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MANAGING AIR TRANSPORT DEMAND AND CAPACITY VIA STOCHASTIC MODELLING APPROACH

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ABSTRACT

In this paper, we investigate the effect of local disturbances in European airports over the global delay characteristics of the air traffic network with and without optimized ground holding program. Network models are constructed in order to simulate balancing the demand and capacity and delay propagation across the network under disruptive events. These models, which are stochastic Queuing Network Models (QNM), are used to run in different scenarios where the capacities of airports are reduced to simulate local disturbances (e.g. heavy rain in the airport areas, air traffic controller strikes, etc.). The impact of a local capacity reduction in the airports to the European network are analyzed, and performances of these models, with and without optimized ground holding implementation (i.e. QNM and QNM-OptGH), are compared.

INTRODUCTION

It is foreseen that the number of commercial flights will grow almost double and 16 trillion passenger-kilometer will be flown by 2035, which is almost %150 of what is flown by airlines today [Airbus, 2015]. The total number of new deliveries for both passenger and freighter aircraft are expected to be close to 33,074, while 12,834 passenger aircraft will be retired or converted to freighter [Airbus, 2015]. However, the airspace have almost a fixed amount of capacity, due to the regulations and safety aspects, and the number of airports and new hubs to be built will be not large enough to accommodate such increase in the demand. Therefore, the Air Traffic Management (ATM) system must go under an operational transformation to increase its efficiency to deal with this challenge, yet introducing radical change into the system is often difficult since it needs to take into account the many tight interdependencies that exist across the subsystems together. Meeting the capacity demand and minimizing arrival flight delays are among the most critical challenges of Flight Path 2050 [ICAO, 2011].

New procedures and concepts that are being developed in SESAR and NextGen are leading to a global paradigm shift from air traffic "control" to efficient air traffic "management" fashion, which requires redesigning the ATM system. The first step to redesign such a complex system is to perform rigorous analysis through the existing information. Once we have the parametric model on the network, then

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one can add stochastic behavioral dynamics to catch the sporadic effects on the system. Airports of the air traffic network are most fragile components of the system as the most influential events to the traffic flow occur in there. Therefore, focusing on the airports on model construction is the most common in such studies.

Several researchers focus on different approaches to model the air transportation network. MITRE Corporation focused on network modeling to mimic local delay propagation and developed two different models to simulate of delay propagation on the nationwide airport and airspace network in the United States. The Detailed Policy Assessment Tool – DPAT [Wieland, 1997], which is the successor of the NASPAC, is able to propagate delays across the network when the capacity of an airport is reduced due to external events, but it does not utilize the information regarding aircraft itineraries, which might lead to unreliable predictions. There are also agent-based simulation models for delay propagation, such as FACET tool [Bilimoria et al. , 2001]. LMINET and LMINET2 [Long and Hasan, 2009] are national queuing network models that are model the airports as $M(t)/E_k(t)/1$ queues. The Approximate Network Delays (AND) model is another popular model that is designed by [Pyrgiotis, 2012; Pyrgiotis, Malone, and Odoni , 2013]. The modeling approach in AND and LMINET2 are similar. However, calculating strategies of the local queuing delays are different. The advantages of this approach are that it is computationally cheap, and it can model both deterministic and stochastic effects.

In this work, we have constructed data analytic approach to model the European ATM Network Flow to quantify the dynamics of delay propagation across the network and balance the demand and capacity. Specifically, we have constructed two different ATM network models allow us to propagate induced delays, which are airport-based queuing network model (QNM) and airport-based queuing network model with optimal ground-holding application (QNM-OptGH) and compared their behaviors under disruptive events (e.g. heavy rain, crew strike) leading airports to mandatory capacity reduction. A case study is performed to apply demand and capacity balancing in airports.

