on path k. In particular, T_0^k denotes the length between the flight's takeoff and the entrance time of first en route control sector on path k. Since most of the links are longer than 1-minute interval and at the next minute, only a proportion of the aircraft in an upstream link will fly to the downstream link, $h_l^k(t)$ is used to indicate the number of aircraft that transit from link l to link $l+1$ on path k at time t, which can be determined by adjusted flights itineraries that are calculated above [2]. The number of aircraft $x_l^k(t)$ in link l on path k at time t can be determined as follows (no flight in the links at $t=0$):

$$x_l^k(t+1) = \begin{cases} x_l^k(t) - h_l^k\left(t - \sum_{i=0}^{l} T_i^k\right) + h_i^k\left(t - \sum_{i=0}^{l-1} T_i^k\right), & t \geq \sum_{i=0}^{l} T_i^k \\ x_l^k(t) + h_i^k\left(t - \sum_{i=0}^{l-1} T_i^k\right), & \sum_{i=0}^{l-1} T_i^k \leq t < \sum_{i=0}^{l} T_i^k \\ 0, & 0 \leq t < \sum_{i=0}^{l-1} T_i^k \end{cases}$$

$$x_0^k(t+1) = \begin{cases} x_0^k(t) + h_0^k(t) - h_0^k(t - T_0^k), & t \geq T_0^k \\ x_0^k(t) + h_0^k(t), & 0 \leq t < T_0^k \end{cases} \tag{5}$$

Then, the number of aircraft in sector s can be counted as:

$$E_s(t) = \sum_{(l,k)\in s} x_l^k(t) \tag{6}$$

Let $C_s(t)$ denote the capacity of sector s at time t. The number of aircraft in the sector should not exceed the sector capacity, this is:

$$E_s(t) \leq C_s(t) \tag{7}$$

By using LTM, the earliest time t_r can be determined when sector overload occurs, then all overflow aircraft should be adjusted to their previous sectors, as well as the previous links. In order to reduce the influence on the demand rates, the flight with later adjusted departure time will be pushed back preferentially. When there is no overload sector, we then calculate air delays of flights which have been pushed back as:

$$W_{f,s} = t_r - (AD(f) + W_{o(f),q}\big(AD(f)\big) - \textstyle\sum_{i=0}^{l} T_i^k) \tag{8}$$

where l is the link that f has been adjusted into. Then all air delays should be transmitted into ground delays by performing further adjustment on the adjusted departure time of those flights by:

$$AD'(f) = AD(f) + W_{f,s} \tag{9}$$

Step 5. Update demand rates of each airport by using the adjust departure and arrival time that are changed due to sector capacity constraints. Then from the period T_r, run AND again. T_r is the period that contains the earliest adjust departure time of flight being pushed back, for it is the earliest period that some other flights' adjusted departure or arrival times in it may also change. After that, we can run LTM again to check the requirement of sector capacity. This loop "LTM-AND-LTM-AND-LTM" continues until no overload sector can be found at any time.

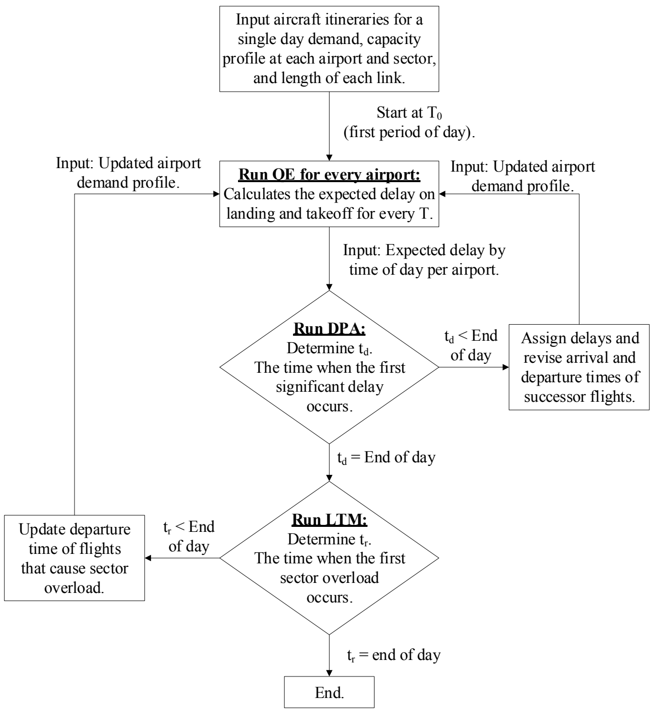

Fig. 1. The schematic of ASND model

To satisfy all airports' and sectors' constraints, the calculations of "LTM-AND-LTM-AND-LTM" may run many times. Some tricks can be used to improve its computing efficiency. For example, from the second time we run LTM, its start time can be set on the earliest adjusted time of flights which have been readjusted, for flights before that time are not changed and the airspace condition will stay the same. When we use DPA to adjust flights after running LTM, we can only run DPA on flights within two hours from the start time, since it is unlikely that there will be no overload sectors during the next two hours. These tricks will greatly reduce running time of ASND.

