A Route-Based Queuing Network Model for Air Traffic Flow Contingency Management

Shin-Lai Tien\(^1\) and Christine Taylor\(^2\)

*The MITRE Corporation, McLean, VA, 22102*

Yi Zhou\(^3\) and Yan Wan\(^4\)

*University of North Texas, Denton, TX, 76201*

and

Craig Wanke\(^5\)

*The MITRE Corporation, McLean, VA, 22102*

Ongoing research is currently focused on the need to improve the strategic traffic flow management decision making processes. The research effort in this paper is part of a greater research initiative aimed at developing quantitative analysis and design capabilities for flow contingency management, which include the design of queuing network models. This paper proposes to use the concept of route assignment for managing aggregate air traffic demand and evaluating flow contingency plans generated by human decision makers. To determine how strategic traffic controls are captured and the computational requirements associated, a simulation experiment is conducted with realistic demand data and weather impact scenarios. System-wide performance results on a realistic plan of strategic control are analyzed, and the computational requirements of arc-based and route-based modeling choices will also be discussed.

**Nomenclature**

\[ \begin{align*}
N & = \text{Set of nodes} \\
A & = \text{Set of arcs} \\
O & = \text{Set of nodes that serves as origin airports; } O \subseteq N \\
D & = \text{Set of nodes that serves as destination airports; } D \subseteq N \\
R_{od} & = \text{Set of routes that serves demand from an origin } o \in O \text{ to a destination } d \in D \\
T & = \text{Set of time steps} \\
s & = \text{The super source node that feeds the traffic into the system} \\
e & = \text{The super sink node where the traffic terminates} \\
f_{r_{ij}}^t & = \text{Inflow to node } i \text{ from node } j \text{ at time } t \text{ on route } r \in R_{od} \\
g_{r_{ij}}^t & = \text{Outflow from node } i \text{ to node } j \text{ at time } t \text{ on route } r \in R_{od} \\
N_{r_{ij}}^t & = \text{Service rate provided (allocated) on the arc from node } i \text{ to node } j \text{ at time } t \text{ for the flow with origin } o \text{ and destination } d \text{ on route } r \in R_{od}. \text{ In addition, } N_{r_{ij}}^t = \sum_{r \in R_{od}, o \in O, d \in D} N_{r_{ij}}^t \text{ is a shorthand notation of the service rate provided on the arc from node } i \text{ to node } j \text{ at time } t
\end{align*} \]

\(^1\) Senior System Engineer, TFM Evolution and System Engineering, 7515 Colshire Drive, M/S N450.

\(^2\) Lead System Engineer, TFM Evolution and System Engineering, 7515 Colshire Drive, M/S N450, and AIAA Member.

\(^3\) Ph.D. Student, Department of Electrical Engineering, and AIAA Student Member.

\(^4\) Assistant Professor, Department of Electrical Engineering, and AIAA Member.

\(^5\) Senior Principal System Engineer, TFM Evolution and System Engineering, 7515 Colshire Drive, M/S N450, and AIAA Member.

In this paper, we introduce the O-D-R network into the FCM modeling framework and examine the tradeoffs between using arc-based and route-based controls to evaluate the effectiveness of using FQN to support decision makings. In Section II, a motivational example is given to illustrate the potential benefits of using the proposed modeling concept. In Section III, a route-based formulation of the FQN is proposed to model demand propagation, capacity reduction and implementation of various human-generated Traffic Management Initiatives (TMIs). The strengths and weaknesses of the model are summarized here as well. In Section IV, the capabilities of the route-based model are demonstrated via simulation of a realistic weather and traffic scenario. An associated contingency plan is thus developed to mitigate delay and evaluated in Section V. Section VI summarizes the conclusions and recommendations for future works.