DATA-DRIVEN NETWORK MODEL WITH/WITHOUT OPTIMAL GROUND HOLDING POLICY

In this section, we have constructed two different models, which are Queuing Network Model (QNM) and Queuing Network Model with Optimal Ground-Holding (QNM-OptGH), to analyze their delay, demand and capacity balancing characteristics through European air traffic network flow. Both of them are stochastic models, whereas second one is combined with deterministic ground holding procedures. Note that, stochasticity on the queueing models inherently reflects uncertain behaviors of the system. One can also construct pure deterministic models by following very similar data-driven approach as well.

Airport-Based Queuing Network Model (QNM)

The airport-based queuing network model consists of mainly two components, which are the local queuing delay calculator (LQDC) and the global delay propagation algorithm. This approach is a recursive process to construct such network model and utilized very similar recursive approach presented in [Pyrgiotis, 2012; Pyrgiotis, Malone, and Odoni , 2013].

LQDC generates local delays according to First Come First Served (FCFS) procedure. During the delay generation process, each airport is modeled as a single server that serves both arrival and departure flights. Airports can be modeled as $D(t)/D(t)/1$, which represents the deterministic arrival and service times, or $M(t)/E_k(t)/1$, which represents the aircraft arrival times distributed according to an Exponential distribution and airport service times distributed according to an Erlang distribution. Parameters of these distributions are inferred from the flight data and capacity declarations of airports. LQDC calculates local delays for each airport separately, and the global effects of local delays are calculated through the propagation algorithm (Algorithm 1).

LQDC considers demand profiles for each airport. These profiles have a discrete structure: one day is

Algorithm 1: Algorithm of Queuing Network Model

Input: Flight Information of All Flights (F), Capacity Profiles of each Airport
Output: Final Departure and Arrival Times of All Flights

Assign $AD(f)$ as $SD(f)$ and $AA(f)$ as $SA(f)$ $\forall f \in F$
Calculate Demand Profiles using $AD(f)$ and $AA(f)$ $\forall f \in F$
Calculate $W_a(t)$ $\forall a \in A$ by using Demand Profiles and Capacity Profiles with LQDC
Determine "significant" delays
while *any "significant" delay exists* **do**
    Update $AD(f)$ and $AA(f)$ $\forall f \in F$ according to:
        $AD(f) = max[SD(f), SD(f) + (AA(f') - SA(f')) + W_{d(f')}(AA(f')) - slack(f', f)]$
        $AA(f) = max[SA(f), AD(f) + W_{o(f)}(AD(f)) + (flight\ time\ from\ o(f)\ to\ d(f))]$
    Calculate Demand Profiles using $AD(f)$ and $AA(f)$ $\forall f \in F$
    Calculate $W_a(t)$ $\forall a \in A$ by using Demand Profiles and Capacity Profiles with LQDC
    Determine "significant" delays
$\forall f \in F$ **assign** Final Departure Time(f) $= AD(f) + W_{o(f)}(AD(f))$
$\forall f \in F$ **assign** Final Arrival Time(f) $= AA(f) + W_{d(f)}(AA(f))$

split into 15 minutes time windows. $\mu_a(h)$ represents demand in an airport a at time window h. It is the total number of flight for both take-off and landing. The other input is $\lambda_a(h)$, which represents the service rate. Through these inputs, LQDC generates $W_a(t)$ local delay function dependent to time in airport a.

In global propagation level, the algorithm uses $W_a(t)$ sequences, connected flights, scheduled and adjusted departure-arrival times of each flights. f represents the current flight while f' represents the predecessor flight of the same aircraft. At the beginning of the propagation algorithm, delay situations are determined. The delay is accepted as "significant" if the departure or arrival time of f needs to be adjusted, such as shifting to other slots is essential because of its predecessor flight f'. Departure and arrival times of all flights are regulated through propagation algorithm and evaluated with the following equations:

$$AD(f) = max[SD(f), SD(f) + (AA(f') - SA(f')) + W_{d(f')}(AA(f')) - slack(f', f)] \quad (1)$$

$$AA(f) = max[SA(f), AD(f) + W_{o(f)}(AD(f)) + (flight\ time\ from\ o(f)\ to\ d(f))] \quad (2)$$