III. SIMULATION AND RESULTS

Detailed, auto recorded flights data were obtained from Operations Management Center of Civil Aviation Administration of China (CAAC). The database details the flights departure and landing in every Chinese mainland airport, providing a comprehensive picture of air transport in China. Each flight record reports the flight number, execute date, schedule/actual departure (arrival) time, and the unique aircraft register number (tail number). Such data allows us to easily reconstruct the path of each aircraft flying in the network. Additional information about airport runway information, airspace structure, and aircraft performance are also provided, to determine airport capacity, flying time, and turnaround time.

The ASND model then is implemented with Python 3.5. The investigated air transport network consists of the 21 busiest airports in China and 2962 links that refer to 151 mainland en route control sectors (89.35% of total). In addition, a 22nd "virtual airport" acts as an un-capacitated source to generate and "absorb" flights. All flights between the 21 busiest airports and some other airports can be taken into account by having the relevant aircraft fly to/from the virtual airport, which include most of daily flights.

The following five sets of inputs are critical to the ASND model.

- Aircraft itineraries, including aircraft tail number, the aircraft type, the airline, the origin and destination airports and the scheduled departure and scheduled arrival times;
- Expected service rate at each airport, which indicates the expected number of arrivals and departures that can be served per sub-period at each airport;
- Minimum turnaround time, which is the shortest necessary time between a flight and its immediate predecessor flight (unload, clean, refuel, load, etc.);
- Link length, which is the expected travel time between the entry point and exit point inside a sector, can be computed from historical traffic data of all flights in the network (one year in the present work from 1 January to 31 December in 2016);
- Sector capacity, which is the maximum number of aircraft that can exit in the sector at the same time, is determined by experienced controllers, referring to several indicators such as maximum capacity of sector in history, weather condition and so on.

To illustrate and validate the ASND, the results from the model of a day should be compared with the actual operation data. In particular, since sector capacity is the bottleneck of civil aviation in China, we would like to select actual operation data of two contrasting days from 2016 for our demonstration. On one of the two days, the volume of flights is more than average throughout the year, while on the other day, it is less than the average. Ideally, the service rates and sector capacities depend largely on some factors, such as weather, and special use of airspace etc. The two days we choose are both have no severe weather or large-scale military activities, so that they can be considered to approximately have the same condition. Therefore, the input of expected service rate at each airport and sector capacities are the same when using ASND to model for the two days, so that it will make it easier for us to analyze our model. We also compare the results obtained from ASND with AND, to demonstrate the improvement our model when investigating flight delays in China. Finally, as ASND is a macroscopic model of airport delays, rather than to predict individual flight delays, we then validate our model by comparing airport hourly delay obtained from our model and real data. A delayed flight is defined by CAAC as one whose actual arrival time is later than its schedule arrival time by more than 15 minutes [13].

The flight data tested here include all the flights within China mainland from 0600 CST on 11 July 2016 to 0559 CST on 12 July 2016, containing 10765 flights. Figure 2 shows flight delay rates at the main airports estimated by AND and ASND, and the actual delay rates (the ratio of delay flights to the total arrival flights) at these airports reported by CAAC. We can see that ASND displays a better result than AND, for flight delay rates are closer to the actual delay rates at most airports, especially the hub ones such as Beijing Capital International Airport (ZBAA), Guangzhou Baiyun International Airport (ZGGG) and Shanghai Pudong International Airport (ZSPD). These results may reveal the actual air transportation in China, that nearly 30 percent of delays are caused by sector limitation. Figure 3 shows the hourly delay distributions from 0800 to 2300 on 11 July computed by the two models and the actual hourly delay distribution at ZSPD. Compared with AND, ASND follows a pattern more similar to the observed data.