I. Introduction

STATEGIC traffic flow management (TFM) aims to address significant capacity/demand imbalance predictions two or more hours in the future. To address the needs of strategic TFM for the Next Generation Air Transportation System (NextGen), decision support tools are needed to quantify the predictions and the outcomes to decision makers. A component of the envisioned system is Flow Contingency Management (FCM), which aims to quantify and mitigate the impact of predicted large-scale congestion, especially resulting from weather or other off-nominal events. In Ref. 2 and 3, a concept of operations for FCM was proposed that integrates probabilistic weather-impact forecasts with a National Airspace System (NAS) queuing network model to aid decision makers in the development of contingency plans for multiple potential outcomes. The resulting contingency plans provide coordinated strategic control actions, including Traffic Management Initiatives (TMIs) that can mitigate the predicted weather-impact. Figure 1 depicts the associated framework for the proposed FCM concept.

In Figure 1, a critical component in the framework is the feedback loop for developing and evaluating contingency plans. This process requires that decision makers or automation specify a set of control actions and evaluate the impact of the proposed plan. As such, a dynamic queuing network model for FCM (FQN) is constructed in Ref. 4 to simulate aggregated demand predictions and evaluate the impact of both the weather-impact and the imposed controls on the system in the proposed contingency plan.

The FQN provides many of the desired capabilities to address the needs of FCM such as modeling the stochasticity inherent in the NAS demand and capacity predictions in the strategic timeframe and capturing delay phenomena resulting from weather-impacted resource constraints and the imposed controls. It also retains the flexibility to select different routing options for each origin-destination (O-D) pair by not pre-determining candidate routes for flows. In the FQN, the O-D demands are treated as multi-commodity flows on a network, i.e. flows are denoted by O-D pair. At every node, it is possible to determine (or optimize) how the flow will travel among the various potential connections or arcs, as it advances to the destination.

Given the envisioned interaction of humans in the decision making process, the control setting in the FQN could be very challenging. As every network node could serve as a flow control knob to direct traffic, a large number of possible locations to set controls are defined, which necessarily complicates the human decision making process. Even though decision makers can utilize computer automation for generating plans as a preliminary solution, they still need to address the operational realities that are not captured in the computer model, e.g. feasibility of reroute strategies.

When the interaction between the FQN and the definition of the congestion mitigation plans involves human inputs, it may be desirable to define an alternative formulation that reduces the number of control locations and provide more intuition on the appropriate demand distribution. A potentially more straightforward approach is to define a queuing model based upon an Origin-Destination-Route Network (O-D-R), which defines the available routes in between each origin-destination network. Such a network provides a single point of control for demand assignment, enabling decision makers to assign the appropriate amount of flow to each route.

In this paper, we introduce the O-D-R network into the FCM modeling framework and examine the tradeoffs between using arc-based and route-based controls to evaluate the effectiveness of using FQN to support decision makings. In Section II, a motivational example is given to illustrate the potential benefits of using the proposed modeling concept. In Section III, a route-based formulation of the FQN is proposed to model demand propagation, capacity reduction and implementation of various human-generated Traffic Management Initiatives (TMIs). The strengths and weaknesses of the model are summarized here as well. In Section IV, the capabilities of the route-based model are demonstrated via simulation of a realistic weather and traffic scenario. An associated contingency plan is thus developed to mitigate delay and evaluated in Section V. Section VI summarizes the conclusions and recommendations for future works.
II. Background and a Motivational Example

The FCM framework employs the concept of heterogeneous network resolution\(^5\). Specifically, the nodes in the network may represent NAS resources at different levels of aggregation, where the selection of the appropriate level of aggregation is determined by the modeling fidelity necessary to capture the control actions. Within the area of control, the origin and destination nodes are defined to represent individual airports, where the flow enters and leaves the network, respectively. The origin and destination nodes are connected by a series of sector boundary nodes that represent directional crossings (i.e., between a pair of sectors two nodes are defined, one for each direction of crossing flow). The arcs connecting the nodes in a given O-D pair network are derived from an analysis of historic sector crossings, or more specifically historic sector triplets (sequence of upstream, current, and downstream sectors), as illustrated in Figure 2. Using sector triplet data, network size can be reasonably limited by only representing realistic flow patterns across sectors, and the transit time through a sector can be captured more accurately.