In these equations, $AD(f)$ is the regulated departure time of flight f. AA is the regulated arrival time, SD is the scheduled departure time and SA is the scheduled arrival time. $o(f)$ is the origin airport of flight f and $d(f)$ is the destination airport. Let $turn(f', f)$ be the turnaround time, which is evaluated as $turn(f', f) = SD(f) - SA(f')$. Let $minturn(f', f)$ be minimum time to handle the ground services of flight f. The $slack(f', f)$ can be given as $slack(f', f) = turn(f', f) - minturn(f', f)$. Once we have the regulated departure and arrival times, demand profiles are updated for each airport. This recursive process between LQDC and propagation algorithm repeats until the any significant delay not to stay in the network. This process is given in Algorithm 1.

Airport Based Queuing Network Model with Optimal Ground-Holding Program (QNM-OptGH)

In QNM, delays are equally distributed to departure and arrival traffic through FCFS procedure in LQDC stage. This approach simply assumes that if a departing aircraft takes x minutes delay, the following arrival aircraft, which is served in the same runway, will take approximately the same amount of delay. Considering the ground delay is preferred to airborne delay, a ground-holding mechanism is integrated into QNM. The pseudo-code of Airport Based Queuing Network Model with Optimal Ground-Holding Program is given as Algorithm 2. In this algorithm, problematic airports are identified at the beginning of algorithm. A problematic airport is defined as the airport that has local delays greater than 15 minutes. If any problematic airport exist then ground holding procedure is activated. We use an optimization based ground holding mechanism. We have chosen to use Mathematical programming [Bertsimas et al. , 2011; Peterson et al. , 2012] to generate the ground delays by minimizing defined cost function.

Algorithm 2: Algorithm of Queuing Network Model with Optimal Ground-Holding

Input: Flight Information of All Flights (F), Capacity Profiles of each Airport
Output: Final Departure and Arrival Times of All Flights

Assign $AD(f)$ as $SD(f)$ and $AA(f)$ as $SA(f)$ $\forall f \in F$
Calculate Demand Profiles using $AD(f)$ and $AA(f)$ $\forall f \in F$
Calculate $W_a(t)$ $\forall a \in A$ by using Demand Profiles and Capacity Profiles with LQDC
Assign $SD_{rev}(f)$ as $SD(f)$ and $SA_{rev}(f)$ as $SA(f)$ $\forall f \in F$
Determine problematic airports ($a \in A$) that ensure the condition of $\max(W_a(t)) > 15$
if *any problematic airport exist* **then**
  Generate Ground Delays using binary integer programming formulation
  Update $SD_{rev}(f)$ and $SA_{rev}(f)$ $\forall f \in F$ according to ground delays
Determine "significant" delays
while *any "significant" delay exists* **do**
  Update $AD(f)$ and $AA(f)$ $\forall f \in F$ according to:
  $AD(f) = max[SD_{rev}(f), SD_{rev}(f) + (AA(f') - SA_{rev}(f')) + W_{d(f')}(AA(f')) - slack(f', f)]$
  $AA(f) = max[SA_{rev}(f), AD(f) + W_{o(f)}(AD(f)) + (flight\ time\ from\ o(f)\ to\ d(f))]$
  Calculate Demand Profiles using $AD(f)$ and $AA(f)$ $\forall f \in F$
  Calculate $W_a(t)$ $\forall a \in A$ by using Demand Profiles and Capacity Profiles with LQDC
  Determine "significant" delays
$\forall f \in F$ **assign** Final Departure Time(f) = $AD(f) + W_{o(f)}(AD(f))$
$\forall f \in F$ **assign** Final Arrival Time(f) = $AA(f) + W_{d(f)}(AA(f))$

