Dynamic Queuing Network Model for Flow Contingency Management

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We introduce a queuing-network model, that can comprehensively represent traffic-flow dynamics and flow-management capabilities in the United States National Airspace System. We envision the introduced model as providing a framework for tractably evaluating and designing coordinated flow-management capabilities at a multi-Center or even NAS-wide spatial scale, and a strategic (2-15 hour) temporal horizon. As such, the queueing-network model is expected to serve as a critical piece of a strategic flow-contingency management solution for NextGen. Based on this perspective, we outline in some detail the evaluation/design tasks that can be performed using the model, as well as the construction of the flow-network underlying the model. Finally, a simple example is presented to illustrate use of the model.

I. Introduction

In the Next Generation Air Transportation System (NextGen), traffic flow management (TFM) operations will require the capability to better predict and manage congestion at longer time horizons, in order to more effectively use the limited capacity of the National Airspace System (NAS). Specifically, a decision support system methodology is envisioned for NextGen, that can account for the uncertainties inherent at these longer look ahead times (LATs) while still providing decision makers with coordinated and efficient options for managing congestion and promoting effective decision making. In response to this need, an operational concept for Flow Contingency Management (FCM) [Taylor2011] was proposed. The FCM operational concept includes an aggregate flow modeling strategy which incorporates the dynamic evolution of weather impact, designs responses to likely weather-impact outcomes, and measures the performance of the strategies developed using metrics of interest to multiple decision makers. A critical component of this strategy is the capability to capture the types of congestion management controls available now and envisioned in the NextGen environment in order to simulate and evaluate how the aggregated traffic flow responds to different options.

We are developing a new dynamic queuing network model of the NAS to enable the evaluation and design of traffic management strategies under weather uncertainties for FCM. Herein we describe the model, identify some analytical gaps that need to be addressed, and present an example of how it can be applied. Our queuing network model has the following features that make it promising for FCM:

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1) Establishes the connection between stochastic weather impact and NAS performance. The model takes stochastic weather impact data as input and simulates NAS flow-level behavior, allowing calculation of performance metrics such as delay statistic. Due to the significant weather uncertainty at the strategic time frame, developing the capability to evaluate NAS performance in response to stochastic weather is critical for the analysis and design of FCM.

2) Captures the impact of realistic management actions’ impact on flows

As the major goal of FCM is to improve decision-making for the implementation of management actions, mathematically capturing the impact of management actions on flows is a critical step toward a systematic FCM design. In our model, we have carefully abstracted five typical management actions that are used in practice or have potential for use in NextGen, including en route rate restrictions such as minute-in-trail (MINIT) and miles-in-trail (MIT), Ground delay program (GDP), Airspace flow program (AFP), routing, and Time-based metering (TBM).

3) Represents traffic as stochastic flows while maintaining route structure information

The model (as a queuing model) tracks traffic as flows rather than individual aircraft, and hence significantly reduces the dimension of the decision space for FCM. A novelty of our queuing model is that it allows the mapping of realistic route information to the structure of a flow network, and hence facilitates FCM design that requires route information.

4) Permits Parameterization from data and interface with operational practice

As a component of the FCM framework, our queuing network model is constructed to provide an effective evaluation and design of FCM strategies based upon aggregated flow structure, demand information, and weather-impact data. Because of the direct correspondence between model components (such as demand, flow, route structure, management actions, backlog) and realistic concepts used in FCM, the model can be easily parameterized from data, and results obtained from the model can be easily interpreted by air traffic managing/control practitioners.

The remainder of the paper is organized as follows. In Section 2, we introduce the concept of queuing network models and discuss the reasons for adopting them within the FCM framework. A brief literature review of the research on queuing modeling is also included. In Section 3, we address the key challenges toward dynamic flow network modeling for FCM, e.g., the construction of queuing network models to capture FCM traffic management actions. In Section 4, the novel dynamic queuing network model is described in detail. Interfacing the queuing network model with the rest of the FCM framework is also discussed. Moreover, analytical challenges in using the queuing network model for FCM design are addressed. Finally, in Section 5, we present a simple example to illustrate the use of the queuing network model for the performance evaluation of FCM designs.

II. Background on Dynamic Queuing Network Models

Driven by the need to design coordinated management strategies NAS-wide, various efforts have been devoted to the construction of network models for the NAS (see [Sridhar2008] and [Griggner2009] for comprehensive reviews). A majority of network models in the literature are deterministic models (e.g., [Bertsimas1994, Menon2002&2003, Bayen2004, Sun2008, Myers2008]); however these models are limited in their capability to capture uncertainties.

Queuing network models represent an alternative to the above deterministic network models, as they provide a natural modeling framework for traffic systems with uncertainty. A queue is comprised of three components: 1) a stochastic arriving/upstream flow that is usually modeled as a stochastic process, 2) a flow-restriction service capturing a limited capability to process flows, and 3) a downstream flow which is shaped by the service acting on it, as shown in Figure 1. A queuing network model is composed of a network of queues, with downstream flows from one queue becoming the arriving flows of other queues in the network. We believe that queuing network models will be a useful modeling framework for assisting in effective FCM decision making for the following reasons:

- **Queuing network models are natural for capturing uncertainties in traffic.** Due to the presence of uncertainties in taxiing, take-off, and en-route flight, etc.(see [Chatterji2002] for statistical analysis of uncertainties), deterministic network models and the subsequent optimization procedures may result in management solutions that are not optimal or implementable in an uncertain environment. At the strategic time-frame, when the traffic system is subject to significant uncertainties due to the lack
of precision in weather prediction, models that can lead to management solutions which are robust to uncertainties are crucial. Queuing network models, as stochastic models with good tractability, naturally serve this need.

- **Queuing models can capture a variety of flow restrictions that are currently used as management strategies or can potentially be brought into operation, such as MINIT, MIT, AFP, and time-based metering.** Low-order statistical analysis, which is typically used to evaluate the performance of queuing systems, provides a natural approach to capture the impact of flow restrictions on flows, and in turn to design coordinated flow restrictions for FCM.

- **Queuing network models capture the aggregation of flows and management strategies, instead of modeling the management of each particular aircraft.** Such aggregation results in a reduced-dimensional description of the NAS, which reduces computational costs and thus facilitates FCM at the strategic timeframe. Since the focus of FCM is on the generation of high-level coordinated management strategies in the NAS, rather than on the control of each individual aircraft, the loss of some detailed information through aggregation does not constitute a critical concern.