Outside of the area of control, the network model represents NAS resources as aggregated clusters of individual resources, and the origin and destination nodes represent multiple airports clustered together using heuristic clustering criteria\(^6\). The origin and destination nodes are connected by a series of Air Route Traffic Control Center (ARTCC) boundary nodes and ARTCC triplets. The associated demand between the O-D pair corresponds to the total demand between the airports represented in the clusters. As the multiple aggregation levels are simply represented as nodes and arcs within the network, an integrated modeling framework is developed that is computationally tractable yet provides the detail necessary to simulate and evaluate the desired flow impact.
The idea of the “route-based” control proposed in this paper would be consistent with the FCM network structure. Given that FCM is a strategic planning tool, a “route” would define how an aggregate demand proceeds from an origin to a destination in a more aggregate sense, as opposed to defining a specific jet route, filed flight plan, or trajectory for an aircraft.

To illustrate how defining specific routes can assist human decision making in FCM, we develop a hypothetical network example. Assume that there are four routes available to travel from Cluster Origin to Cluster Destination, where each route carries 25% of the demand, as shown in Table 1. Its corresponding FCM network is illustrated in Figure 3. Supposedly, sector S7 has reduced capacity due to weather impact and is expected to accumulate serious delays if no diversion is enacted. Decision makers would like to initiate a reroute program with the goal to avoid using S7 while evenly balancing two arrival flows at Cluster Destination. In the proposed route-based control, this routing strategy can be achieved with minimal effort if decision makers decide to reallocate the demand of Route #4 to Route #2 so that the two arrival arcs carry an equal share of the demand. The total cost of the reroute would be the difference in flight times of both routes multiplied by the actual demand, which could be simply estimated, based on the demand associated with the duration of the reroute. The new split fraction is summarized in Table 1.

### Table 1  Route Set of An Example O-D Network

<table>
<thead>
<tr>
<th>Route ID</th>
<th>Sequence of Nodes</th>
<th>Demand Split Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Initial</td>
</tr>
<tr>
<td>#1</td>
<td>Origin C1 S1 S2 S3 S4 Destination</td>
<td>25%</td>
</tr>
<tr>
<td>#2</td>
<td>Origin C1 S1 S2 S3 S8 Destination</td>
<td>25%</td>
</tr>
<tr>
<td>#3</td>
<td>Origin C1 S6 S2 S3 S4 Destination</td>
<td>25%</td>
</tr>
<tr>
<td>#4</td>
<td>Origin C1 S6 S2 S7 S8 Destination</td>
<td>25%</td>
</tr>
</tbody>
</table>

In contrast, in the O-D formulation from Ref. 4, there are three locations that need to determine the split fractions of downstream flows. To meet the goal of this reroute program that sector S7 is no longer used and the arrival flows are balanced, there actually exists more than one set of arc split fractions that can achieve the reroute goal, but not all of them would result in an equivalent route flow allocation as expected by decision makers. For example, in Table 2, Alternative 1 and Alternative 2 both satisfy the goal of this reroute program. Alternative 1 is the corresponding arc fraction setting for the route allocation decision in Table 1. However, the split fractions of Alternative 2 imply that the new demand fractions of Route #1 and #3 are 0% and 50%, respectively, and thus render a different reroute cost.
In this specially created example, we highlight that without utilizing route demand information the arc-based formulation cannot capture the cost of the reroute and thus may limit the decision makers’ insight into the appropriate mitigation response. This limitation in the arc-based formulation also prohibits the estimation of schedule delays and complicates the implementation of TMI programs such as Airspace Flow Program (AFP), since arc flow is only distinguishable by O-D pair, not by route.

In the rest of the paper, we formulate a route-based queuing network model for FCM and conduct a simulation analysis in order to demonstrate the model’s capability to propagate demand implement control strategies. With the realistic traffic and weather scenario, the simulation is expected to show that the route-based formulation has equivalent fidelity as the arc-based one.