Let $F = \{f_1, f_2, ..., f_n\}$ be the set of flights during time period $T = \{t_1, t_2, ..., t_m\}$ and $A = \{a_1, a_2, ..., a_l\}$ be the set of airports in network. Then, $C_{a,t}$ be mixed capacity of airport a during sub-period t. Let the scheduled departure time period of flight f become d_f and scheduled arrival time period become e_f. Then, two new sets are defined to present the possible departure and arrival time periods for flight f as $D_f = \{d_f, d_f + 1, d_f + 2, d_f + 3\}$ and $E_f = \{e_f, e_f + 1, e_f + 2, e_f + 3\}$, respectively. Ground delay is restricted with 3 sub-periods, which is 45 minutes in our model, D_f and E_f are generated according to this restriction. Let $x_{f,t}$ and $y_{f,t}$ be binary decision variables for departure and arrival, and:

$$x_{f,t} = \begin{cases} 1 & if\ flight\ f \in F\ departs\ at\ time\ t \in T \\ 0 & otherwise \end{cases}$$

$$y_{f,t} = \begin{cases} 1 & if\ flight\ f \in F\ arrives\ at\ time\ t \in T \\ 0 & otherwise \end{cases}$$

the summation of all $x_{f,t}$ variables for flight f must be equal to 1 and it is also true for $y_{f,t}$ because of the fact that a flight only departs at a specific time window and arrives also at a specific time window, so others must be equal to 0. Let f^{dep} and f^{arr} symbolize the origin and destination airports of flight f. Flight duration and minimum turnaround time of flight f are symbolized by $f^{duration}$ and $f^{minTurn}$, respectively. Let f' be predecessor flight of flight f. Then, the binary integer programming formulation become:

$$min \sum_{f \in F} (\sum_{t \in D_f} tx_{f,t}) - d_f \tag{3}$$

subject to

$$\sum_{f:f^{dep}=a} x_{f,t} + \sum_{f:f^{arr}=a} y_{f,t} \leq C_{a,t} \quad (t,a) \in T \times A \tag{4}$$

$$\sum_{t \in E_f} ty_{f,t} - \sum_{t \in D_f} tx_{f,t} = f^{duration} \quad \forall f \in F \tag{5}$$

$$\sum_{t \in E_{f'}} ty_{f',t} - \sum_{t \in D_f} tx_{f,t} \leq -f^{minTurn} \quad \forall f' \in F \tag{6}$$

$$\sum_{t \in D_f} x_{f,t} = 1 \quad \forall f \in F \tag{7}$$

$$\sum_{t \in E_f} y_{f,t} = 1 \quad \forall f \in F \tag{8}$$

$$x_{f,t} \in \{0,1\}, \quad y_{f,t} \in \{0,1\} \tag{9}$$

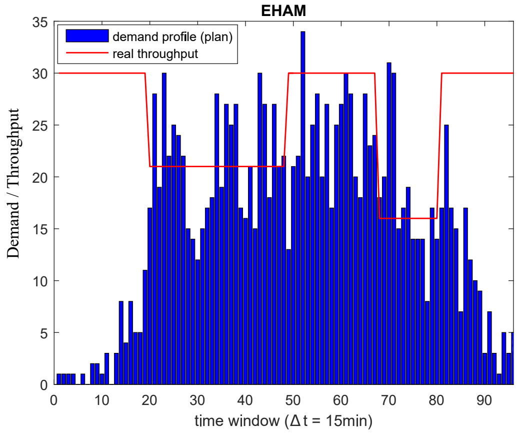
The cost function (3) corresponds to total ground delays taken by all flights in the network, and the aim is to minimize this total delay. Constraints (4) consist of capacity restriction of airports and mixed capacity approach is used to generate these constraints. Constraints (5) are about flight duration and there exist an approach that flights do not take any airborne delays. The optimization problem is designed to determine the ground delays, so mainly effects of ground delays are investigated without airborne delays. Delay propagation due to consecutive flights performed by the same aircraft is taken into account by constraints (6). Constraints (7) and (8) are necessary to assign departure time of a flight to only one-time window and arrival time, respectively. And, constraints (9) declare the binary values of decision variables.

The solution of binary integer programming formulation gives the ground delays that is seen from line 6 to 9 in Algorithm 2. At the beginning of problem, d_f and e_f in optimization are taken as $SD(f)$ and $SA(f)$ for each flight f ∈ F, then $SD_{rev}(f)$ and $SA_{rev}(f)$ are updated according to outcomes of optimization.

