From Aircraft Tracking Data to Network Delay Model: A Data-Driven Approach Considering En-Route Congestion

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Abstract:

En-route congestion causes delays in air traffic networks and will become more prominent as air traffic demand will continue to increase yet airspace volume cannot grow. However, most existing studies on flight delay modeling do not consider en-route congestion explicitly. In this study, we propose a new flight delay model, Multi-layer Air Traffic Network Delay (MATND) model, to capture the impact of en-route congestion on flight delays over an air traffic network. This model is developed by a data-driven approach, taking aircraft tracking data and flight schedules as inputs to characterize a national air traffic network, as well as a system-level model approach, modeling the delay process based on queueing theory. The two approaches combined make the network delay model a close representation of reality and easy-to-implement for what-if scenario analysis. The proposed MATND model includes 1) a data-driven method to learn a network composed of airports, en-route congestion points, and air corridors from aircraft tracking data, 2) a stochastic and dynamic queuing network model to calculate flight delays and track their propagation at both airports and in en-route congestion areas, in which the delays are computed via a space-time decomposition method. Using one month of historical aircraft tracking data over China’s air traffic network, MATND is tested and shown to give an accurate quantification of delays of the national air traffic network. “What-if” scenario analysis is conducted to demonstrate how the proposed model can be used for the evaluation of air traffic network improvement strategies, where the manipulation of reality at such a scale is impossible. Results show that MATND is computationally efficient, well suited for evaluating the impact of policy alternatives on system-wide delay at a macroscopic level.

Keywords: en-route congestion; trajectory clustering; queuing network; flight delay

1 Introduction

Air travel demand increases steadily over the past ten years. Such rapid growth resulted in greater degrees of congestion in air traffic networks; subsequent flight delay wastes travelers’ time and fuel and takes a toll on economic activities and the environment. To reduce flight delays, it is

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critical to analyze the capacity, efficiency, and congestion risks of the existing air traffic network, and then carry out strategic planning and tactical management accordingly.

Among many factors contributing to flight delays, en-route congestion becomes prominent in crowded airspace in the world, including Europe, the US, and China. Airspace may seem plentiful compared to the amount of aircraft maneuvering in it. However, airspace does get congested in areas with a high flight density, such as the merging areas of air traffic flows from different directions. Fig. 1 illustrates how en-route congestion is formed. In this figure, Sector A reaches its capacity (i.e., 15 aircraft). No other aircraft is allowed to enter Sector A. Aircraft in Sectors B and C that need to pass Sector A now have to divert or hold. In practice, this problem is solved by strategically adjusting the departure times and routes of the involved flights to balance the air traffic flow among different sectors, resulting in en-route delays. For instance, when a sector is predicted to undergo congestion, the involved flights are delayed at the departure airports or their routes are partly changed to avoid aggravating the congestion of this sector.

According to a report by CAPA, an aviation consultancy, “The biggest contributor to aviation delay in Europe is a lack of Air Traffic Control (ATC) capacity. En-route ATC capacity accounted for 25.5% delays in 2017, and airport capacity another 15.5% of interruptions.” (CAPA, 2018) Fig. 2 shows the airspace overload situation in Europe. The en-route delay has also been reported as the fastest-growing source of delays in Europe, with an average yearly rate of 17% from 2005 to 2010 (Eurocontrol, 2010). Similar developments have also been seen in some areas of the US. This is the main reason why both the US and Europe have initiated huge programs called Next Generation Air Traffic Control (NextGen) in the US and Single European Sky ATM Research (SESAR) in Europe (FAA, 2019; SESAR Joint Undertaking, 2020). One of the common aims shared in both programs is to increase airspace capacity. In China’s case, the airspace available for airline flights is even more limited - about 80% of airspace is controlled by the military, not open for civilian traffic (Hsu, 2014). There is a shortfall in airspace and air routes for civilian traffic in a previous study using actual flight tracking data (Ren and Li, 2018). As shown in Fig. 3, the en-route airspace resources are much more limited in China than in the USA, resulting in a higher risk of en-route congestion. However, most existing studies on flight delay modeling do not consider en-route congestion explicitly.
Existing studies on modeling and prediction of flight delays can be grouped into three categories in general. The first category involves agent-based simulations. The state-of-the-art models in this category are the two agent-based models that include details of the entire National Airspace System (NAS), the Airspace Concept Evaluation System (ACES) (Meyn et al., 2006) and the Future ATM Concepts Evaluation Tool (FACET) (Bilimoria et al., 2001), both of which are currently used by the National Aeronautics and Space Administration (NASA) and the Federal Aviation Administration (FAA). ESCAPE is a scalable EUROCONTROL air traffic management (ATM) real-time simulation platform (Eurocontrol, 2020). More recently, Fleurquin and Campanelli’s team developed two agent-based models to simulate flight delay propagations in the USA and European networks (Campanelli et al., 2016; Fleurquin et al., 2014, 2013). These simulation models enable a wide range of capabilities and provide accurate results with detailed information.
However, because of the extensive input preparations required, these simulation tools are cumbersome and cannot be used for rapid evaluations of policy-oriented ATM improvement strategies.

The second category uses statistical, data mining, or econometric methods and historical data to model and predict delays. Xu et al. (2008) used regression models to estimate local delays and propagated delays at major airports in the USA. Rebollo and Balakrishnan (2014) used a random forest approach to predict departure delays from 2–24 h into the future. Some studies have focused on scheduling from the perspective of airlines. Beatty et al. (1999) and AhmadBeygi et al. (2008) used delay trees to track how delays propagate within an airline’s network. Fricke and Schultz (2009) analyzed the individual inbound delay’s impact on the turnaround process duration and stability. Kafle and Zou (2016) proposed an econometric model to analyze delay propagations. Results provide estimates on how much propagated delay will be generated out of each minute of newly formed delay, for the US domestic aviation system as well as for individual major airports and airlines. Unfortunately, these methods are not suited for evaluating improvement strategies in the ATM procedure and infrastructure, because the ATM procedure and infrastructure are not explicitly modeled in these methods.

The third category develops analytical models based on queuing networks, which is the most promising approach for addressing the problems of interest in this study. The basic idea of these models is to treat airports in the network as a set of individual interconnected queuing systems, and recursively compute the delay propagation over the entire network considering the dynamic characteristics of airport capacity and aircraft queues. Peterson et al. (1995a, 1995b) developed a recursive approach based on a semi-Markov model to compute the queue lengths and waiting times of aircraft landings in a hub-and-spoke configuration with a single hub airport. A national-scale airport network model, LMINET, was developed by Long et al. (1999) and an updated version was described by Long and Hasan (2009). Tandale et al. (2008) presented a family of queuing network models for incorporating trajectory uncertainties at national, regional, and local scales. Pyrgiotis et al. (2013) developed the Approximate Network Delays (AND) model, a stochastic and dynamic queuing network model to compute local and propagated delays within the NAS using aircraft itinerary information. This model was first conceptualized by Malone (1995) in her Ph.D. thesis. The AND model is very fast computationally, thus making possible the exploration at a macroscopic level of the impacts of a large number of scenarios and policy alternatives on system-wide delays. However, these models are generally based on airport networks and do not take en-route constraints into account. They are inadequate in cases where the airspace is restricted and en-route congestion is significant.