<table>
<thead>
<tr>
<th>Diversion Location (Arc Start Node)</th>
<th>Arc End Node</th>
<th>Initial Demand Split Fraction</th>
<th>Alternative 1</th>
<th>Alternative 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>C1/S1</td>
<td>50%</td>
<td>75%</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>C1/S6</td>
<td>50%</td>
<td>25%</td>
<td>50%</td>
</tr>
<tr>
<td>S6/S2</td>
<td>S2/S3</td>
<td>50%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>S2/S7</td>
<td>50%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>S2/S3</td>
<td>S3/S4</td>
<td>67%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>S3/S8</td>
<td>33%</td>
<td>50%</td>
<td>50%</td>
</tr>
</tbody>
</table>

### III. A Route-Based Queuing Network Model

#### A. Formulation based on Route Options

The dynamic queuing network model in Ref. 4 provides the building blocks for the route-based formulation. Let us define a network $G = (N, A)$, where $N$ is the node set and $A$ is the arc set. Without loss of generality, it is assumed that there is a super source node $s$ that feeds the traffic into the system and a super sink node $t$ where the traffic terminates. For each O-D pair, a set of candidate routes $R_{od}$ are identified. A route here is defined by an origin node, a sequence of intermediate nodes, and a destination node. Since it is O-D specific, the O-D notation for flow variables may be dropped for succinctness. The queuing effect is modeled by dynamic stochastic service rates provided at each node. This formulation differentiates the service rate and backlogs at each queue by Origin-Destination-Route (O-D-R) triplets. Under a discrete-time approximation, the fundamental queuing phenomena are governed by the following functional relations:

$$g_{r_{ij}}^f = f_{r_{ij}}^{t+\tau_{r_{ij}}}$$

for all $r \in R_{od}, o \in O, d \in D, t \in T$  \hspace{1cm} (1)

$$g_{r_{ij}}^{t+1} = \min\{b_{r_{ij}}^f + f_{r_{ij}}^{t+1}, M_{r_{ij}}^{t+1}\}$$

for all $r \in R_{od}, i, j, l$ in succession on $r$ \hspace{1cm} (2)

$$b_{r_{ij}}^{t+1} = \max\{0, b_{r_{ij}}^f + f_{r_{ij}}^{t+1} - M_{r_{ij}}^{t+1}\}$$

for all $r \in R_{od}, i, j$ in succession on $r$ \hspace{1cm} (3)

$$f_{r_{so}}^t = p_{r_{so}}^t \times Demand(o, d, t)$$

for all $r \in R_{od}, o \in O$  \hspace{1cm} (4)
Eq. (1) is the flow conservation constraint which states that the flow entering arc (i,j) arrives at j after a nominal travel time. In particular, $t_{i,so} = 0$ is always true, and thus $f_{i,so} = g_{i,so}$. Eq. (2) states the outflow from j after being served at the queue of j, where $M_{j}$ is Poisson-distributed with a given service rate $N_{j}$ and could follow any type of distribution for stochastic queues. Eq. (3) describes the backlog formation at j. Both Eq. (2) and (3) describe the discrete-time approximation of a continuous stochastic queue. The service rate could also be deterministic, depending on the modeling needs for various TMI controls (as modeled in Ref. 4).

This discretization is tractable and operates as follows: For each queue at every unit time interval, the updated backlog is determined by the existing backlog (i.e. number of aircraft waiting in the queue), the inflow (number of aircraft approaching a boundary intersection point in a unit time interval), the service rate provided (maximum number of aircraft that can be served in a unit time). If the sum of the existing backlog and inflow is larger than the service rate, the outflow will equal the service rate, and the updated backlog will be the difference; otherwise, the existing backlog and inflow will pass to the downstream, and the updated backlog is zero.

Eq. (4) describes the demand of an O-D pair split by route at an origin node. Each route has a proportion rate, which can be either specified by manual input or determined through optimization. The demand generation function itself should address the uncertainty at a strategic timeframe, and it can be estimated from historic data or modeled as a stochastic process, e.g. Poisson process. However, modeling demand uncertainty for FCM is an area of ongoing research and beyond the scope of this study.