![Figure 1: An illustration of queuing models](image)

**A. Literature Review of Queuing Models**

Queuing models have been explored by different groups in air traffic research. We review these relevant air traffic studies to illustrate the current status of queuing research and identify the challenges and research needs in order to implement queuing models within the FCM framework. In air traffic research, queuing models have long been used to analyze particular local processes that are subject to uncertainty. To cite a few, [Horangic1990] considered various queuing models to evaluate airport delays; in [Idris2001], a queuing model was constructed to estimate the taxi-out time at an airport; in [Moreau2005], queuing models were used to evaluate the performance of en route restrictions (measured by delay and backlog) on a single stream flow.

Of particular relevance to our development, queuing network models have been pursued in the literature for the evaluation of NAS performance. Some works focus on modeling a network of airports with departing and arriving traffic represented as queues ([Malone1995], [Shortle2003]). In [Frollow1989], a NAS-wide simulation model, NASPAC, was developed to evaluate changes such as airport capacity variation, airport improvements, and demand growth. Later, in [Long1999], a static queuing network model incorporating both airports and en-route centers was developed. More recently, in Tandale2008, an M/M/m Jackson Queuing Network capturing intra-Center flows was used to analyze NAS performance and the efficiency of route selection. Markovian service times and flows (such as the ones captured in M/M/1 and M/M/n models) are typically adopted for queuing network modeling, due to the tractability it allows for queuing analysis. In [Wan2008], abstractions of an M/D/1 queue to capture MIT/MINIT restrictions were sought and a linear network model was developed, allowing the design of flow restrictions for optimal NAS-performance in the steady-state situation. [Hansen2008] sought to use M(t)/E_k(t)/n models for low-precision NAS-wide modeling where the use of Erlang-K distributions to model flow-restriction service times allows more flexibility in capturing the realistic flow-restricted services. Moreover, the dynamic modeling framework captures the time-varying features of the NAS. Analysis of this queue network representation is complicated: an approximation study can be found in Malone1995.

**III. Modeling Challenges of using Queuing Models for FCM**

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6 A steady-state situation implies that the statistics of the states reach constant values, which usually occur when the queuing model is run for a sufficiently long time.

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As seen from the literature review, queuing network models have been widely used in NAS modeling, but have not been developed or studied with enough sophistication to assist in the evaluation and design of FCM at the strategic timeframe. Here, we identify the major research needs to achieve a queuing model development that meets the needs of the FCM decision-support system. First, a queuing network model needs to analyze aggregated traffic flows while still capturing routing options in the NAS. Second, the queuing model must be reasonably easy to parameterize from data and to configure for practical needs. For instance, schedule information needs to be easily reflected in flows. Also, appropriate aggregation levels for the queuing network model need to be determined so as to achieve the balance between computational costs and the ease of transforming strategic decisions to tactical management actions. The most significant modeling challenge is the use of queuing models to capture a variety of management strategies used in FCM. The strategies that we intend to incorporate include MIT, MINIT, AFP, rerouting, GDP, and possibly time-based metering. MIT and MINIT restrictions have been investigated in [Wan08]. The other restrictions need to be carefully modeled. Here let us discuss the challenge on capturing the control actions in detail, and leave the discussion of the rest to Section 4.

A. Discussion on Different Control Actions:

In order to design effective traffic management strategies for FCM, we must capture the relevant control actions available to manage congestion. Specifically, we consider five control actions that are currently in practice or potential for use in NextGen, including MIT/MINIT, routing, time-based metering, GDP, and AFP. In this section, we elaborate on how each of these control actions could be captured within FCM. We emphasize here that most of the control actions described here are, to a certain extent, different from the ones implemented currently in the operational environment. For instance, the control actions other than the rate restrictions (MIT/MINIT) are typically concerned with dealing with individual aircraft. Here instead, we abstract these control actions as flow restrictions that have the roles of shaping flows. Therefore, we begin by presenting the TMIs as currently viewed at a flight specific level and then discuss how these can be captured as control actions to shape flows.

Rate restrictions (MIT/MINIT)

Implementations of MIT and MINIT are specified by the minimum allowable separation distance or traveling time between successive aircraft. MIT and MINIT can be viewed as the control actions that manage flows on specific routs. A MIT/MINIT restriction can be captured by a deterministic service time in a queuing model, such as the M/D/1 queue or G/D/1 queue. Specifically, in a deterministic service time queue model, each aircraft in the coming flow takes a fixed service time to pass a flow-restriction point; any additional arriving aircraft will be waiting in the queue and will pass the restriction-point on a first-come basis. The service time equals the duration of the MINIT restriction, or the MIT restriction divided by the aircraft traveling rate.

Routing

With regard to routing, a choice of alternative routes is provided to each aircraft to avoid convective weather or other adverse situations. In order to permit route selection, queuing-network models need to distinguish among flows with different destinations, as the final destination of an aircraft in the flow influences the route choice at each location. As basic queuing network models do not capture this choice, it is necessary to enhance the models for this purpose. In queuing models, route selection can be abstracted as setting the fraction of flows in each possible direction at flow splitting points.

Time-based Metering

Time-based metering requires aircraft to be delivered to fixes at pre-computed times, so as to reduce the discrepancy between demand and capacity. The metering plan along an aircraft’s route is assigned based upon the arrival rate at the destination airport, and is achieved through speed adjustment, vectoring, and holding. This differs from MIT and MINIT which are flow restrictions; time-based metering is an aircraft-specific TFM action. At the aggregate level, time-based metering may be abstracted using an M/M/n model. The use of multiple parallel servers allows aircraft meeting the prescheduled time to pass a server at an earliest possible time. Further studies need to be carried out to determine the feasibility of the proposed model and model parameter identification.

GDP

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A GDP is a traffic management procedure that delays aircraft at their departure airport so as to resolve the imbalance of demand and capacity at the arrival airport. The delay assigned to an aircraft at the departure airport is determined by the allowable arrival rate at the arrival airport. To capture a GDP within our aggregated modeling framework, we can abstract the GDP by shaping the demand at the departure airport through the deployment of departure rate restrictions using a queuing model such as M/E_k(t)/n or M/M/n. We note that because the implementation of a GDP is tied to specific origin-destination pairs, the flows in the queuing network model need to be organized into origin-destination pairs so as to facilitate this implementation. Again, more studies need to be conducted on the model identification for GDPs.

AFP

When AFPs are enacted, aircraft that are scheduled to pass through constrained airspaces are managed through the assignment of estimated departure clearance time (EDCT). An aircraft-specific EDCT is assigned based upon the time required for an aircraft to cross an AFP constrained area. The procedure can be modeled similar to GDP, but only for flows intersecting the constrained airspace. Because GDP-type management strategies are involved, flows again need to be labeled with the origin airport.