Incorporating en-route constraints in delay modeling presents significant challenges. If we model the capacity and demand at each sector’s level, a significant amount of detailed information is needed from the air navigation service provider (ANSP) to build up the en-route structure, such as sector maps, published airways, navigational aids, metering fixes, and individual flight trajectories. In addition, the capacity of each sector is difficult to estimate. Majumdar and Polak (2001) provided a framework for modeling Europe’s airspace en-route capacity by considering the factors that affect controller workload and then using a model of controller workload, aided by the appro-
Appropriate analytical techniques, to estimate airspace capacity. Cho et al. (2011) incorporated the convective weather effects into the analytical sector workload model to estimate en-route capacity under convective weather. Welch (2015) described a new workload-based capacity model that improves upon the FAA’s current Monitor Alert capacity model.

Unlike the existing papers, this paper proposes a new data-driven approach to learn the en-route structure from large-scale air traffic surveillance data and capture the en-route delay effects through conceptual en-route “congestion points”, rather than modeling the capacity and demand of each sector. Our proposed approach is enabled by the availability of aircraft tracking data. While FAA, Eurocontrol, and other ANSPs normally maintain the most comprehensive and highest-quality air traffic surveillance data for a particular region, it is increasingly easy to obtain air traffic surveillance data via public and commercial sources. Several commercial and non-commercial websites track aircraft positions via the crowd-sourced distributed networks of Automatic Dependent Surveillance — Broadcast (ADS–B) receivers and make the tracking data publicly available, e.g., FlightAware, Flightradar24, OpenSky Network, and VariFlight. Several studies have reported data mining techniques that use these surveillance data to learn typical traffic flows and patterns in the terminal area (Conde Rocha Murca et al., 2016; Eckstein, 2009; Enriquez, 2013; Gariel et al., 2011; Rehm, 2010). However, to the best of our knowledge, there have been no attempts to connect these flow identification tools with network delay modeling.

In summary, we propose a novel flight delay model, named as Multi-layer Air Traffic Network Delay (MATND) model, to capture the impact of en-route congestion on flight delays over an air traffic network and to automatically learn the structure of a national air traffic network from historical aircraft tracking data via unsupervised learning methods. The model includes two parts: 1) a data-driven method to learn and construct a national air traffic network consisting of airports and en-route congestion points as nodes and operational air routes as links. The operational air routes are extracted using clustering algorithms and then a score function is constructed to identify conceptual en-route congestion points from historical aircraft tracking data; and 2) a stochastic and dynamic queuing network model to compute delays and predict their propagation over the constructed network. The queuing network model estimates delays at each airport and en-route congestion point and tracks the propagation of these delays and their impacts on subsequent flight operations. To demonstrate its performance, the model is implemented on an air transport system consisting of the 56 busiest airports in China (as ranked by annual passenger traffic (Civil Aviation Administration of China (CAAC), 2018, 2016). Using the proposed MATND model, decision-makers can predict the risk of flight delays under various operational scenarios, such as network structure modifications, infrastructure improvements, or changes in air traffic management procedures.

This work contributes to the literature of flight delay modeling in the following ways: 1) it is the first attempt to capture en-route congestion in flight delay modeling; 2) an unsupervised learning scheme is proposed to extract the nodes (airports, en-route congestion points) and links (operational air routes) of a national air traffic network from aircraft tracking data; 3) Analysis based on real-world data provides insights on current bottlenecks of the air traffic network and potential improvement strategies in China.
The remainder of this paper is organized as follows. Section 2 describes both the aircraft-tracking data and the flight schedule data used in this research. Section 3 presents the proposed methodology, including multi-layer air traffic network construction and flight delay modeling. Section 4 discusses the implementation and validation of the model for the air transport system in China. Section 5 describes scenario analysis to illustrate how to use the proposed model to evaluate the impact of infrastructure improvements and network structure modifications on the air transport system behavior. Finally, Section 6 summarizes our study and suggests future research directions.

2 Dataset

Only datasets available to the public are used in this method. The details of the input dataset used in this study are described below:

(1) Aircraft tracking data

The aircraft tracking data used in this study were collected from Flightradar24 every minute for 30 consecutive days (November 1–30, 2016), including flight ID, latitude, longitude, altitude, speed, origin airport, destination airport, aircraft type, and aircraft registration. We selected flights departing from and arriving at the 56 busiest airports in China. The database was used to identify operational air routes and locate the geographic positions of en-route congestion points.

(2) Flight schedule data

Flight schedule data over the same spatial and temporal scales as the aircraft tracking data were collected from VariFlight, including flight ID, origin airport, destination airport, scheduled departure/arrival time, and real departure/arrival time for each flight. The database was used to determine the demand and service profiles of each queuing system in the stochastic and dynamic queuing network, and this information was then used to estimate the demand rates and the service rates.

3 Methodology

This section describes the methods developed to model delays and their propagation over a national air traffic network considering en-route constraints using the historical aircraft tracking data and flight schedule data described in Section 2, which are used to construct the Multi-layer Air Traffic Network Delay (MATND) model in this paper. The framework of the proposed model is shown in Fig. 4. The model includes two parts: 1) a data-driven method to construct a national multi-layer air traffic network consisting of airports and en-route congestion points as nodes, and operational air routes as links; 2) a stochastic and dynamic queuing network model to simulate delays and their propagation over the network. These parts are explained in detail in the following subsections.
3.1 A data-driven method for multi-layer air traffic network construction

The first part of the framework involves developing a data-driven method to construct a multi-layer air traffic network of China by considering en-route airspace constraints. The network consists of airports, operational air routes, and en-route congestion points. The multi-layer air traffic network is illustrated as Fig. 5. Instead of just using airports as the nodes of the network, we also incorporate en-route points identified using historical data. In this way, we consider potential en-route congestion. Fig. 6 shows the workflow of constructing this multi-layer air traffic network. Clustering analysis is performed on the resampled flight trajectories to identify operational air routes. Then, the whole air space is divided into different grids where a score function is computed to evaluate the congestion level of each grid. Those grids with a high score are considered as the bottleneck of the system, and are recognized as en-route congestion points in this method.
3.1.1 Operational air route identification

We identify the operational air routes used by airline flights by applying a machine learning, clustering algorithm, DBSCAN (Ester et al., 1996), on the flight trajectory data within each origin-destination (OD) pair. No prior information on the airspace structure is needed to identify these operational air routes using this method. Using DBSCAN, the number of air routes linking airport pairs can be automatically determined based on the data distribution patterns. Abnormal flight tracks can emerge as a result of vectoring or other special conditions, and these are treated as outliers by DBSCAN. Several studies have demonstrated that DBSCAN is an effective technique for identifying operational air routes (Conde Rocha Murca et al., 2016; Ren and Li, 2018).

Two key input parameters, Minpt and Epsilon, may result in changes to the clustering result. Epsilon is the maximum radius of neighborhood distance between points and Minpt is the minimum number of points in an Epsilon neighborhood. For our dataset, the clustering result is not sensitive to Minpts when it is between 3 and 10, so we set Minpt as 5 for all cases. The value of Epsilon is set differently for each airport pair to find the best result that matches the distribution pattern. We
compute the k-nearest neighbor distances – where k equals \( \text{Minpt} \) – plot these k-distances in descending order for all data points, and find the first “valley” of the sorted k-distance graph (Ester et al., 1996). This “valley” point corresponds to a threshold point where a sharp change in the gradient occurs along the k-distance curve, representing a change in density distribution amongst data points. The k-distance value of the threshold point is used as the \( \text{Epsilon} \) value for DBSCAN (Ester et al., 1996).

In this study, by applying DBSCAN on the dataset described in Section 2, a total of 1376 air routes linking the 56 busiest airports in China are identified from 169140 trajectories, as shown in Fig. 7.