B. Modeling TMIs

The proposed model provides a generic formulation for simulating flow propagation on a capacitated network. For the purpose of FCM, the model must also simulate the implementation of congestion mitigation plans. A set of TMIs, such as ground delays, sector or flow controlled area rate restrictions, rerouting, or other necessary initiatives, may be proposed in a congestion mitigation plan to alleviate the congestion due to an imbalance between predicted capacity and predicted demand. Such a mitigation plan outlines where, when and which actions are to be implemented and how to best capture use of available capacity to reduce the overall impact of a forecasted weather scenario on the NAS.

In the proposed FCM network structure, each enroute node will represent one directional boundary crossing pattern and is associated with one reference sector and one of its downstream neighbors. Stochastic flows may originate at the origin nodes, traverse the sector boundary nodes, and terminate at the destination nodes. The design of management actions or TMIs thus requires controlling the flow rate at either origin or sector boundary nodes, depending on TMI types. The set of mitigation controls proposed to manage the flow will result in changes to flow propagation. There are several TMIs that are considered within the FCM framework:

1) Mile-In-Trail/ Minute-In-Trail (MIT/MINIT):

*Control Inputs:* A sector exit node, MIT rate (unit of time/aircraft), start/end times.

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 routes passing through a specified node. 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. If a MINIT is imposed on the end node of a particular arc (i,j) at time t, say $\delta$ minutes between aircraft, the reduced capacity $f_{ij}^{t}$ would be the upper bound of total flow rates and shared by all the routes that use arc (i,j). Since the nominal transit time on arc (i,j) might be different by routes, the upstream demands may arrive at the downstream queue at various times and are governed by Eq. (1), that is $f_{ij}^{t} = g_{ij}^{t} - f_{ij}^{t-\delta}$. With the service rate determined for each route, the queues will be processed by using Eq. (2)-(3).

2) Ground Delay Program (GDP):

*Control inputs:* An O-D pair, departure airport-specific GDP rate (min/aircraft), GDP start/end times.

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 an aggregated modeling framework, we can abstract the GDP control by shaping the demand at the departure airport. The
controlled rate at a GDP airport will be decomposed to the route level and apportioned to all the routes heading toward the same destination. At each origin airport, once the route-specific service (departure) rates are determined, the queues caused by GDP are processed by using Eq. (2)-(3).

3) Airspace Flow Program (AFP):

Control inputs: An affected route, departure rate (min/aircraft), AFP start/end times.

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. With the route information, the impacted routes that will pass through capacity-constrained areas may be identified a priori, so the reduced service rate can be estimated and imposed on the departure demand of a particular O-D-R triplet.

4) Rerouting:

Control inputs: An affected route, new demand proportion rate \( p_{\text{new}} \), start/end times.

If a rerouting option is considered prior to departure, it can be modeled by determining the proportion of demand allocated to individual routes. If a reroute option is suggested for a specific route prior to departure, the demand originally assigned to the affected route will be re-distributed to other available routes. Then, route-specific service rates need to be re-calculated based on the new departure demand distribution. If there is an existing backlog for that route and \( p_{\text{new}} = 0 \), which indicates that the route is completely unusable, its backlog needs to be assigned to other available routes heading to the same destination. If there are no available routes, the queue will build up until the routing restriction is lifted. Note that providing airborne rerouting options is neither straightforward for this route-based formulation, nor fully envisioned at a strategic timeframe for flow management. For enroute flights of a particular O-D pair, rerouting might be designed at the node shared by two or more routes. The flexibility of rerouting options around weather zones will greatly depend on the resolution of the network and route generation processes.

C. Capturing System Performance

The propagation of flow through the network is subject to the operational constraints on the system, such as airport arrival rates, sector capacities, etc. as well as the weather-impact restrictions defined by the weather-impact scenarios. Basic metrics such as airport delay, airport throughput, sector count, and sector delay can be easily summarized, which can give decision makers a quick sense of the performance of proposed congestion mitigation strategies in the presence of uncertain weather. Using the FCM network model described in Figure 2, the delay incurred in a sector can be obtained by calculating cumulative backlog counts over a period of time at all the arcs associated with that sector. Before leaving the current sector (S1), flows may be subject to rate controls due to downstream congestion (at S6), and backlogs may be formed at the boundary of the current and downstream sectors. To collect sector statistics from the queuing model’s outputs, not only backlog but also transition traffic should be taken into account.