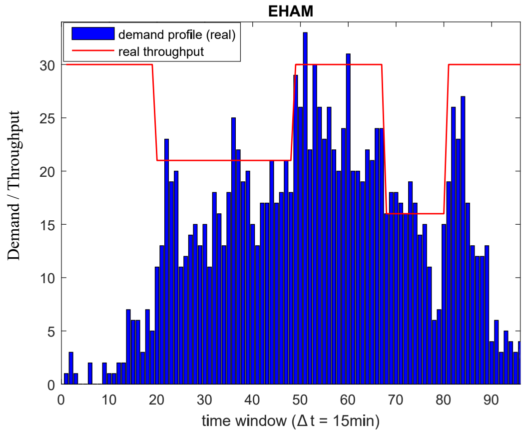
SIMULATION RESULTS

To build a proper air traffic network for Europe, we have utilized historical flight data. It is known the fact that an airport generates delays when it reaches its capacity limit. Airports that operate far from its limit do not mostly generate a delay into the network. Because of this reason, minor airports in Europe are grouped into an aggregated airport that has infinite capacity. Moreover, non-European airports are also grouped into same aggregated airport. Using this approach, the total number of airports in European Air Traffic Network is reduced into 103 airports, which includes 102 major European airports and a single aggregated airport to construct reduced dimensional model of large-scale European air traffic network.

For an implementation purpose, real flight traffic data for a specific day (i.e. May 30, 2016) is used, where 30% and 45% capacity reduction in EHAM (Amsterdam Schiphol) from 05:00 to 12:00 and from 17:00 to 20:00, 10% capacity reduction in EGLL (London Heathrow) from 07:30 to 12:30 and 25% capacity reduction in EDDF (Frankfurt) from 07:45 to 09:30 are applied. These reduction rates are generated comparing planned and real demand profiles of airports. As an example, demand profiles in EHAM are presented in Figure 1. When planned and real demands are compared, it is observed that real throughput is smaller than planned demand from 05:00 to 12:00 and from 17:00