The results of Wuhan Tianhe International Airport (ZHHH) is another evidence for the validity of ASND. Figure 4 shows the hourly delay distributions from 0800 to 2300 on 11 July computed by the two models and the actual hourly delay distributions at ZHHH. Compared with AND, in some hour periods the delay aircraft estimated by ASND become fewer. Although we just added sector capacity constraints into the network, it can be found that not all airports' delays have become more serious and delays at some airports like ZHHH have even eased and become closer to the real data. It demonstrates that ASND does not simply increase the delays at all airports, but more appropriately simulates the actual operation.

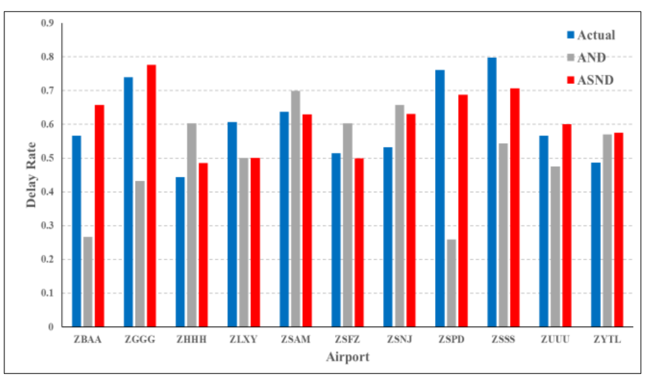

Fig. 2. Delay rates at major airports on 11 July

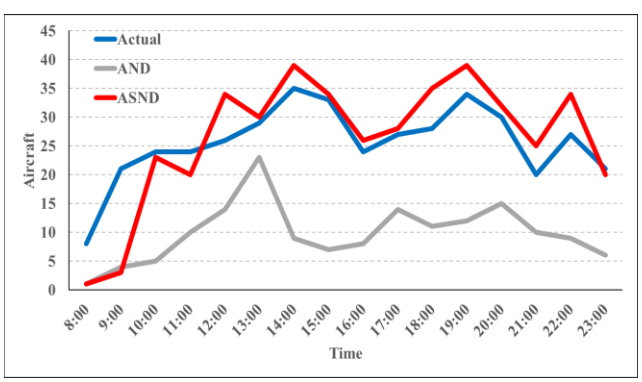

Fig. 3. Hourly delay destributions of ZSPD on 11 July

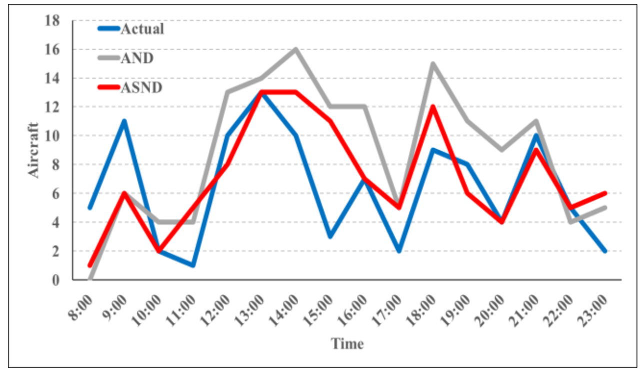

Fig. 4. Hourly delay destributions of ZHHH on 11 July

The second validation test is based on the flights operated between 0600 CST on 1 January 2016 and 0559 CST on 2 January 2016, containing 9138 flights (less than the daily average). Because of fewer flights on that day, sector capacity constraints should have less influence on flight delays compared with 11 July. Figure 5 shows the flight delay rates at airports estimated by AND and ASND, and the actual delay rates at these airports reported by CAAC. It can be seen that the difference between results of the two models are not obvious and they are both consistent with the actual operation. In fact, the amount of delayed flights obtained by ASND is 2022, 320 more than the result computed by AND, while on 11 July, the increase number is 1572. Figure 6 shows the hourly delay distributions from 0800 to 2300 on 1 January computed by the two models and the actual hourly delay distributions at ZBAA. We can see that expect for the first two hours, ASND and AND obtain similar results, which reveals that sector compacity constraints have a limited impact on delays, even at the busiest airport in China. These results above conform to our expectations.