IV. Queuing Network Model

As discussed in the previous sections, significant research is required to extend available modeling approaches to capture FCM decisions. In this section, we provide our initial research results that demonstrate the progress of our work on addressing these issues. Specifically, we discuss the queuing network model developed, that incorporates the management actions discussed in the previous section. Moreover, we describe the interfacing issues of the network model with the entire FCM framework, and also identify the analytical challenges that define major research directions.

A. Description of the Fundamental Queuing Network Model

We develop a queuing network model that shows promise in facilitating FCM strategies. The set of management actions currently considered in this model include route selection and MIT/MINIT restriction design. Here, we first discuss two general considerations underlying the queuing network model, and then describe mathematically the dynamic queuing network model with these management decision parameters integrated.

First, in order to permit the design of routing (and GDP) management strategies, the queuing network model needs to be constructed from sub-networks with origin-destination (O-D) pairs as discussed in the previous section. Specifically, rates for the O-D pair sub-networks will be obtained from schedules as discussed previously, whereupon stochastic Poisson process models of these rates will be used to describe the originating flows. Moreover, since MIT and MINIT are en route flow restrictions acting on total flows from all directions along a route, the sub-networks need to be overlapped and integrated, as shown in Figure 2.

In the network model, nodes are classified into three categories: 1) flow merging/splitting points, 2) aggregated origin and destination airports, and 3) boundary intersection points. The definitions for the first two categories are straightforward and in general, we can consider a directed route as beginning at an origin airport (category 2 node), traversing through a number of flow merging/splitting points (category 1 nodes) and terminating at a destination airport (category 2 node). To understand the third category, let us consider the NAS as partitioned into regions (e.g. sectors, a cluster of sectors, etc.). The intersections between region boundaries and directed routes are denoted as boundary intersection points. Let us denote a link as the portion of a directed route between two connected nodes belonging to category 1 and/or 2. We note that a boundary intersection point can be uniquely determined by the ends of a link and the region index that the flow enters. As such when we refer to a node, we mean a node belonging to the categories 1 and 2 without specific clarification, while a link and region index specify boundary intersection points.
Second, before formulating the model, let us discuss the modeling of en route restrictions as queues, as this aspect of the model differs significantly from many previous efforts on flow-network modeling and requires further development. En route restrictions such as MIT/MINIT restrictions are modeled using G/D/1 queues (i.e., general coming flow, deterministic service rate, and single serve queue), to represent the required aircraft separation. The MIT/MINIT restrictions manage flows entering regions at the boundary intersection points. Due to the lack of tractability of a continuous-time M/D/1 queue model in our framework, we instead use a discrete-time approximation of the M/D/1 model. The discrete-time G/D/1 queue operates as follows: at every unit time interval, if the backlog b (number of aircraft waiting in the queue) plus the rate of inflow u (number of aircraft approaching a boundary intersection point in a unit time interval) is larger than the service rate N (maximum number of aircraft that can be served in a unit time), N aircraft pass to the downstream and the backlog at the next time interval becomes b-N+u. If instead, b+u is less than N, then all b+u aircraft can pass to the downstream and the backlog at the next time interval is 0.

Now let us formally introduce the queuing network model. To ease the presentation here, we first present the model that allows the implementation of the two most fundamental management actions----MIT/MINIT and routing. In Section 3.2, we will extend the model to incorporate the remaining three management actions, namely, time-based metering, GDP, and AFP. Mathematically, the variables used in the flow network model are defined as follows:

- \( f_{od}[k] \) represents the demand from origin o to destination d. This demand is modeled as a stochastic process (e.g., Poisson process).
- \( f_{odi}[k] \) denotes the rate of flow (i.e., the number of aircraft in a unit time) traveling from an origin o to a destination d, that are entering the link from node i to node j at time instance k.
- \( g_{odi} \) denotes the rate of flow (i.e., the number of aircraft in a unit time) from the origin o to destination d, that are leaving the link from node i to node j, at time instance k.
- \( ijm \) represents a boundary intersection point uniquely determined by link \((i,j)\) and region \(m\).
- \( b_{ojm}[k] \) represents the total backlog of the flow from node i to node j, upon entering the boundary of region \(m\), at time instance \([k]\).
- \( b_{d}[k] \) represents the backlog at destination d, at time instance k.
- \( u_{ojm}[k] \) represents the rate of downstream flow from node i to node j, right before entering the boundary of region \(m\).
- \( d_{ojm}[k] \) represents the rate of downstream flow from node i to node j, right after entering the boundary of region \(m\).
• \( p_{odi} \) represents the fraction of flow (from origin o to destination d) that is entering node i and heading to node j.
• \( N_{ijm} \) represents the number of aircraft allowed to enter section m along the path \((i,j)\) in a unit time.
• \( N_{id} \) represents the number of aircraft allowed to enter the destination d from node i in a unit time.
• \( K_{ij} \) is the number of time steps for an aircraft to travel from node i to node j, where nodes i and j are directly connected. Here the nodes may include boundary intersection points.
• \( \Gamma_{ijm} \) is the capacity for link \((i,j)\) in region m.
• \( \Gamma_m \) is the total capacity for region m.
• \( \Gamma_d \) is the total capacity for destination d.

The flow network model is described by the following dynamics and constraints. Note that all flow variables \( f, g, b, u, d \) are stochastic processes.

At each flow junction point, the total inflow equals the total outflow.

\[
\begin{align*}
g_{odi}[k] &= \sum_{i, \text{s.t. link}(i,j) \text{ exists}} f_{odi}[k], \quad \forall j, \text{s.t. link}(o,i) \text{ exists} \quad (1) \\
\sum_{i, \text{s.t. link}(i,j) \text{ exists}} p_{odi} &= 1 \quad (2) \\
1 \geq p_{odi} \geq 0 \quad (3)
\end{align*}
\]

As a special case, at the origin airport, we have

\[
g_{odi}[k] = \sum_{i, \text{s.t. link}(o,i) \text{ exists}} f_{odi}[k] \quad (4)
\]

Here \( p_{odi} \) is subject to two constraints:

\[
\sum_{i} p_{odi} = 1, \quad (5) \\
1 \geq p_{odi} \geq 0 \quad (6)
\]

Note that the introduction of the fraction variable \( p_{odi} \) permits the selection of routes to improve the NAS performance.