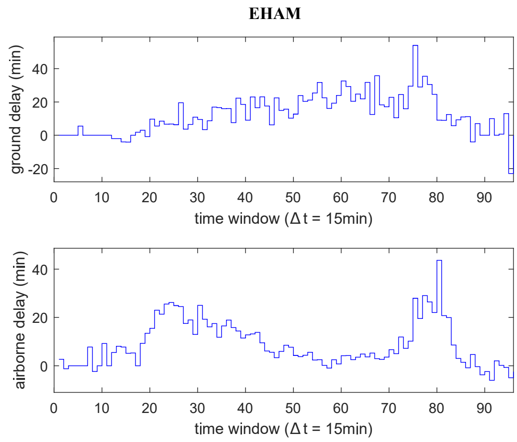


(a) Planned Demand

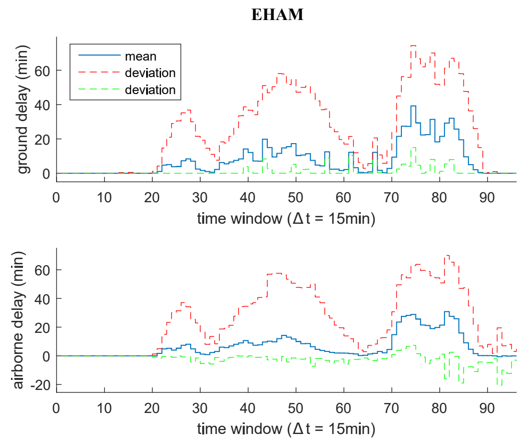


(b) Real Demand

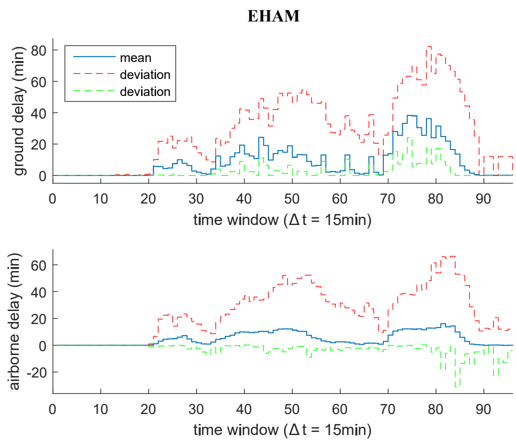
Figure 1: Demand Profiles for EHAM



(a) Real Situation



(b) Results of QNM

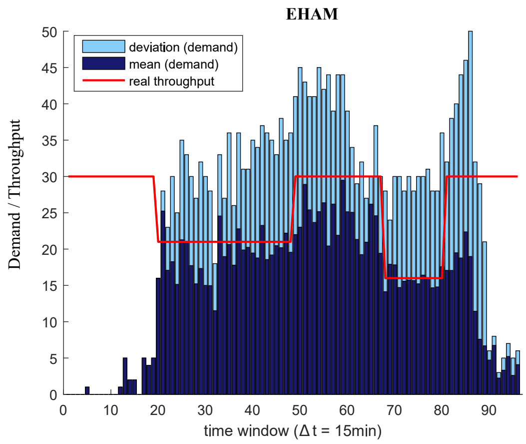


(c) Results of QNM-OptGH

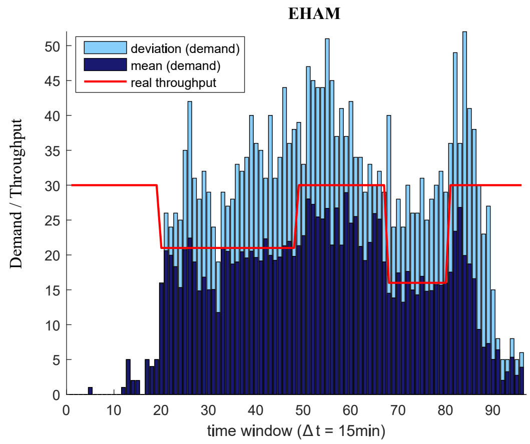
Figure 2: Delays in Real Situation and Simulation Results for EHAM through QNM and QNM-OptGH

to 20:00. By comparing the planned and real demands, real throughput is generated, and capacity reduction rates are calculated as 30% and 45%, respectively. Demand profiles of only eight busiest airports are analyzed to generate the capacity reduction of these airports for this specific day, and only three of them have regulated. These reduction rates and flight plans are used as inputs to network models, and simulation results are presented in the rest of this section. The performances of network models are analyzed and compared according to simulation results. The models are compared to stochastic network models, so 100 different simulations are executed for each model to understand the performance of them by comparing the means and deviations and show the impacts of stochasticity on the network.

In Figure 2, total ground and airborne delays within the hourly time windows in EHAM are shown to give the comparison calculated delays with the real situation. From the Figure 2b and 2c, it is observed ground delays in QNM-OptGH is greater than in QNM, while QNM-OptGH has smaller airborne delays. Ground delay policy in QNM-OptGH causes to shift delays from airborne to ground when compared with QNM.