![Fig. 7 Plan view of operational air routes in China](image)

3.1.2 En-route congestion point identification

In most existing research, the en-route airspace is represented by a set of en-route sectors in an ATM system. However, sector-based en-route airspace models require extensive input information, i.e., sector maps. Furthermore, it is difficult to estimate the sector capacity accurately, because their characteristics and ATC tactics vary across different sectors and controllers. To tackle these challenges, our approach is to identify conceptual en-route congestion points from the aircraft tracking data directly. The conceptual en-route congestion points are defined as en-route airspace areas that have a high risk of air traffic congestion.

We propose a data-driven algorithm to identify the conceptual en-route congestion points according to the principles discussed above. First, the whole airspace is divided into grids as shown in
Fig. 8. The operational flight routes recognized in the previous step are plotted as gray lines, while the airspace grids are represented as red rectangles. In this work, the grid size is defined as 20NM. The grid size can be adjusted within a range, where the upper limit is a typical size of an en-route sector (50 – 100 NM), and the lower limit is constrained by the computational time as a result of the total number of grids for the area of interest.

Then, three metrics are formulated to evaluate the risk level of congestion of each grid: the traffic load, the number of operational routes, and the entropy of route directions. Afterward, a score function is constructed by combining these three metrics. A grid with a higher score indicating a higher traffic load and a more complex route structure in this region, which is more likely to reach its capacity. Aircraft that fly through these regions have a high chance of experiencing delays or diversion. For the $i$th grid of the airspace, its score is computed as follows:

$$\text{Score}_i = \omega_1 \tilde{T}_i + \omega_2 \tilde{R}_i + \omega_3 \tilde{E}_i$$

(1)

$$E_i = -\sum_j^N p_j \log p_j$$

(2)

$$\tilde{T}_i = \frac{T_i - T_{\text{min}}}{T_{\text{max}} - T_{\text{min}}}, \quad \tilde{R}_i = \frac{R_i - R_{\text{min}}}{R_{\text{max}} - R_{\text{min}}}, \quad \tilde{E}_i = \frac{E_i - E_{\text{min}}}{E_{\text{max}} - E_{\text{min}}}$$

(3)

where $\{\tilde{T}_i, \tilde{R}_i, \tilde{E}_i\}$ are the standardized values of $\{T_i, R_i, E_i\}$, respectively, using Eq. (3) for standardization. $T_i$ represents the total traffic load in the $i$th grid, $R_i$ denotes the number of operational routes in the $i$th grid, and $E_i$ is the entropy in the $i$th grid. $\omega_1$, $\omega_2$, and $\omega_3$ are the corresponding coefficients. $(T_{\text{min}}, T_{\text{max}})$, $(R_{\text{min}}, R_{\text{max}})$, and $(E_{\text{min}}, E_{\text{max}})$ are the minimum and maximum values of all $T_i$, $R_i$, and $E_i$, respectively. $E_i$ evaluates the diverseness of route directions in this grid, and it is computed using Eq. (2), where $N$ represents the total number of flight directions within.
this grid and \( p_j \) is the probability that aircraft flies in the \( j \)th direction, which can be inferred using flight trajectory data. The detailed calculation of \( E_i \) is explained using Fig. 9.

Suppose the airspace is divided into 9 grids as shown in Fig. 9. There are four flight routes passing grid \( G \), namely, flight routes 1, 2, 3 and 4. Four grids share the same border with grid \( G \) (i.e., grid \( A, B, C, \) and \( D \)). We use the grids that before entering and after exiting grid \( G \) to identify the direction for these flight routes. For example, flight route 1 passing through grids \( \{ B, G, A \} \) successively. Thus, the first direction for grid \( G \) is \( d_{BA} \). Likewise, we can find three flight directions in grid \( G \), that is, \( \{ d_{BA}, d_{BD}, d_{BC} \} \), denoted as direction \( \{1, 2, 3\} \), respectively. So, \( N = 3 \) for this case. Moreover, let the traffic load for each flight route be 100. Therefore, the total traffic load \( L_{sum} \) of grid \( G \) is 400 and the traffic load for each direction \( L_j = \{100, 200, 100\} \), \( j \in \{1, 2, 3\} \). Finally, the probability of each flight direction \( p_j \) can be calculated by dividing \( L_j \) by \( L_{sum} \), and the entropy for grid \( E_G \) can be computed using Eq. (2). Specifically, \( p_j = \{0.25, 0.5, 0.25\} \), and \( E_G = 3.47 \) for this example. The entropy value \( E \) for all the grids in the whole space are calculated using the method discussed above, and then \( \tilde{E}_G \) denoted as the standardized value of \( E_G \) is computed according to Eq. (3).

We observe that the heat maps for the number of flight routes and traffic load follow similar patterns, while the heat map for entropy is quite different. Therefore, we fix \( \omega_1 = \omega_2 = 1 \), and iterate \( \omega_3 \) over \{0.4, 0.6, 0.8, 1, 2, 3\} to compute the scores of the grids of the whole airspace. Results show that although the score values may be different with different combinations of \( \{\omega_1, \omega_2, \omega_3\} \), those grids with a high score value are quite stable. We choose the top 75 grids that are insensitive to different settings of parameters as the grids at a high risk of congestion. The heat map of the mesh grids when \( \{\omega_1 = 1, \omega_2 = 1, \omega_3 = 2\} \) and the standardized score value distribution is shown in Fig. 10. Fig. 10 (a) shows the spatial distribution of the grids with different score values; a higher score is shown with denser color. Fig. 10 (b) shows the score value distribution and the turning point is around 0.6. Grids with score values larger than 0.6 are considered as with a high level of congestion risks. These grids are further clustered into 30 clusters as conceptual en-route congestion points, as shown in Fig. 11. In this step, DBSCAN is used to perform the clustering,
and the Minpt and Epsilon are set as 2 and 50NM, respectively. A sensitivity analysis was performed to select the DBSCAN parameters. We found that results are not sensitive to different settings of parameters. The number of clusters found is stabilized around 30.

![Heat map and score distribution](image1)

**Fig. 10** Heat map and score distribution of mesh grids ($\omega_1 = 1, \omega_2 = 1, \omega_3 = 2$)

![En-route congestion grids and airports](image2)

**Fig. 11** En-route congestion grids and airports

The 30 conceptual en-route congestion points identified via this approach were verified by comparing with the busiest en-route waypoints published in CAAC (2016). In Fig. 11, the top 10 busiest waypoints published by CAAC are indicated by red diamonds, and the en-route congestion points identified through our method are represented by green dots. The gray lines depict the operational air routes. 7 out of the top ten busiest waypoints published by CAAC are recognized by our method. Note that en-route airspace with temporary congestion, such as weather impact, temporary airspace restrictions, are not recognized in this method.
3.2 A stochastic and dynamic queuing network model to calculate delays and track their propagation

The second part of the proposed framework involves a stochastic and dynamic queuing network model that treats each airport or each en-route congestion point as a node of the queuing system to model flight delays and their propagation. The core concept of the proposed Multi-layer Air Traffic Network Delay (MATND) model is similar to the AND model proposed by Pyrgiotis et al. (2013), which combines a numerical queuing engine (QE) to compute the approximate delays at each airport or en-route congestion point with a delay propagation algorithm (DPA) to track the propagation of these delays from one node to another over the period of interest.

![Figure 12: Time-space network concept in MATND.](image)

(A node is an airport or a conceptual en-route congestion point.)