For a specific route on arc \((i,j)\), we can compute the following metrics:

\[
\text{backlog}_{rij}^t = b_{rij}^t \quad (5-1)
\]

\[
\text{trans\_traffic}_{rij}^t = \sum_{t=t_{-}^{rij}}^{t} g_{rij}^t \quad (5-2)
\]

\[
\text{count}_{rij}^t = \text{backlog}_{rij}^t + \text{trans\_traffic}_{rij}^t \quad (5-3)
\]

Thus, metrics associated with arcs are further aggregated for a specific sector:

\[
\text{sector\ backlog}^t = \sum_{(i,j)\in\{\text{links associated with a sector}\}} \sum_{r\in\{\text{routes on (i,j)}\}} \text{backlog}_{rij}^t \quad (6-1)
\]

\[
\text{sector\ trans\_traffic}^t = \sum_{(i,j)\in\{\text{links associated with a sector}\}} \sum_{r\in\{\text{routes on (i,j)}\}} \text{trans\_traffic}_{rij}^t \quad (6-2)
\]

\[
\text{sector\ count}^t = \sum_{(i,j)\in\{\text{links associated with a sector}\}} \sum_{r\in\{\text{routes on (i,j)}\}} \text{count}_{rij}^t \quad (6-3)
\]
As airports are defined as a network node in the FCM network, airport statistics, such as throughput and backlog, are readily available. Another metric that might be of interest to decision makers is the schedule delay of arrivals. As schedule delay is a potential cost term for the objective function in many NAS-wide TFM models reviewed in Ref. 1, the proposed route-based formulation allows arrival delays to be directly calculated. When a flow leaves its origin on a specific route, its nominal travel time to the destination can be calculated by summing the nominal transit time of all arcs on that route. It is assumed that in this queuing model there will be no early arrival since the nominal arc transit time is deterministic, and the delays encountered en route are always nonnegative. The cumulative arrival delay of a particular route \( r \) over the planning horizon can be calculated as follows:

\[
\sum_{t=t_{r}}^{t_{f,final}} g_{rs,de} - g_{r,de}
\] (7)

Note that the metrics stated above do not represent an exhaustive set of possible objectives and can be obtained directly from the queuing model’s outputs without much modeling effort. As more FCM control actions are captured, metrics may be aggregated based on various performance areas so that decision makers would be well informed of possible impacts and their causes. For example, it is crucial for decision makers to know whether delay at an airport or sector is caused by capacity reduction due to weather or by the control actions in a mitigation strategy, so that the effectiveness of control actions can be distinguished. Mitigation strategies can thus be modified or synthesized accordingly.

In addition, the uncertainty inherent in the prediction of demand and weather-impact complicates the decision making process. The risk of congestion and the robustness of control actions are also of decision makers’ concerns. Given the stochastic nature of the FCM network model, the uncertainty can be quantified to help understand the disturbance due to imperfect predictions on weather impact and demand.

Furthermore, spatial and temporal variation of demand makes it challenging to find the balance between congestion mitigation and equity. Equity metrics can thus be formed to quantify the proportionality of delay allocation to each observation subjects, such as airports, Origin-Destination pairs, centers/sectors, user categories, geographical locations, etc. Section V has further illustrations.

D. Pros and Cons of Using the Route-Based Formulation

Either using arc-based or route-based formulation for a general-purpose TFM model is an arbitrary modeling choice based on modeler’s judgment and preference. However, under the proposed FCM modeling framework\(^5\), network resolution will be heterogeneous, e.g. a finer resolution is used for the control areas as a result of weather impact whereas aggregation is applied outside of these areas. An origin or destination node, depending on its location to the control areas, might represent one or a group of geographically nearby airports. As such, due to demand aggregation and abstract network structure, choosing an FQN that retains route information will impact the estimation of the impacts on demand resulting from control actions.