At each boundary intersection point, an MIT restriction (or other flow-restriction capability), denoted by \( N_{ij} \), acts to shape the flow (summation of flows associated with all source and destination pairs), achieving a reduced down-stream flow (captured by \( b \)) at the cost of increased backlog (captured by \( b \)).

\[
\begin{align*}
b_{ijm}[k+1] &= \max(0, b_{ijm}[k] + u_{ijm}[k+1] - N_{ijm}) \quad (7) \\
d_{ijm}[k+1] &= \min(N_{ijm}, b_{ijm}[k] + u_{ijm}[k+1]) \quad (8) \\
N_{ijm} \leq \Gamma_{ijm} \quad (9) \\
\sum_{i,j} N_{ijm} \leq \Gamma_m \quad (10)
\end{align*}
\]

Equations (7) and (8) describe the discrete-time approximation of the G/D/1 model. Equations (9) and (10) describe the capacity constraints for flow restriction variables \( N_{ijm} \). As a special case, at the destination airport, we have

\[
b_{d}[k+1] = \sum_{i, \text{s.t. link}(i,d) \text{ exists}} \max(0, b_{id}[k] + u_{odi}[k+1] - N_{id}) \quad (11)
\]

where

\[
\sum_{i, \text{s.t. link}(i,d) \text{ exists}} N_{id} \leq \Gamma_d \quad (12)
\]

We assume that aircraft travel at a constant speed along the route between any two connected nodes, which include boundary intersection nodes. As such, the flows in the network are subject to the following constraints.

\[
\begin{align*}
u_{ijm}[k] &= \sum_{\text{all (o,d) pairs}} f_{odi}[k] \\
\sum_{\text{all (o,d) pairs}} f_{odi}[k] &= d_{ijm}[k] / K_{ijm} \\
u_{odi}[k] &= d_{ijm}[k] / K_{ijm} \\
f_{odi}[k] &= \max(0, b_{odi}[k] - K_{ij})
\end{align*}
\]

The above network model allows the design of management actions including routing, and MIT/MINIT. Specifically, the design of parameters \( p_{odi} \) permits route selection and \( N_{ijm} \) implements the MIT/MINIT strategies. It is worth noting that, in general, there may be flow restrictions in the network that are not amenable to design, in the sense that their parameters are fixed (or vary due to uncontrollable factors such as weather). Broadly, we will assume that a subset of the flow restrictions is designable by management actions.
Note that our queuing network model is different from the flow network models in the literature, including the existing queuing models, in the following respects.

- The model captures flows as stochastic processes, and hence traces stochastic backlogs and downstream flows at network nodes. The definition of congestion (measured using the backlog) is more realistic in such queuing-type models as compared to the definition arising from deterministic models (e.g., myers2008).
- The overlapped O-D pair flow network model structure facilitates the performance analysis and the design of management actions. Different from many queuing network models in the literature which are implicit in relating parameters to management actions, we explicitly incorporate in the model the control parameters that reflect in-practice management actions.
- The model is dynamic and can capture the transient dynamics of the NAS. Unlike most queuing network models in the air traffic management literature which are only focused on steady-state analysis, the dynamic model provides a framework for transient analysis, which is especially important when we consider the impact of transient weather events.
- Weather uncertainties can be transformed to stochastic description of capacity constraints $\Gamma$, so as to facilitate weather-driven FCM design. We will discuss some preliminary results in this direction in [Zhou2011].

B. Expanding the Fundamental Queuing Network Model to Allow the Design of GDP/AFP/Time-based Metering

Let us expand the above fundamental queuing network model to incorporate the design of GDP, AFP, and Time-based metering.

The implementation of a GDP at a destination $d$ can be reflected by reshaping the stochastic departure rates for all origins $o$ that are paired with the destination $d$. We use a discrete-time version of an G/M/n queue (i.e., general coming flow, memoryless service rate, and n-serve queue) to capture this process. To do that, we replace Equation (4) with the following set of equations:

$$b_{od}(k+1) = \max(0, b_{od}(k) + f_{od}(k) - M_{od}(k)) \quad (4.a)$$

$$g_{odoi}(k+1) = \min(b_{od}(k) + f_{od}(k), M_{od}(k)) \quad (4.b)$$

Here, $M_{od}(k)$ is Poisson-distributed with rate $N_{od}$. $b_{od}(k)$ represents the backlog at origin $o$ that is paired with the destination $d$. The selection of a subset of destination airports $d$, and the design of $N_{od}$ for all origin airports $o$ that are paired with these destination airports leads to the aggregated GDP design. We note that Equations 4(a) and 4(b) describe the flows at origin airports that are impacted by the GDP restrictions. These restrictions placed at the origin airports do not propagate impact to the destination airport until the nominal flight time has passed; this delay in impact is captured by Equations 13-16, which describe the en-route flow behavior.

The implementation of an AFP can be modeled as reshaping the stochastic departure rates for all origins $o$ that have flows intersect with the weather zone. We again consider a discrete-time version of a G/M/n queue for this process. The following two equations describe this process:

$$b_{odoi}(k+1) = \max(0, b_{odoi}(k) + p_{odoiw} f_{odoi}(k) - M_{odoi}(k)) \quad (4.c)$$

$$g_{odoi}(k+1) = \min(b_{odoi}(k) + p_{odoiw} f_{odoi}(k), M_{odoi}(k)) + (p_{odoi} - p_{odoiw}) f_{odoi}(k), \quad (4.d)$$

Here, $M_{odoi}(k)$ is Poisson-distributed with rate $N_{odoi}$. $b_{odoi}(k)$ represents the backlog associated with the flow that travels from origin $o$ to node $i$ and then finally to destination airport $d$. $p_{odoiw}$ specifies the percentage of flow that intersects with the weather zone among the flows from origin $o$ to node $i$ and then to destination airport $d$. $p_{odoiw} = \sum_{j, \ldots, l, m} p_{odoip}_{odoij}\ldots p_{odlm}$, such that $m$ is located in the weather zone. The selection of the subset of flows that intersect with the weather zone, and the design of the rates $N_{odoi}$ for these flows leads to the aggregated AFP design. A more precise modeling of AFP can be obtained through the design of a single departure rate restriction for all of the aggregated flows originating from $o$ and intersecting with the weather zone. It is interesting to explore the difference for these two methods in terms of performance.
To permit the design of TBM, we consider the adoption of G/M/n queues at metering fixes. For now, let us assume that metering fixes overlap with boundary intersection points. There might be multiple queues at a metering fix. Each G/M/n queue acts on the flows that are destined to a common destination airport o. For fixes that TBM is implemented, Equations 7-12 are replaced by:

\[
\begin{align*}
  b_{ijmd}[k+1] &= \max(0, b_{ijmd}[k] + u_{ijmd}[k+1] - M_{ijmd}[k]) \\
  d_{ijmd}[k+1] &= \min(M_{ijmd}[k], b_{ijmd}[k] + u_{ijmd}[k+1]) \\
  \sum dN_{ijmd} &\leq \Gamma_{ijm} \\
  \sum dN_{ijmd} &\leq \Gamma_m 
\end{align*}
\]

(7a) \hspace{1cm} (8a) \hspace{1cm} (9a) \hspace{1cm} (10a)