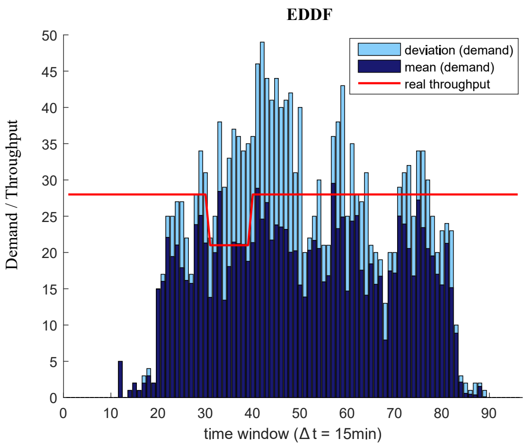


(a) Balanced Capacity-Demand according to QNM

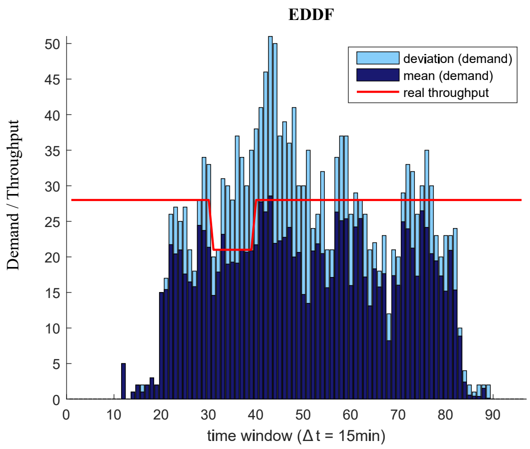


(b) Balanced Capacity-Demand according to QNM-OptGH

Figure 3: Balanced Capacity-Demand Profiles for EHAM



(a) Balanced Capacity-Demand according to QNM



(b) Balanced Capacity-Demand according to QNM-OptGH

Figure 4: Balanced Capacity-Demand Profiles for EDDF

Under capacity reduction, demand and real throughput profiles for the results of QNM and QNM-OptGH are shown in Figure 3 and Figure 4 for EHAM and EDDF. These figures are generated through 100 simulation run for each model, and deviations from average demand trend are also shown with light blue bars while average demand trend is shown with dark blue bars. Considering average demand profile, it can be said that demand and capacity are in balance, however, capacity excesses are seen due to stochastic nature of the models. Moreover, it can be seen that QNM-OptGH outperforms QNM in demand capacity balancing. In Figure 4a and 4b, it is realized that capacity excess due to stochasticity in QNM is more than in QNM-OptGH when mean demand profiles is compared.

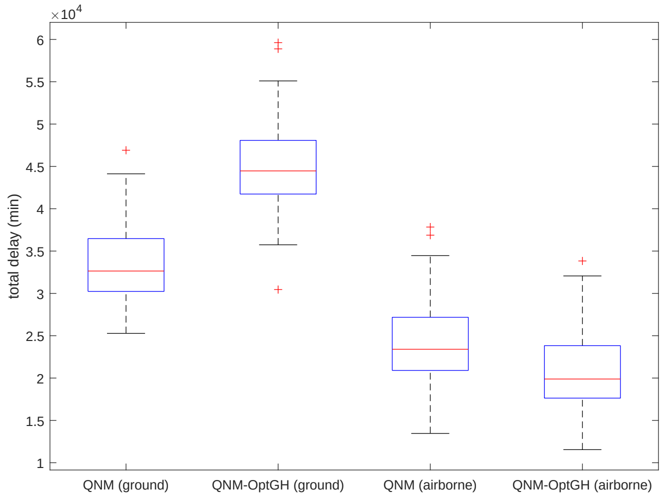


Figure 5: Box-plots of Total Delays in Network through QNM and QNM-OptGH

To understand the global impacts of models, the box-plots of total delays in network for these models are presented in Figure 5. The figures show that QNM model generates smallest total ground delay, while QNM-OptGH generates highest total ground delay. And, vice versa is correct for airborne delays. This is a natural result of shifting strategy of delays from airborne to ground in ground holding programs.

CONCLUSION

This paper presented two different network models to simulate the delay propagation and balance the demand and capacity in case of capacity reduction at certain airports in the European air transportation network. Design principles and algorithms of these models were explained and presented throughout of the paper. Then, these models were compared in balancing demand/capacity with several simulations through real air traffic data of certain days that disrupted by capacity reductions issues. The comparison results were given, also provides validation for the models.

Through these simulations, It was observed that ground delay policy integrated into QNM shifts the delays from arrival to departure traffic to prevent the costly airborne delays. It was also seen that QNM-OptGH has efficient than QNM from perspective of demand and capacity balancing. The future work will be to add air sector and trans-sector queues into the network in order to capture demand and capacity balancing in en-route sectors, which will enable to centrally control traffic flows.

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