![Figure 13: A simplified schedule for an aircraft](image)

MATND considers the air traffic system as a dynamic network. Flight delays on this network are calculated using the time-space decomposition method. The concept of the time-space decomposition method is shown in Fig. 12, where we can see the dynamic network is different from the static one as the nodes in the network are connected by flights at different periods, and the characteristics (e.g., service profiles, demand profiles) at each node can be adjusted during the iteration.
of the network. For better illustration, a simplified schedule for an aircraft is given as Fig. 13 A simplified schedule for an aircraft. There are two flights \( \{f', f\} \) in this example, where \( f' \) is the predecessor flight of \( f \). The aircraft first arrives at airport \( a \) and finishes its flight \( f' \). Then the aircraft starts its next flight \( f \), departing from airport \( a \), then passing through the en-route point \( e \) and finally arriving at airport \( b \). MATND models the airports as a single server that serves both arrivals and departures, and en-route points as a single server that serves passing through airplanes.

![Diagram](image)

**Fig. 14 Delay calculation flow chart of MATND**

The flow chart of MATND is shown in **Fig. 14**. MATND can compute flight delays over a network for a period \( T \) (usually 24 h) via iterative calculations on sub-periods,
$h_j$, $j = 1, 2, \ldots, m$, i.e., $m = 96$, each of which is 15 min long ($\Delta T$). Starting at the beginning time $h = T_0$, the flights $F_{a,h}$ and $F_{e,h}$ at airport $a$ and en-route point $e$, respectively, are collected. QE is then executed for each flight $f \in \{F_{a,h}, F_{e,h}\}$ individually, and the expected delay $W_a(t)$ and $W_e(t)$ of each flight $f$ are estimated. The DPA then determines whether the delay incurred by any flight is significant enough to result in propagation. If so, the earliest time $t^*$ at which this propagation condition is met is identified. All flight operations terminated before $t^*$ are unaffected; these flights are classified as processed and are not affected by any subsequent iterations of the algorithm. For all unprocessed flights affected by the propagation, DPA adjusts their arrival and departure times, and the demand rates at corresponding airports are updated accordingly. The QE is rerun at each node based on the updated demand rates. The QE-DPA process is executed iteratively until $h$ reaches the end of time $T_{end}$.

It is worth noting that QE runs on a finer-grain time step than $\Delta h$. Therefore, we denote the instantaneous demand and service rates used by the QE as $\lambda(t)$ and $\mu(t)$, respectively, where $t \in \mathbb{R}, T_0 \leq t \leq T_{end}$. Also, an index function is formulated to map time $t$ into the sub-period $h_j$. The index($t$) is given by $j = \text{index}(t) = \left\lfloor \frac{t}{\Delta T} \right\rfloor$.

The assumptions used in the MATND model are as follows: (1) No flight can depart earlier than its scheduled departure time; (2) Flights can arrive at the destination airport before their arrival time; (3) En-route delays occurring at a congestion point cannot be pushed back to upstream en-route points or the origin airport; (4) Flight cancellations are not incorporated into the model; and (5) Ground delays are not considered in the model.

### 3.2.1 Modeling each airport as a queuing system

The aircraft arrival and departure process at the runway system of an airport is simulated using a queuing model with a nonstationary Poisson arrival process, time-dependent $k$th-order Erlang service-time distribution, a single server, the first-come-first-served (FCFS) service principle, and an infinite waiting room (we denote this model type as $M(t)/E_k(t)/1$) (Malone, 1995; Pyrgiotis et al., 2013).

The expected waiting time at a particular time of such a queuing model is calculated using a numerical queuing engine, DELAYS, developed by Kivestu (1976) and Malone (1995). The state-transition diagram of this queuing system consists of $(kN + 1)$ stages, where $N$ is the queue capacity (Larsen and Odoni, 1981). To approximate such an infinite-capacity system, $N$ must be sufficiently large that the probability of having $N$ or more customers in the system is very small. As the number of equations $(kN + 1)$ to be solved in the queuing system becomes very large, finding the exact solution requires significant amounts of computer memory and CPU time. For this reason, we use an approximation of the $M(t)/E_k(t)/1/N$ system that solves a set of $(N + 1)$ difference equations, instead of the $(kN + 1)$ Chapman–Kolmogorov equations (Kivestu, 1976). Extensive computational experiments performed by Malone (1995) indicate that Kivestu’s approach approximates the numerical solution of $M(t)/E_k(t)/1$ very accurately and is much faster than the exact method.
The expected waiting time, $W_a(t)$ at time $t$ of airport $a$, is calculated as follows:

$$W_a(t) \approx \frac{L_a(t)}{\mu_a(t)}$$

(4)

$$L_a(t) = \sum_{j=1}^{N} (j - 1)p_{a,j}(t)$$

(5)

where $L_a(t)$ is the expected number of aircraft in the queue of airport $a$ at time $t$, $\mu_a(t)$ is the service rate of airport $a$ at time $t$, and $N$ is the capacity of the queue. $p_{a,j}(t)$ denotes the estimated state probability, more specifically, the probability of having $j$ airplanes in airport $a$’s queuing system at time $t$. The state probabilities are estimated using Kivestu’s approximation approach (Kivestu, 1976).

$$p_j(t_{l+1}) = p_0(t_l)\alpha_{l+1}(j) + \sum_{i=1}^{j+1} (j - 1)p_i(t_l)\alpha_{l+1}(j - i + 1),$$

(6)

$$j = 0, 1, ..., N$$

$$t_{l+1} = t_l + \left(\frac{k + 1}{k}\right)\left(\frac{1}{\mu(t_l)}\right)$$

(7)

$$\alpha_{l+1}(r) = \frac{\left(\frac{\lambda(t_l)}{\mu(t_l)}\right)^r e^{-\frac{\lambda(t_l)}{\mu(t_l)}}}{r!}$$

(8)

where $t_l$ is the epoch time of $l^{th}$ aircraft completes the arrival/departure process. Given initial conditions for the system at time $t_0$, we can compute the state probabilities of any epoch $t_l$.

The initial state of the queuing system affects the expected waiting time. Normally the system is assumed to have an empty state at the beginning of the day. According to the aircraft tracking data we collected, the whole airspace is almost empty at 4:00 AM (HKT). Therefore, in this study, the modeling horizon starts at $T_0 = 4:00$ AM and ends at $T_{end} = 4:00$ AM on the following day. The mathematical formulation of an empty state is given as Eq. (9).

$$p_j(0) = \begin{cases} 1, & j = 0 \\ 0, & j = 1, 2, ..., N \end{cases}$$

(9)

The initial values of $\lambda(t_l)$ are set based on the demand profile of the target interval at each airport, which is estimated through the scheduled aircraft itinerary information. The service rate $\mu(t_l)$ is simplified to be a fixed number, the capacity of an airport, in this study. Fig. 15 shows the demand and service profiles at Beijing Capital International Airport (PEK) over a single day. The demand profile reflects the number of scheduled flights per 15 min, whereas the service profile reflects the number of served flights per 15 min. The initial value of $\lambda(t_l)$ of each airport is defined as the expected number of scheduled arrivals and departures in each sub-period. The service rate $\mu(t_l)$
of each airport is estimated empirically based on historical data. We count the number of flights served (including arrivals and departures) per 15 min for each airport within a one-month period, which includes 2880 sub-periods. The service rate is conservatively defined as the lower bound of the number of flights served that covers 90% of the sub-periods in the monitored period. Fig. 16 shows the demand and service rates at PEK airport based on operational flight data for one month.