Here, \( M_{ijmd}[k] \) is Poisson-distributed with rate \( N_{ijmd} \); \( b_{ijmd}[k] \) represents the backlog associated with the flow passing through the boundary intersection point \( ijm \), and ending at the destination airport \( d \). As a special case, at the destination airport, we have

\[
\begin{align*}
  b_d[k + 1] &= \sum_{\forall i, \text{s.t. link}(i,d) \text{ exists}} \max(0, b_d[k] + u_{iodd}[k+1] - M_{id}[k]), \\
  \sum \forall i, \text{s.t. link}(i,d) \text{ exists} N_{id} &\leq \Gamma_d
\end{align*}
\]

(11a) \hspace{1cm} (12a)

\( u_{ijmd}[k] \) can be obtained through the following equations describing the enroute behavior.

\[
\begin{align*}
  u_{ijmd}[k] &= \sum \forall o \text{ godij}[k-k_{ijm}] \\
  \sum \forall o \text{ pairs} f_{odi}[k] &= d_{ijmd}[k-k_{ijm}, ijm] \\
  u_{ijnd}[k] &= d_{ijmd}[k-k_{ijm}, ijn] \\
  f_{odi}[k] &= g_{odi}[k-ki] 
\end{align*}
\]

(13a) \hspace{1cm} (14a) \hspace{1cm} (15a) \hspace{1cm} (16a)

For simplicity, we may assume that there is only one restriction placed at a metering fix, and do not apply different control actions to different destination airports. If this is the case, we simply replay the G/D/1 constraint at each boundary intersection point with the G/M/n constraint. The details of the model are straightforward, and hence are omitted here.

Further investigations need to be devoted to the construction of the queuing network model. The flow network can be simplified based on the set of management strategies of interest and the design variables needed. For instance, \( \rho_{odi} \) can be restricted to take either a zero or one value, provided that only one route is selected for an O-D pair. The flow merging/splitting points and boundary points may be merged if desirable.

### C. Interfacing the Queuing Network Model to the Rest of the FCM Framework

As stated previously, the design of the queuing network model proposed in this research is motivated by the capability requirements for FCM. In [Taylor2011], a detailed description of the overall concept and proposed FCM...
framework, shown in Figure 3, was presented and is briefly discussed in this section to provide clarity and context for the queuing network model described.

Examining Figure 3, we notice that the elements of the framework are grouped into the four components and distinguished by color. At the top of Figure 3 are the data elements (shown in red) that define the information requirements for FCM, namely flight schedule, airspace configuration, and weather data. Next, the modeling framework components, shown in green, consist of the network framework and aggregate demand definitions. Although the modeling framework essentially provides the data necessary to develop the flow contingency plans, additional analysis is required to translate the flight schedule and relevant airspace configuration data into an appropriate description for the flow contingency planning components.

The flow contingency development, shown in orange, derives the flow contingency plans for FCM from the data and modeling framework and requires three separate analyses, namely weather impact, queuing model and flow contingency development. The weather impact model analyzes the weather data and configuration data, using the network model, to define areas of the NAS that will be (potentially) impacted by weather. This information, as well as the aggregated demand, is provided to the queuing model which simulates these impacts and in conjunction with flow contingency development defines the flow contingency plans for the different potential weather impact outcomes. The flow contingency plans are then relayed to the strategic planning component (shown in blue), which consists of user inputs (in the form of priorities), a formal framework for strategic plan development and an analysis that defines the current point decision plan which relies on incremental decision planning.

Viewing Figure 3, we see that the queuing network model is integral to the capabilities envisioned for FCM, namely the simulation and design of control actions to mitigate performance loss in the presence of weather-impact.

1. **Performance Evaluation and Optimal Design of FCM Strategies**

   With the above queuing network model, we propose a methodology to evaluate and design effective FCM strategies with respect to performance measures of interest to stakeholders in the NAS. A variety of performance measures are of interest. One of these measures is concerned with the total cost in the NAS (or in multiple critical regions) over a time-span subject to the capacity constraints described in the model. We note that the costs are directly related to the statistics of backlogs/delays that are captured in the queuing-network model. However, the backlogs/delays implemented by various management strategies may be also associated with different costs. For instance, en route delays and ground delays are obviously associated with different costs. Moreover, routing introduces extra costs due to the extra en route time and fuel costs.

   Fairness issues may also need to be considered in the optimization problem. As pointed out in [Roy2009], optimal design usually leads to an unfair solution. More efforts are needed to obtain optimal designs in the network models, when fairness constraints are imposed.

2. **Inputs to the Queuing Network Model**

   The proposed queuing-network model can be adapted to networks with any aggregation level. In order to use the queuing model for FCM design, we need to first parameterize the queuing network, to reflect the operational reality of the planning period under consideration. We call the parameterized queuing network model a queuing network instance. To obtain a queuing network instance, we require the following inputs from the other modules within the FCM framework.

   - Flow-network structure from the Flow-network Description module is required. We need to choose the appropriate aggregation levels of the queuing model elements (e.g., nodes, routes) to allow the design of management actions at a meaningful scale for FCM. Parameters $k_{ij}$ for all adjacent node pairs $i$ and $j$ need to be estimated. The selection of an appropriate aggregation level for flows should be closely tied to the congestion level of flows (which might be related to weather severity, but does not have to be). This insight also tells us that the flow network structure might be dynamic, dependent on the change of weather.
Demand rate (e.g., $f_{od}$) needs to be estimated. We need to study the stochastic flow model process to estimate the flow rates from data. Typically, time-varying Poisson flow models are used to model the demand, and have been proved in various studies (see e.g., [Moreau2005]).

Capacity constraints such as route capacity $\Gamma_{ijm}$, region (region) capacity $\Gamma_m$, and destination capacity $\Gamma_d$ need to be provided from the weather impact model.

If we start the planning at the beginning of a day, the above inputs are sufficient to run an instance of the queuing network model. However, if the planning occurs at some time during a day, the current flight information for all en-route flights will be used to derive initial conditions for all the state variables in the queuing network model. If the schedule information is available, it can significantly aid in the queuing analysis and design. In this case, schedule information will be translated to deterministic flow rates, and management actions are designed for the deterministic flows and the stochastic flows as a whole. If the schedules have already taken into account of management actions, the deterministic flows can be viewed as flows that are not designable.

3. **Simulation and Design Outputs from the Queuing Network Model**

The direct outputs from the simulation of the dynamical queuing network model include the time-course statistics of coming flow, crossing flow, and backlog at all management nodes in the network. These statistical data capture the transient dynamics of the NAS in response to dynamical weather uncertainties. From these data, important decision-making indicators such as airport delay, airport throughput, sector count, sector backlog can be obtained, which help the design of a variety of FCM management actions NAS-wide in the presence of dynamical uncertain weather.