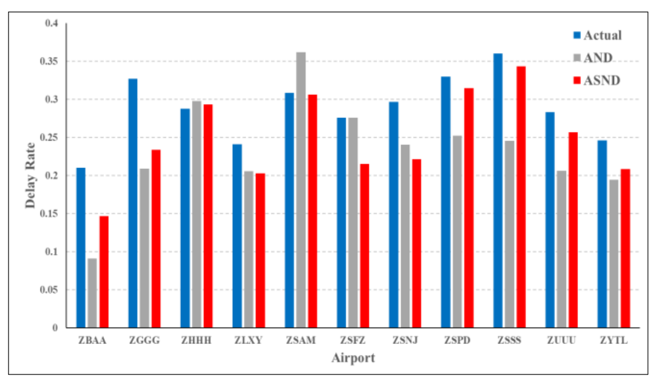

Fig. 5. Delay rates at major airports on 1 January

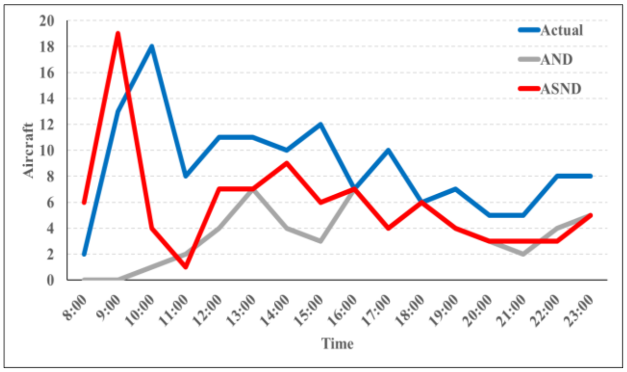

Fig. 6. Hourly delay destributions of ZBAA on 1 January

IV. CONCLUSIONS

This paper develops an Airport-Sector Network Delays model for flight delay estimation within air transport network. Performance of the proposed model is evaluated in this paper by comparing with the actual delay data and results of AND. It is found that ASND is well-suited for simulating delays in air transport system where either airports or airspace could be the bottleneck of system, such as the system in China. It can be used to explore critical sectors or airports within air transport network and simulate the scenario when some sectors' or airports' capacities decrease suddenly. Since some potential delays can be identified by ASND in air transport network, it is able to support the pre-warning system for serious flight delays and strategies concerning demand management.

Ongoing work involves further validation of ASND. More major airports and sectors can be added into the model to make it more complete. In addition, uncertain capacities can be considered, which means the sector capacity will not be fixed during a piece of time, but randomly fluctuation within a certain range, which will approach to the actual operation better.

ACKNOWLEDGEMENT

This research was supported by the National Natural Science Foundation of China (Grant Nos. 61773203, U1833126), and the State Key Laboratory of Air Traffic Management System and Technology (Grant No. SKLATM201707).

REFERENCES

[1] Pyrgiotis N, Malone K. M, Odoni A. Modelling delay propagation within an airport network. Transportation Research Part C Emerging Technologies, 2013, pp. 60-75.

[2] Cao Y, Sun D. Link Transmission Model for Air Traffic Flow Management. Journal of Guidance Control & Dynamics, 2011, pp. 1342-1351.

[3] Shao Q, Luo X, Wu K. The Analysis of Flight Delay in Airport Based on Bayesian Networks. Science Technology and Engineering, 2012, pp. 8120-8124.

[4] Hansen M. Micro-level analysis of airport delay externalities using deterministic queuing models: a case study. Journal of Air Transport Management, 2002, pp. 73-87.

[5] Chatterji G, Sridhar B. National Airspace System Delay Estimation Using Weather Weighted Traffic Counts. 2004.

[6] U.S. Congress Joint Economic Committee. Your Flight Has Been Delayed Again: Flight Delays Cost Passengers, Airlines, and the U.S. Economy Billions.Washington, DC. 2008

[7] Pan R, Lishuai L, Characterizing air traffic networks via large-scale aircraft tracking data: A comparison between China and the US networks , Journal of Air Transport Management. 2018, pp. 181-196

[8] Civil Aviation Administration of China operation monitoring center. 2015 National Civil Aviation Flight Operation Efficiency Report. Civil Aviation Administration of China.Beijing. 2016

[9] Menon P. K, Sweriduk G D, Lam T, et al. Computer-Aided Eulerian Air Traffic Flow Modeling and Predictive Control. Journal of Guidance Control & Dynamics, 2006, pp. 12-19.

[10] Sun D, Bayen A M. Multicommodity Eulerian-Lagrangian Large-Capacity Cell Transmission Model for En Route Traffic. Journal of Guidance Control & Dynamics, 2008, pp. 616-628.

[11] Cao Y, Sun D. Comparison of the Performances of Two Aggregate Air Traffic Models AIAA Guidance, Navigation, and Control Conference. 2013.

[12] Pyrgiotis N. A stochastic and dynamic model of delay propagation within an airport network for policy analysis. Massachusetts Institute of Technology, 2012.

[13] Statistics methods of civil aviation flight normality. Civil Aviation Administration of China.Beijing. 2016