![Graph showing demand and service rates at PEK airport](image1)

Fig. 15 Demand profile and service profile at PEK during a single day

![Graph showing demand rate and service rate at PEK](image2)

Fig. 16 Demand rate and service rate at PEK based on flight scheduling data for one month

### 3.2.2 Modeling each en-route congestion point as a queuing system

In the proposed model, we treat the process of an aircraft passing through an en-route congestion point as a queuing process. This is because when an en-route sector is congested, flights may be instructed by air traffic controllers to slow down, enter a holding pattern, stay in upstream sectors (even receive a ground delay at their origin airport), or divert to a different route. Except for the route diversion, all other en-route congestion effects can be modeled as a queueing system, similar to the congestion effects at airports.
Each en-route congestion point is modeled as an $M(t)/E_k(t)/1$ queuing model, which is similar to the queuing system applied at the airports. The expected waiting time of en-route congestion point $e$ at time $t$, $W_e(t)$, and the expected number of aircraft in the queue of en-route congestion point $e$ at time $t$, $L_e(t)$, are calculated as follows:

\[ W_e(t) \approx \frac{L_e(t)}{\mu_e(t)} \]  

\[ L_e(t) = \sum_{j=1}^{N} (j - 1)p_{e,j}(t) \]  

where $p_{e,j}(t)$ is the probability of having $j$ airplanes at en-route congestion point $e$ of the queuing system at time $t$, and $\mu_e(t)$ is the service rate at time $t$. The state probabilities are estimated in the same way as the airport queuing system, using Kivestu’s approximation approach (Kivestu, 1976), as described in Section 3.2.1.

The demand profile at each en-route congestion point cannot be generated directly from the flight schedule data, which only contains the flight information at airports. Using the multi-layer air traffic network constructed in Section 3.1, given the demand profile of each airport and the usage probability of each air route, we can obtain the demand profile of each air route. The average time required from each origin airport to the en-route point along a specified air route is estimated based on the historical aircraft tracking data. Together with the demand profile of each air route, we estimate the demand profile at each en-route congestion point. The service profile is obtained from the ADS-B aircraft trajectory data directly. Fig. 17 shows the demand and service profiles at an en-route congestion point during a single day. The demand and service rates are estimated by the same method used for the airport queuing system. Fig. 18 indicates the demand rate and service rate at a randomly selected en-route congestion point.
3.2.3 Delay propagation through the air traffic network

The Delay Propagation Algorithm (DPA) propagates significant delays generated at any node of the network (both airports and en-route congestion points) to the “downstream” itinerary of this aircraft. We adopted the same DPA as in the AND model (Pyrgiotis et al., 2013) except that we added en-route congestion points as nodes that may generate local delays and propagate significant delays in the network. The difference between DPA in AND and the one in MATND is illustrated in Fig. 19. DPA in MATND incorporates the en-route points into the algorithm. Thus, delays can be generated at these en-route points and propagated to downstream flights as well.
The main idea of DPA can be described as follows:

1) Determine if the delay is significant enough to propagate downstream.
2) Propagates significant delays to the downstream itinerary of an aircraft (the itinerary of an aircraft consists of both airports and en-route congestion points).
3) Re-schedule the arrival and departure times of delayed flights.
4) Update the demand rates of all airports and en-route congestion points.

Whether a delay is significant or not is determined by two important parameters in DPA, ground time buffer (A_Buffer) and en-route buffer (E_Buffer) shown as Fig. 13. A simplified schedule for an aircraft. We adopted the same definition of ground time buffer as it is used in the AND model, while added the en-route buffer in our method. If we denote the immediate predecessor flight of each flight \( f \) as \( f' \), the parameter A_Buffer indicates the ground time buffer between two consecutive flights of the same aircraft at an airport, which could absorb flight delays at the airport. Flight \( f \) will still depart on time as long as the arrival of \( f' \) is delayed by less than A_Buffer. The en-route buffer E_Buffer is the buffer between the scheduled flight time and the actual flight time. In actual operations, even though a flight may suffer a departure delay, it can still arrive on time or even early because the scheduled flight time issued by airlines is longer than the actual flight time. The en-route buffer can, therefore, absorb departure delays. Delays that cannot be absorbed by A_Buffer and E_Buffer are recognized as significant delays, and the downstream itinerary executed by the aircraft must be adjusted. In this study, A_Buffer and E_Buffer are set to fixed values for all flights. More details on DPA calculations can be found in the paper by Pyrgiotis et al. (2013).

4 Model testing and analysis of the China air traffic network

In this section, we demonstrate the application of the MATND model to a large-scale multi-layer air traffic network in China using a set of historical aircraft tracking data and flight schedule data over China airspace from November 1 to 30, 2016. A detailed data description is presented in Section 2. In this dataset, we filtered OD pairs whose traffic flow averages less than one flight per day. As a result, 836 OD pairs in China remain for analysis. The total number of scheduled commercial flights over the period of interest is 261,609. Among these flights, 169,969 (65% of the total) can be captured by the aircraft tracking data collected from Flightradar24.
A multi-layer air traffic network was constructed based on these data. The network includes 836 air routes linking the 56 busiest airports in China and 30 en-route congestion points. The parameter estimation results for the queuing system at each airport and en-route congestion point are listed in Appendix A1.

4.1 Model testing

To test the model performance, we used MATND to predict flight delays across China’s national air traffic network and compared the results with the delays predicted by the AND model, benchmarking with the actual delays on that day.

Fig. 20 shows the average delay per departure/arrival at each of the 25 busiest airports over one month. The results predicted by MATND (grey bars) are shown together with those by AND (orange bars) and actual observations (blue bars). MATND predictions are closer to the actual value for both departure delays and arrival delays, whereas the AND predictions are much lower than the actual values. The Root Mean Square Errors (RMSEs) of MATND for both departure and arrival delays are much smaller than the RMSEs of AND, as shown in Table 1. This result demonstrates that MATND is more effective than AND for predicting flight delays in national air transport systems where en-route congestion is significant, such as China’s air traffic network.
Table 1 Comparison of prediction accuracy

|                   | MATND | AND   |
|-------------------|-------|-------|
| Departure delay   | 14.87 | 27.24 |
| Arrival delay     | 3.9   | 9.53  |

Fig. 21 and Fig. 22 present a detailed analysis of flight operations at Guangzhou Baiyun International Airport (CAN). Fig. 21 shows the number of departures/arrivals at CAN predicted by MATND (grey line), AND (orange line), as well as the actual values (blue line). We observe that both AND and MATND provide fairly accurate airport throughput predictions. In terms of flight delay predictions, MATND performs much better than AND, as shown in Fig. 22. At each hour of the day, the average delay per flight predicted by AND is much lower than the actual value and the MATND prediction since AND does not consider en-route congestion.
4.2 Delay analysis of China air traffic network

MATND can be used to understand bottlenecks in the current network regarding traffic congestion. Using MATND, we can trace the flight delay over a network by whether it is caused by an airport or en-route local congestion or network propagation effect from upstream. The detailed calculation method of how much delay is caused by a local (either airport or en-route congestion) source and how much is due to upstream sources is described in Appendix A2.