The design outputs from the queuing network model are in the form of aggregated rates associated with time and location. Specifically, the design variables associated with each strategy are summarized in Table 1.

<table>
<thead>
<tr>
<th>Management Actions</th>
<th>Design Output Variables</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIT/MIINIT</td>
<td>$N_{ijn}$</td>
<td>Flow rate entering each region boundary</td>
</tr>
<tr>
<td></td>
<td>$N_{id}$</td>
<td>Flow rate entering each destination</td>
</tr>
<tr>
<td>Routing</td>
<td>$p_{odij}$</td>
<td>The fraction of flow toward each direction at the transshipment nodes</td>
</tr>
<tr>
<td>GDP</td>
<td>$N_{od}$</td>
<td>Departure rate of flow at each origin that is paired with certain destination</td>
</tr>
<tr>
<td>AFP</td>
<td>$N_{odoiwa}$</td>
<td>Departure rate of flow at each origin that is paired with certain destination and insects with the weather zone</td>
</tr>
<tr>
<td>TBM</td>
<td>$N_{ijmd}$</td>
<td>Rate for flows entering each region boundary and destined to a destination</td>
</tr>
<tr>
<td></td>
<td>$N_{id}$</td>
<td>Flow rate entering each destination</td>
</tr>
</tbody>
</table>

Other outputs include: integrated flow and weather simulator, prediction of future policies associated with different weather scenarios, performance statistics estimates, and possibly partitioning plan for the tactical time-frame.

Investigation needs to be carried out to translate the aggregated rates to contingency plans understandable and implementable at the ATCSCC.

4. **Simulation of the Model**

We have developed the software that simulates the NAS dynamics using the queuing network model. The simulation software tracks the inflow, backlog, and cross-flow at all O-D specific nodes according to the recursive equations developed in Section IV. In the case that there are multiple flows subject to one constraint or MIT restriction, the control action assigned to each flow is subject to the following rules: if the total backlog...
of all flows is greater than the total available constraint/MIT restriction, each flow is assigned a control restriction proportional to its backlog; otherwise, all backlogs are allowed to cross, and the remaining control restriction for each flow is assigned as proportional to its inflow.

5. Analytical Challenges

We have proposed the development of a queuing network model that abstracts all promising FCM traffic management strategies. The queuing network model will be used to simulate, analyze, and design FCM strategies in response to probabilistic weather prediction. As there is significant weather uncertainty in the strategic timeframe, the performance evaluation and design of FCM strategies must take into consideration the range of possible weather scenarios. As opposed to deterministic network models which can only rely on intensive Monte Carlo simulations to obtain statistically meaningful results, queuing models show promise in permitting efficient performance evaluation and design for FCM. Here we identify the critical gaps in the analytical aspect along with the existing advances in addressing these gaps, and briefly describe our preliminary development in these directions.

1) Analysis of queuing (network) models (e.g., G/D/1 and G/M/n) with service rates modulated by stochastic weather impact.

Since stochastic weather can be captured using Markov chains (see Section 3.4.1), these queuing models are referred to as queues with Markov modulated service processes. Such models have already been adopted in the literature to capture services with random occurring breakdowns. Some studies have been devoted to the steady-state analysis of these types of queues models. For instance, studies on M/M/n queues with Markov modulated service processes can be found in [Baykal-Gursoy2006] and the references therein. More studies need to be devoted to other types of queuing models with Markov modulated service processes, and networks of these queues.

2) Transient analysis of queuing (network) models

When severe weather events occur, queuing models of the NAS usually do not have a steady-state, or cannot reach the steady-state before the severe weather fades. As such, a steady-state analysis of queuing models may not provide an informative measure for performance evaluation. Unfortunately, precise transient analyses of queuing models usually involve heavy computational costs. Approximation studies need to be pursued to address this difficulty. [Peterson1995] provides a study on this topic, in which transient moments of queue lengths are studied for landing processes at a network of airports.

3) Design of complicated queuing network models involving a variety of control actions and subject to weather uncertainty

The design of flow restrictions is complicated by the nonlinearity inherent in typical queuing systems, the stochasticity, and the time-varying nature of queuing models required for FCM. We are pursuing approximation studies, as well as dynamic programming and jump-linear-control-based approaches to address the design problem. Jump-linear models refer to linear models with parameters modulated by Markov chains (please refer to e.g., [Fang2002] and [Roy2005] for the analysis and control of jump-linear models).

4) The robustness of strategic time-frame management to tactical time-frame implementation

As tactical management actions are employed to best react to local constraints and improved weather forecasts, these changes to the management structure must be easily incorporated within the strategic FCM framework. The local TFM management in various regions (e.g., groups of regions) in the NAS needs to be decoupled in such a way that local modifications at the tactical level do not introduce huge disturbances to overall NAS performance. By employing a clustering algorithm at the strategic time-frame, we can identify groups of regions that require information-sharing during the decision making process, thereby decomposing the tactical timeframe NAS management problem into semi-standalone management problems. We will evaluate the impact of stochastic weather events on this decomposition, and design a dynamic and rational decomposition algorithm that is weather-dependent and identifies partitions of the NAS that require communication.

We are in the process of developing analytical tools to address the above analytical challenges. Specifically, for a stochastic flow entering a probabilistic weather zone, we have developed approaches to predict the statistics of transient delay dynamics effectively. Please refer to [Zhou2011] for the complete study.
V. Illustrative Examples

In this section, let us present three examples, the first and second of which show the simulation of the queuing network model in a simple and then more realistic example, and the third illustrates the use of the queuing network model in analyzing and designing FCM strategies in the presence of uncertain weather. We stress that the examples only illustrate some of the features of the queuing-network model, and may not consider many of the intricacies present in a real-world situation. Nevertheless, we include the examples here to give a first illustration of the model.

A. A Four O-D Pair Network Example

In this example, we consider a four O-D pair network as shown in Figure 4. The network is composed of three sectors S3, S5 and S6, and four airport resources S1, S2, S11 and S16. Nodes 1 and 2 are departure airports, 11 and 16 are destination airports, and the rest of the nodes are sector boundary points, at which both flow merge/split and en-route management actions are implemented. The four sub-networks (marked with different colors on arcs) are associated with O-D pairs 1-11, 2-11, 1-12 and 2-12. The demands to departure airports 1 and 2 follow Poisson distribution with rates shown in Figure 5. We simulated the example for the following five cases. For each case, we simulate the dynamics for 100 sample runs and obtain the statistical dynamics of the backlog at each node, sector count for each sector (all aircraft along the arcs in the sector together with backlog accumulated because of the downstream sectors), and departure and arrival backlogs/throughputs for each airport, at every 15 minute time step.