The main challenge of using the proposed route-based formulation is the size of the formulation. Compared with the arc-based model\(^5\), the variables of arc inflows, outflows, backlogs now carry an additional route index, and the flow propagation constraints of Eq. (1)-(3) are also associated with routes. Thus, the size of the route-based formulation increases polynomially with the number of routes considered. One of the remedies could be generating the “representative” routes a priori. By pre-selecting the set of useful routing options for a given instance, the number of variables can be reduced, which also aides in the computational efficiency of the model. The tradeoff between the richness of routing options and computational complexity would require further study.

On the other hand, unlike the arc-based formulation that needs to determine/optimize the flow diversion fraction at each transition node in the network in order to propagate the flows to the downstream nodes\(^7\), the route-based formulation determines flow directions at the origin airports, as stated in Eq. (4). Allocating the proportion of demand traveling along each route at the departure node is more straightforward to the human decision makers since it is easier to see which routes will be impacted when evaluating weather scenarios or implementing traffic management initiative like AFP or rerouting. Furthermore, due to network abstraction, the route-base formulation can more precisely model traffic propagation as the transit times for the entire route are more accurate. Given this structure, we can also better approximate system performance metrics such as schedule delay.

IV. Simulation of Flow Contingency Management

A. Simulation Setup:
To demonstrate the proposed model and the FCM decision framework, an example problem is derived from historic traffic and weather. The weather forecasts are taken from September 26, 2010, where only weather contained within the Atlanta ARTCC (ZTL) is considered in this example. The weather-impact model in Ref. 7 provides a probabilistic trajectory of weather-impact for the given probabilistic weather forecast shown in Figure 4. Weather-impact is then translated into reduced capacity of ZTL sectors, which is a necessary input of the proposed queuing model.

As the corresponding traffic on that date is obviously impacted by the weather event, we instead utilize traffic predictions from a date with relatively little weather impact. Traffic from August 30, 2010 provides the demand flow in this example since it has extremely low weather coverage and few TMIs and thus little impact on traffic in ZTL. The actual departure rate for each O-D pair from ETMS data is analyzed for every 15-minute time bin.

The network representation is derived from historic filed flight plans for August 30, 2010. Note that this date was purposely chosen to coincide with the traffic day selected for the analysis in order to best represent the actually flown traffic options. To define the level of aggregation for the different NAS resources, we selected ZTL as the area of control. Using the approach described Ref. 5, we construct the relevant connections for each O-D layer of the network in order to describe the entire network shown in Figure 5. All origin and destination pairs outside of ZTL are aggregated into clusters by using the clustering method in Ref. 6, and the individual airports within ZTL are represented as individual nodes. Outside of ZTL, the enroute nodes are represented as connecting ARTCC boundaries and within ZTL sectors, enroute nodes are defined as connections between sector boundaries.

For the proposed route-based model, the route information is collected from the given network structure and therefore a route is defined by an origin node, a sequence of boundary crossings and a destination node. This definition is sufficient for the purposes of FCM as the FCM model intends to capture traffic flow behavior and is not designed to analyze individual flights or specific jet routes. The resulting O-D-R network defines 3,773 routes for 1,722 cluster pairs. Table 3 provides the details on the network size. In this example, the number of arcs in the route-based model is about 46% more than that in the arc-based model, which illustrates the difference in the formulation size of both models.
Table 3. FCM Network Statistics

<table>
<thead>
<tr>
<th>Network Property</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Airport Clusters</td>
<td>68</td>
</tr>
<tr>
<td>Number of Cluster Pairs with Demand</td>
<td>1,722</td>
</tr>
<tr>
<td>Number of FCM Network Nodes</td>
<td>1,006</td>
</tr>
<tr>
<td>Number of Routes</td>
<td>3,773</td>
</tr>
<tr>
<td>Number of FCM Network Arcs</td>
<td>By O-D 16,242</td>
</tr>
<tr>
<td></td>
<td>By O-D-R 23,768</td>
</tr>
</tbody>
</table>

Table 4 summarizes the top 10 airport clusters that have arrival demand at ATL on the traffic day. Depending on the cluster, the number of routes varies: while the close-in MCO cluster has 14 routes observed in the traffic day, the MSY cluster only has 3. The length of routes (here measured by the number of nodes) is positively correlated to the flight time. In this particular example, the availability of routing options relies on what has been observed in this one-day historical data. Future study could expand the options by either extending the observation periods or dynamically generating routes during the simulation.