A summary of flight delays caused by different sources over China’s air traffic network based on the operations in November 2016 is calculated and shown in Table 2. The average delay experienced by a flight is ~16 min, which is consistent with the actual situation in China in 2016 (CAAC, 2016, 2018). The local delay incurred at en-route congestion points (5.0 min) is smaller than the local delay at airports (6.4 min) on average. However, the propagated delay at en-route congestion points (15.6 min) is greater than the propagated delay at airports (9.5 min) on average. Fig. 23 shows the expected local delay and propagated delay at the 25 busiest airports in China. These results show that delay propagation effects are more severe at en-route congestion points than at airports.

| Table 2 Summary of flight delays caused by different sources over China’s air traffic network based on the operations in November 2016 (minutes per flight) |
|-------------------------------------------------|-----------------|-----------------|
| Average local delay                             | 6.43            | 4.99            |
| Average propagated delay                        | 9.54            | 15.57           |

Fig. 23 Average delay per flight at 25 busiest airports

5 Demonstration of MATND for evaluating improvement strategies

In this section, we demonstrate how to use MATND for evaluating air traffic network improvement strategies. Using MATND, we can quickly conduct “what-if” scenario analysis to estimate the effectiveness of infrastructure investment, technology improvement, or managerial changes on delay reduction at the system-level for the current network. For example, the following questions can be answered by running simulated scenarios via MATND:
• With a limited airport expansion budget, which airports in the national network should be prioritized to invest if the goal is to reduce local flight delay and overall network delay?

• If airport expansion is not possible in the near term due to financial or policy constraints, how much delay can be reduced by improving en-route capacity?

• Are there any airports that would benefit more from en-route capacity improvement rather than runway expansion?

5.1 Airport capacity improvement

In this analysis, the improvement strategy is to increase the capacity of the airport runway. We use MATND to test how much delay would be reduced if an airport is expanded by building one more independent runway. In the test, the service rate of the queuing system at the airport increased by \( \frac{1}{n} \) times, where \( n \) is the number of existing runways at this airport. For example, there are currently two runways at Chengdu Shuangliu International Airport (CTU) and the capacity of this airport is 52 flights per hour. Adding one new independent runway would increase the capacity to 78 flights per hour.

Fig. 24 shows the reduction in flight delays across the whole network when one new runway is built at each of the 25 busiest airports. The results indicate that the impact of adding a new runway is dependent on the airport, and the delay reduction is very limited if investing in only one airport. On average, the total delay reduction is 0.185 min per flight across the whole network. The maximum delay reduction, 0.307 min per flight, occurs when a new runway is built at PEK. The minimum delay reduction is 0.027 min per flight at Wuhan Tianhe International Airport (WUH).

Moreover, building a new runway may even increase network propagation delay. The blue bar and orange bar represent the reduction percentage of local delay and propagated delay, respectively. We can see that there are orange bars with negative values in Fig. 24, which indicates that building a new runway at these airports (CAN, CKG, SZX, and WUH) can increase network delay propagation.

Fig. 24 Delay reduction per flight across the network from building one new runway at the airport
We can further evaluate how many airports need to be expanded to have a significant delay reduction over the whole network via MATND. We rank airports by the resultant system-level delay reduction if a new runway is built at each airport, then simulate how much delay reduction can be achieved if these runways are added into the system accumulatively. Fig. 25 shows that a 20% delay reduction can be achieved at the system-level if all top 10 airports are expanded with a new runway. The marginal reduction in delay decreases with the number of airports joining this program increases.

![Graph showing system-level delay reduction by the number of airports to be expanded](image)

**Fig. 25 System-level delay reduction by the number of airports to be expanded**

### 5.2 En-route capacity improvement

Airport expansion, especially building new runways, is capital intensive and subjected to many social-political constraints. In contrast, increasing airspace capacity could be easier and faster to be implemented. Airspace capacity may be realized by opening up more airspace for civil aviation activities, modifying operational procedures or rules (e.g., re-design sector, more progressive traffic management), deploying better surveillance and communication technologies, or developing advanced operational concepts (e.g., dynamic airspace and 4D trajectories). In this analysis, we computed the amount of delay reduction that can be achieved if the capacity of en-route congestion points increases hypothetically by 10% to 200%.

As shown in Fig. 26, if the en-route capacity is improved by just 20%, a 32% delay reduction in total flight delays can already be reached, while the greatest delay reduction is 41% when the en-route capacity is doubled. It should also be noted that the delay reduction from en-route capacity improvement is capped at around 40%, where the continued improvement of 60% - 200% extra en-route capacity has a negligible effect.

![Graph showing delay reduction vs. en-route capacity improvement](image)
Fig. 26 System-level delay reduction by the capacity improvement of en-route congestion points

Fig. 27 shows how much delay reduction at the 25 busiest airports can be achieved if the capacity of en-route congestion points increases by 20%. The local delays would remain almost the same, while the propagated delays would reduce significantly.

5.4 Individual airports’ response to en-route and runway capacity improvement

In this analysis, we compare the effectiveness of en-route capacity improvement and runway capacity improvement for individual airports, focusing on delay reduction of flights to/from that airport. We identify if any airports that would benefit more from mitigating en-route congestion than enhancing runway capacities, and vice versa. For each airport, we use MATND to compute potential delay reductions that can be achieved for flights to/from that airport if a new runway is built or if the en-route congestion connected to that airport is eliminated.
Counter-intuitively, 14 out of the 25 airports being analyzed would benefit more from en-route capacity improvement rather than runway capacity improvement, as shown in Fig. 28 and Fig. 29. The prominent ones in this category are Chengdu airport (CTU), Shanghai Hongqiao Airport (SHA), and Kuming Changhui Airport (KMG). The other 11 airports will indeed reduce more delay if a runway is built than en-route capacity increases. The results confirm that the capacity bottleneck in the current air traffic network of China is en-route airspace capacity rather than runway capacity for more than half of the busy airports.

6 Conclusion

We have developed a novel data-driven method for air transport network abstraction and simulation, named as Multi-layer Air Traffic Network Delay (MATND) model. In this model, en-route constraints are explicitly modeled within a multi-layer air traffic network consisting of airports,
en-route congestion points, and the air routes linking them. Then, it computes delays due to con-
gestion at individual airports and en-route congestion points and estimates the propagation of
delays throughout the network.

Using actual flight data, we demonstrated that MATND is a powerful tool, from a macroscopic
perspective, for delay prediction and bottleneck identification in a national air transport system.
We also showed that MATND can be used to evaluate a broad range of alternative policies and
strategies in air traffic management improvement, such as infrastructure improvements and net-
work structure modifications. For the current air traffic network of China, there are more than half
of airports that would benefit more from en-route capacity improvement rather than runway ca-
pacity improvement for flight delay reduction.

One direction of future work is to consider Ground Delay Programs (GDPs) in the delay propaga-
tion algorithm. GDPs are an explicit or implicit part of the air traffic flow management
in many countries, including China. Some airborne delays are shifted to ground delays, and
hence the delay mechanism has been changed. Thus, the propagation of delays through the
network needs to be modified in the MATND model. Another direction is to develop
simulation-based optimization models to reduce flight delays through infrastructure
improvement, better scheduling, or Air Traf-fic Flow Management policies.