1) Nominal Condition: At the normal condition, there is no control strategy in action. Airport 1 and airport 2 have departure rate 8 and 7 per time interval. Airports 11 and 16 are subject to arrival rate constraints 3 and 4. Sector 3, 5, and 6 are associated with capacity constraints 4, 3, and 3. Here, the capacity constraints represent the maximum amount of aircraft allowed to enter a sector in a unit time interval.

2) Reduced Capacity: Due to the occurrence of bad weather, the capacity constraint for sector 5 is reduced from 3 to 1 during the span from 14:00 to 17:00.

3) GDP: Because sector 5, which is subject to the reduced capacity, is along the routes from airport 1 to 11 and 2 to 11. GDP is implemented at airport 1 in the O-D sub-network 1-11 and airport 2 in the O-D sub-network 2-11, with a reduction of departure rate to 2 from 12:00-16:00.

4) MIT: In this case, we replace the GDP strategy in case 3 with MIT placed at flows into sector 5 further upstream. Specially, nodes 4, 10, 6, 9 are assigned with MIT rates 2, 2, 0.2, 0.2 per time interval from 13:00 to 16:00.

5) Routing: To account for the reduced capacity in case 2, instead, we apply rerouting to reduce the flows into sector 5. Specifically, during 13:00-16:00, the flow fractions from node 1 to 4, 1 to 6 and 1 to 7 in the O-D sub-network 1-11 are changed to 0.1, 0.1, and 0.8. Also, during the same time span, the flow fractions from node 2 to 9, 2 to 10, and 2 to 12 in the O-D sub-network 2-11 are changed to 0.1, 0.2, and 0.7.
Figure 4: Four O-D sub-network example. Sector boundaries are marked by dashed lines. Four O-D sub-networks are differentiated by the colors of edges. Flow fractions are marked on the edges. Purple numbers marked on edges indicate the transit time measured in the unit of hour.

Figure 5: Demand rate for airports 1 and 2 in the four O-D sub-network example

Let us discuss some selected simulation results to show that the simulation captures the expected effect of capacity constraints, weather events, GDP, MIT, and rerouting. Figure 6 shows a snapshot from the video of the average backlog for case 1 and case 2 at the same moment. Clearly in the nominal setting, sector capacities are sufficient; however when the capacity of sector 5 is reduced, sector 5 becomes congested as reflected by the backlog accumulated at the sector entry nodes 3, 5, 6, and 8. The congestion of sector 5 can also be inferred from Figure 7, which shows time-course average sector counts. Comparing sector counts (marked by the black curve) for sector 5 during the normal condition (left figure) and the reduced capacity condition (middle figure), we observe a cutoff on the curve of the reduced capacity condition during 14:00-17:00, which indicates sector congestion. The rightmost figure in Figure 7 also shows the effectiveness of the rerouting management strategy. As flights that were planned to traverse sector 5 are rerouted to avoid this congested section, the count of aircraft in sector 5 remains in the safe range. This is reflected by the reduced height of the black curve compared to those in the left two figures. Finally, let us examine the impact of GDP and MIT from the plots in Figure 8. Comparing the arrival backlog and departure backlog subfigures in the left and middle figures, we can see that GDP delays flows arriving at airport 11 to reduce the demand-capacity imbalance, whereas at a cost of
introducing backlog at departure airports. The comparison of arrival backlog in the leftmost and rightmost figure in Figure 8 shows the placement of en-route restrictions at the designated places delays traffic to both destination airports so as to avoid the bad weather hours. From the above discussions, we can see that these simulation outputs provide rich information about the dynamics of the network that would benefit the design of management strategies.

Simulation of queuing network models is reasonably time-efficient as only the flow dynamics at management locations are tracked. For this small example, simulation and analysis for one sample run in all take less than a second on a common university desktop for teaching purposes. We will leave more rigorous estimation of computational time and modification of the algorithm for computational effectiveness in the future.

Figure 6: Snapshots from the video of backlogs at all nodes. x and y dimensions show the location of the nodes and z dimension shows the mean backlog for 100 sample runs. Plots from left to right are associated with case 1 (normal condition) and case 2 (reduced capacity condition).

Figure 7: Time-course average sector counts. Plots from left to right are associated with case 1 (normal condition), case 2 (reduced capacity condition) and case 5 (rerouting in action).

Figure 8: Time-course airport usage statistics. Left four, middle 4, and the right 4 plots are associated with case 2 (reduced capacity), case 3 (GDP) and case 4 (MIT).
B. The Atlanta Example

We also simulated real-world scenarios, namely the behavior of the NAS at a normal day (August 30, 2010) and a bad weather day (September 26, 2010). For the bad weather day, we generated different weather scenarios using the influence model [Xue2011] and simulated the NAS behavior with different control plans. As our focus in this paper is not on the simulation, but on the introduction of the dynamic queuing network model, here we only illustrate the setting of the example, present the scale of the problem, and show very selected simulation results.

On September 16, there was low ceiling and rain developed within and around ZTL center, which significantly impacted the performance of traffic in this area. As our focus is on the behavior of ZTL, in formulating the network instance, we abstracted regions outside the Atlanta center at center levels, and regions in Atlanta center at a sector level. This abstraction highly improves tractability without losing much information of interest. Also, the aggregation of airports outside the Atlanta center is at a much more abstract scale compared to the aggregation inside ZTL. To summarize, the network instance for the NAS is composed of 68 airport clusters (with 22 within the ZTL center area), 260 regions (including 68 departure airports, 68 arrival airports, and all sectors within the ATL area), 1074 nodes (including 68 departure airports, 68 arrival airports, and all of the sector boundary points), and 16243 O-D specific arcs.

Figure 9 shows the snapshots of the sector backlog at the normal weather and one bad weather scenario at the same time. We could see from the snapshots that there is increasing backlog in the Atlanta center due to the occurrence of bad weather. We also compared the simulated arrival traffic to ATL with the actual arrival traffic at the normal day (see Figure 10). As can be seen from the comparison, the simulation resembles the real traffic despite the significant abstraction in the network formulation.

![Figure 9: Snapshots from the videos of sector backlogs (in the ZTL center) for a normal day (left) and a bad weather day (right). The locations of the sectors are plotted according to their latitude and longitude. The z dimension shows the total backlog of all flows entering each sector.](image-url)
C. Multiple Flows in Stochastic Winter Weather

This example is concerned with traffic flows to a cluster of nearby airports that will be impacted by a winter-weather event. The majority of the traffic arriving at this cluster of airports can be viewed as coming from four different origins, i.e., for the purpose of flow-management design the source airports for the traffic can be clustered into four groups with traffic flow originating at each. In this case, we will model the demand for each of these flows as Poisson processes with average rates of 25 aircraft per hour (major flow), 12 aircraft per hour (moderate flow 1), 11 aircraft per hour (moderate flow 2), and 2 aircraft per hour (minor flow of very-long-distance traffic), respectively, for the duration of the planning horizon (see Figure 11). We note that the average demand for the destination cluster is thus 50 planes per hour. During good weather conditions, the capacity of the airspace near the destination airport is more than sufficient to handle this demand. Note that in real operations, the flow rates would be time-varying, and the queuing model handles this case as well, but for simplicity, this example uses time-invariant flow rates.

A winter-weather event is anticipated in the destination airspace over a 7-10 hour time period. During the winter-weather event, terminal-area as well as en-route constraints will reduce the capacity of the destination airspace to 35 aircraft per hour. Thus, a flow-contingency plan is needed to address the demand-and-capacity imbalance. The exact duration of the winter-weather is uncertain, but a ten-hour event (say between noon and 10 PM) is a conservative estimate. In particular, the end time of the event is uncertain, and winter weather may cease as early as 7 PM, but no later than 10 PM.
Several management capabilities are available to handle the capacity-and-demand imbalance. First, GDPs can be implemented on all, or a subset of, the major flow and two moderate flows. In the case where GDPs are used alone, they must be implemented for the entire potential 10 hour weather-event, since the distance of the origin clusters to the destination does not permit reaction to a shorter-duration weather event. We note that the GDP will tend to reduce flow rates proportionally (in an average sense) on the impacted flows. We also assume that another rate-reduction capability is available for the major flow (specifically, an AFP or perhaps a future airspace construct) that allows us to tune the rate on the major flow compared to the other flows. This capability must also be implemented for the maximum possible duration of the event. Finally, an en-route flow restriction can be implemented, that acts together on the major flow and moderate flow 1 (in the form of a MINIT restriction). In particular, given the uncertainty in end-time of the winter-weather event, we also have the option to implement a GDP for flows arriving over a shorter time interval (say 7 hours), and then use the MINIT restriction to modulate the rates thereafter; the en-route restriction has the advantage that it can be flexibly implemented based on the weather condition (though at the cost of requiring en-route restriction of traffic).

This example can be directly formulated in the queuing-network framework introduced above. As a step toward FCM design, let us use the queuing model to compare several flow management strategies. In particular, we will use the queuing model to easily compute the delays and backlogs incurred by the implementation of each strategy to enable proper strategy selection. Specifically, we consider the following five possible strategies for flow management:

1. Strategy 1: Use a GDP that acts on the major flow.
2. Strategy 2: Use a GDP that acts on the two moderate flows.
4. Strategy 4: Use a GDP that acts on the moderate flow, as well as an AFP on the major flow to tune the flow rate on the major flow compared to the others.
5. Strategy 5: Use a shorter-duration GDP (for all three flows) together with an en-route restriction

We will also compare these strategies to a nominal case where strategic flow-management is not used, or is put in place in an ad hoc fashion.

Let us compare the performance of the Strategies. Figures 12-15 show statistics of the numbers of aircraft delayed at each source airport, as well as statistics of the total number of aircraft delayed, as a function of time. In particular, for each of the three GDP strategies, the mean numbers of aircraft delayed (waiting) at each source airport is plotted vs. time, as is the mean total number of waiting aircraft. We note that these statistics can be obtained through the analysis given in [Zhou11], or through Monte Carlo simulation. These preliminary results demonstrate that delays can be distributed effectively among source airports through use of GDPs that concurrently delay multiple flows, albeit at a cost of increased complexity for traffic managers.

Finally, let us briefly compare the performance of the flow management strategies with the nominal strategy that does not initiate management actions, as well as a strategy that mimics current operating practice in the NAS. If no FCM strategy is implemented, a significant capacity imbalance would result at the destination, with up to 150 aircraft being forced to wait in the air to enter the capacity-constrained airspace. In practice, current operators would not permit such an imbalance, since many flights would be forced to divert to alternate airports. Instead, a ground stop or GDP would be imposed. However, current operators would not have the benefit of comparing different possible strategies in terms of the delays/backlogs incurred. Furthermore, it is quite possible that their enacted strategy would be reactive to the weather conditions – possibly leading to excess delay and unnecessary cancellations. A primary benefit of the queuing-model representation is its use in quickly estimating costs associated with different possible flow-management strategies, thus facilitating contingency selection.
Figure 12: Aircraft Delay Statistics when a GDP is applied to the major flow (Strategy 1). The upper plot shows the mean number of aircraft that have been delayed (i.e., are waiting) at each source airport, as a function of time. The lower plot shows the mean of the total number of delayed aircraft vs. time.

Figure 13: Aircraft Delay Statistics when a GDP is applied to the two moderate flows (Strategy 2). The upper plot shows the mean number of aircraft that have been delayed (i.e., are waiting) at each source airport, as a function of time. The lower plot shows the mean of the total number of delayed aircraft vs. time.

Figure 14: Aircraft Delay Statistics when a GDP is applied to the all three flows (Strategy 3). The upper plot shows the mean number of aircraft that have been delayed (i.e., are waiting) at each source airport, as a function of time. The lower plot shows the mean of the total number of delayed aircraft vs. time.
Figure 15: Aircraft Delay Statistics when a GDP is applied to two moderate flows and AFP is applied to the major flow (Strategy 4). The upper plot shows the mean number of aircraft that have been delayed (i.e., are waiting) at each source airport, as a function of time. The lower plot shows the mean of the total number of delayed aircraft vs. time.

Figure 16: Aircraft Delay Statistics when a shorter-span GDP and a MIT are applied to all three flows (Strategy 5). The left-upper plot shows the mean number of aircraft that have been delayed (i.e., are waiting) at each source airport, as a function of time. The left-lower plot shows the mean of the total number of delayed aircraft vs. time. The right plot shows the mean of the number of aircraft delayed in flight.

VI. Conclusions

We have introduced a queuing network model for air traffic flow management. The developed model is an effort to comprehensively capture the dynamics of air traffic and traffic management at the level of traffic flows, so as to permit evaluation and design of management strategies at a NAS-wide scale and strategic time horizon. As such, our queuing-network model enhances existing modeling capabilities significantly in several directions, including by permitting 1) representation of a wide range of current and potential future traffic-management actions; 2) analysis of traffic flows under weather uncertainty; and 3) parameterization of the underlying flow network from data. While our study of the queuing-network model is in its nascent stages, we believe that it will play a central role as a prediction and design tool in our proposed flow contingency management method.

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