References

AhmadBeygi, S., Cohn, A., Guan, Y., Belobaba, P., 2008. Analysis of the potential for delay
propagation in passenger airline networks. J. Air Transp. Manag. 14, 221–236.
https://doi.org/10.1016/j.jairtraman.2008.04.010

Beatty, R., Hsu, R., Berry, L., Rome, J., 1999. Preliminary evaluation of flight delay propagation
through an airline schedule. Air Traffic Control Q. 7, 259–270.
https://doi.org/10.2514/atcq.7.4.259

Bilimoria, K.D., Sridhar, B., Grabbe, S.R., Chatterji, G.B., Sheth, K.S., 2001. FACET: Future
ATM concepts evaluation tool. Air Traffic Control Q. 9, 1–20.
https://doi.org/10.2514/atcq.9.1.1

Campanelli, B., Fleurquin, P., Arranz, A., Etxebarria, I., Ciruelos, C., Eguíluz, V.M., Ramasco,
J.J., 2016. Comparing the modeling of delay propagation in the US and European air traffic
networks. J. Air Transp. Manag. 56, 12–18.
https://doi.org/10.1016/j.jairtraman.2016.03.017
CAPA, 2018. European airspace control. The promise: delays. The need: action [WWW Document]. URL https://centreforaviation.com/analysis/reports/european-airspace-control-the-promise-delays-the-need-action-424075 (accessed 6.4.20).

Cho, J., Welch, J., Underhill, N., 2011. Analytical workload model for estimating en route sector capacity in convective weather, in: 9th USA/Europe ATM R&D Seminar. Berlin, Germany.

Civil Aviation Administration of China (CAAC), 2016. 2015 National civil aviation flight operational efficiency report. URL http://www.cata.org.cn/HYYJ/HYYJ/201607/P020160722436820051914.pdf (accessed 6.4.20).

Civil Aviation Administration of China (CAAC), 2018. 2017 National civil aviation flight operational efficiency report. URL http://www.caac.gov.cn/XWZX/MHYW/201803/P020180329429997641224.pdf (accessed 6.4.20).

Conde Rocha Murca, M., DeLaura, R., Hansman, R.J., Jordan, R., Reynolds, T., Balakrishnan, H., 2016. Trajectory clustering and classification for characterization of air traffic flows, in: 16th AIAA Aviation Technology, Integration, and Operations Conference. American Institute of Aeronautics and Astronautics, Reston, Virginia, pp. 1–15. https://doi.org/10.2514/6.2016-3760

Eckstein, A., 2009. Automated flight track taxonomy for measuring benefits from performance based navigation, in: 2009 Integrated Communications, Navigation and Surveillance Conference. IEEE, pp. 1–12. https://doi.org/10.1109/ICNSURV.2009.5172835

Enriquez, M., 2013. Identifying temporally persistent flows in the terminal airspace via spectral clustering, in: Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013). pp. 10–13.

Ester, M., Kriegel, H.P., Sander, J., Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise, in: Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining. Portland: AAAI Press, pp. 226–231.

Eurocontrol, 2010. Network operations report for 2010: Monitoring & reporting. URL https://www.eurocontrol.int/sites/default/files/publication/files/network-operations-report-2010-yearly.pdf (accessed 6.16.20).

Eurocontrol, 2020. ESCAPE: world-class ATC real-time simulator [WWW Document]. URL https://simulations.eurocontrol.int/solutions/escape-world-class-atc-real-time-simulator/ (accessed 6.4.20).

Federal Aviation Administration (FAA), 2019. NextGen implementation plan 2018-19. URL https://www.faa.gov/nextgen/media/NextGen_Implementation_Plan-2018-19.pdf (accessed 6.16.20).

Fleurquin, P., Ramasco, J.J., Eguiluz, V.M., 2013. Systemic delay propagation in the US airport network. Sci. Rep. 3, 1159. https://doi.org/10.1038/srep01159
Fleurquin, P., Ramasco, J.J., Eguíluz, V.M., 2014. Characterization of delay propagation in the US air-transportation network. Transp. J. 53, 330–344.

Fricke, H., Schultz, M., 2009. Delay impacts onto turnaround performance: Optimal time buffering for minimizing delay propagation, in: USA/Europe Air Traffic Management Research and Development Seminar (ATM2009).

Gariel, M., Srivastava, A.N.A.N., Feron, E., 2011. Trajectory clustering and an application to airspace monitoring. IEEE Trans. Intell. Transp. Syst. 12, 1511–1524.
https://doi.org/10.1109/TITS.2011.2160628

Hsu, K., 2014. China’s airspace management challenge. U.S.-China economic and security review commission staff report. URL https://www.uscc.gov/sites/default/files/Research/China’s Airspace Management Challenge.pdf (accessed 6.4.20).

Kafle, N., Zou, B., 2016. Modeling flight delay propagation: A new analytical-econometric approach. Transp. Res. Part B Methodol. 93, 520–542.
https://doi.org/10.1016/j.trb.2016.08.012

Kivestu, P.A., 1976. Alternative methods of investigating the time dependent M/G/k queue. M.S. thesis. Massachusetts Institute of Technology.

Larsen, R.C., Odoni, A.R., 1981. Urban operation research: logistical and transportation planning methods, Prentice Hall.

Long, D., Hasan, S., 2009. Improved predictions of flight delays using LMINET2 system-wide simulation model, in: 9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO), Aviation Technology, Integration, and Operations (ATIO) Conferences. American Institute of Aeronautics and Astronautics.
https://doi.org/doi:10.2514/6.2009-6961

Long, D., Lee, D., Johnson, J., Gaier, E., Kostiuk, P., 1999. Modeling air traffic management technologies with a queuing network model of the national airspace system (No. NASA/CR-1999-20898). McLean, Virginia.

Majumdar, A., Polak, J., 2001. Estimating capacity of Europe’s airspace using a simulation model of air traffic controller workload. Transp. Res. Rec. J. Transp. Res. Board 1744, 30–43. https://doi.org/10.3141/1744-05

Malone, K.M., 1995. Dynamic queueing systems: behavior and approximations for individual queues and for networks. Ph. D. thesis. Massachusetts Institute of Technology.

Meyn, L., Windhorst, R., Roth, K., Drei, D., Van, Kubat, G., Manikonda, V., Roney, S., Hunter, G., Huang, A., Couluris, G., 2006. Build 4 of the Airspace Concept Evaluation System, in: AIAA Modeling and Simulation Technologies Conference and Exhibit.
https://doi.org/10.2514/6.2006-6110

Peterson, M.D., Bertsimas, D.J., Odoni, A.R., 1995a. Models and algorithms for transient queueing congestion at airports. Manage. Sci. 41, 1279–1295.
https://doi.org/10.1287/mnsc.41.8.1279
Peterson, M.D., Bertsimas, D.J., Odoni, A.R., 1995b. Decomposition algorithms for analyzing transient phenomena in multiclass queueing networks in air transportation. Oper. Res. 43, 995–1011. https://doi.org/10.1287/opre.43.6.995

Pyrgiotis, N., Malone, K.M., Odoni, A., 2013. Modelling delay propagation within an airport network. Transp. Res. Part C Emerg. Technol. 27, 60–75. https://doi.org/10.1016/j.trc.2011.05.017

Rebollo, J.J., Balakrishnan, H., 2014. Characterization and prediction of air traffic delays. Transp. Res. Part C Emerg. Technol. 44, 231–241. https://doi.org/10.1016/j.trc.2014.04.007

Rehm, F., 2010. Clustering of flight tracks, in: AIAA Infotech@Aerospace 2010. American Institute of Aeronautics and Astronautics, Reston, Virginia. https://doi.org/10.2514/6.2010-3412

Ren, P., Li, L., 2018. Characterizing air traffic networks via large-scale aircraft tracking data: A comparison between China and the US networks. J. Air Transp. Manag. 67, 181–196. https://doi.org/10.1016/j.jairtraman.2017.12.005

Russo, R., 2016. Capacity planning and assessment network operations planning. URL https://www.icao.int/ESAF/Documents/meetings/2016/Air%20Traffic%20Services%20System%20Capacity%202016/1%20Network%20Operations%20Planning.pdf (accessed 6.4.20).

SESAR Joint Undertaking, 2020. European ATM master plan - Executive view. https://doi.org/10.2829/650097 (accessed 6.16.20).

Tandale, M., Menon, P., Rosenberger, J., Subbarao, K., Sengupta, P., Cheng, V., 2008. Queueing network models of the national airspace system, in: The 26th Congress of ICAS and 8th AIAA ATIO. American Institute of Aeronautics and Astronautics, Reston, Virginia. https://doi.org/10.2514/6.2008-8942

Welch, J., 2015. En route sector capacity model final report, ATC-426. Lexington, Massachusetts. URL https://www.ll.mit.edu/sites/default/files/publication/doc/2018-12/Welch_2015_ATC-426.pdf (accessed 6.16.20).

Xu, N., Sherry, L., Laskey, K.B., 2008. Multifactor model for predicting delays at U.S. airports. Transp. Res. Rec. J. Transp. Res. Board 2052, 62–71.
## Appendices

### A1 Estimated queuing engine parameters of airports and en-route congestion points

Table 3 Estimated parameters of the queuing system at each airport

| Airport | Service rate (per 15 min) | k | Airport | Service rate (per 15 min) | k | Airport | Service rate (per 15 min) | k |
|---------|---------------------------|---|---------|---------------------------|---|---------|---------------------------|---|
| BAV     | 2                         | 4 | KHN     | 4                         | 2 | TAO     | 7                         | 2 |
| CAN     | 14                        | 2 | KMG     | 13                        | 3 | TNA     | 6                         | 2 |
| CGO     | 8                         | 2 | KWE     | 8                         | 3 | TPE     | 4                         | 3 |
| CGQ     | 6                         | 3 | KWL     | 2                         | 2 | TSA     | 2                         | 3 |
| CKG     | 12                        | 2 | LHW     | 6                         | 3 | TSN     | 6                         | 5 |
| CSX     | 8                         | 2 | LJG     | 3                         | 3 | TXN     | 2                         | 3 |
| CTU     | 13                        | 3 | LXA     | 2                         | 5 | TYN     | 5                         | 2 |
| CZX     | 2                         | 3 | LYA     | 2                         | 3 | URC     | 8                         | 3 |
| DLC     | 7                         | 3 | LYG     | 2                         | 3 | WNZ     | 4                         | 3 |
| DLU     | 2                         | 4 | MFM     | 2                         | 3 | WUH     | 9                         | 3 |
| FOC     | 6                         | 2 | NGB     | 4                         | 2 | WUX     | 3                         | 3 |
| HAK     | 8                         | 2 | NKG     | 9                         | 2 | XIY     | 12                        | 2 |
| HET     | 4                         | 3 | NNG     | 6                         | 2 | XMN     | 9                         | 3 |
| HFE     | 4                         | 3 | PEK     | 18                        | 3 | XNN     | 3                         | 2 |
| HGH     | 11                        | 2 | SHA     | 13                        | 2 | XUZ     | 2                         | 4 |
| HKG     | 5                         | 3 | SHE     | 8                         | 3 | YIW     | 2                         | 4 |
| HRB     | 8                         | 3 | SJW     | 4                         | 3 | YNT     | 3                         | 4 |
| INC     | 4                         | 2 | SYX     | 7                         | 2 | ZUH     | 4                         | 2 |
| JJN     | 2                         | 4 | SZX     | 13                        | 2 |         |                           |   |

Table 4 Estimated parameters of the queuing system at each en-route congestion point

| En-route index | Service rate (per 15 min) | k | En-route index | Service rate (per 15 min) | k | En-route index | Service rate (per 15 min) | k |
|----------------|---------------------------|---|----------------|---------------------------|---|----------------|---------------------------|---|
| 1              | 9                         | 1 | 11             | 4                         | 1 | 21             | 5                         | 1 |
| 2              | 20                        | 2 | 12             | 7                         | 1 | 22             | 3                         | 1 |
| 3              | 12                        | 1 | 13             | 5                         | 1 | 23             | 2                         | 1 |
| 4              | 12                        | 1 | 14             | 7                         | 1 | 24             | 5                         | 1 |
| 5              | 7                         | 2 | 15             | 5                         | 2 | 25             | 3                         | 1 |
| 6              | 10                        | 1 | 16             | 4                         | 1 | 26             | 2                         | 1 |
| 7              | 13                        | 1 | 17             | 4                         | 1 | 27             | 2                         | 1 |
| 8              | 11                        | 1 | 18             | 8                         | 1 | 28             | 4                         | 1 |
| 9              | 10                        | 1 | 19             | 3                         | 1 | 29             | 5                         | 2 |
| 10             | 8                         | 1 | 20             | 6                         | 2 | 30             | 2                         | 1 |
A2 Calculation of flight delay caused by different sources

The total flight delay over a network can be evaluated by whether it is caused by airport or en-route local congestion or network propagation effect, via the following four measures: average local delay at an airport, average propagated delay at an airport, average local delay at an en-route congestion point and average propagated delay at an en-route congestion point. The measures are defined as Eqs. (12) - (15) and the notations are given as Table 5.

- **Average local delay at an airport**: the average delay incurred on takeoff or landing at an airport.

\[
\frac{1}{\|f \in F\|} \sum_{\{f \in F|d(f) = a\}} W_a(AA(f))
\]  

(12)

- **Average propagated delay at an airport**: the average delay observed at an airport can be attributed to the earlier flights of the same aircraft.

\[
\frac{1}{\|f \in F\|} \sum_{\{f \in F|d(f) = a\}} [AA(f) - SA(f)]
\]  

(13)

- **Average local delay at an en-route point**: the average delay incurred when passing through an en-route congestion point. Note since there is an E_Buffer within each flight (as described in Section 3.2.3), some en-route delay can be absorbed by E_Buffer. Thus, E_Buffer should be subtracted from the effective local delay generated by en-route points.

\[
\left\{ \frac{1}{\|f \in F|en(f) = e\|} \sum_{\{f \in F|en(f) = e\}} W_e(AE_e(f)) \right\} - E_Buffer
\]  

(14)

- **Average propagated delay at an en-route point**: the average delay observed at an en-route point can be attributed to the delays incurred by the earlier flight of the same aircraft.

\[
\frac{1}{\|f \in F|en(f) = e\|} \sum_{\{f \in F|en(f) = e\}} [AE_e(f) - SE_e(f)]
\]  

(15)

| Symbol | Description |
|--------|-------------|
| \(f\)  | A flight    |
| \(F\)  | The set of all flights |
| \(o(f)\) | Origin airport of \(f\) |
| \(d(f)\) | Destination airport of \(f\) |
| \(en(f)\) | An en-route point passed by \(f\) |
| \(SA(f)\) | Scheduled arrival time of \(f\) |
| \(AA(f)\) | Adjusted arrival time of \(f\), \(AA(f) \geq SA(f)\) |
| \(SE_e(f)\) | Scheduled arrival time of \(f\) at en-route point \(e\) |
| \(AE_e(f)\) | Adjusted arrival time of \(f\) at en-route point \(e\), \(AE_e(f) \geq SE_e(f)\) |
| \(W_a(t)\) | Waiting time at time \(t\) of airport \(a\) |
| \(W_e(t)\) | Waiting time at time \(t\) of en-route congestion point \(e\) |