Table 4. Top 10 Arrival Clusters at ATL

<table>
<thead>
<tr>
<th>Cluster Name *</th>
<th>Percentage of Arrival Demand at ATL **</th>
<th>Num. of Routes</th>
<th>Avg. Flight Time per Route (Hr)</th>
<th>Avg. Num. of Nodes per Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCO</td>
<td>12.90%</td>
<td>14</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>IAD</td>
<td>7.10%</td>
<td>7</td>
<td>1.5</td>
<td>5</td>
</tr>
<tr>
<td>DTW</td>
<td>6.90%</td>
<td>8</td>
<td>2.3</td>
<td>7</td>
</tr>
<tr>
<td>CVG</td>
<td>6.00%</td>
<td>6</td>
<td>1.3</td>
<td>5</td>
</tr>
<tr>
<td>MIA</td>
<td>6.00%</td>
<td>5</td>
<td>1.5</td>
<td>5</td>
</tr>
<tr>
<td>EWR</td>
<td>5.50%</td>
<td>3</td>
<td>1.9</td>
<td>7</td>
</tr>
<tr>
<td>RDU</td>
<td>4.10%</td>
<td>12</td>
<td>1.2</td>
<td>6</td>
</tr>
<tr>
<td>MEM</td>
<td>3.80%</td>
<td>6</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>MSY</td>
<td>3.40%</td>
<td>3</td>
<td>1.1</td>
<td>6</td>
</tr>
</tbody>
</table>

* Airport cluster is named after the airport of the highest traffic in the same cluster.
** There are in total 48 airport clusters that have arrival demand at ATL on August 30, 2010.

B. Apportioning Arc Service Rate by Route

The weather impact model provides estimated capacity reductions of NAS resources, e.g. airports and sectors. To be utilized by the queuing network model, capacity estimates have to be converted into arc service rate \( r_{ij} \). In the route-based formulation, the service rate of arc \((i, j)\) is shared by all the routes that pass that arc. The determination of the ‘optimal’ service rate of arcs associated with a constrained NAS resource will require future study. The scope of this paper is limited to concept development and validation. Hence, to facilitate the proposed discrete-time simulation, a modeling alternative is to allocate available arc capacity by route proportionally to the amount of route flows and backlogs. This is intended to yield the same total outflow rate from a NAS resource as the single simulated queue before the proportional allocation so as to meet the target rate set by the TMIs. There are several situations to be considered when allocating the arc capacity (or the maximum service rate) by routes, depending on the existence of backlogs and rate control. An apportioning method used by this paper is described as follows:

\[
N^r_{ij} = \begin{cases} 
N^r_{ij}, & \text{if } r \text{ is subject to rate control;} 
\frac{b^r_{ij}}{b^r_{ij}} (r^r_{ij} - g^r_{ij}), & \text{if } r^r_{ij} = 0, b^r_{ij} > 0, \text{and } r \text{ is not rate controlled;} 
\frac{b^r_{ij}}{b^r_{ij}} + \frac{r^r_{ij} - g^r_{ij}}{r^r_{ij} - b^r_{ij}}, & \text{otherwise.}
\end{cases}
\]

where
\( N^r_{ij} \) = the controlled rate for route \( r \),
\( b^r_{ij} \) = the sum of backlog excluding those subject to rate control,
\( g^r_{ij} \) = the sum of outflows subject to rate control,
\( r^r_{ij} \) = \( \max(r^r_{ij} - g^r_{ij} - b^r_{ij}, 0) \), and
\( \bar{r}^r_{ij} \) = the sum of inflows excluding those subject to rate controls.
C. Simulation Results of ATL without Weather Impact

The proposed route-based model is simulated on the previously described FCM network, which aggregates airspace outside ZTL into center levels and clusters airports outside ZTL. This network abstraction highly improves tractability and limits the focus on the development of weather impact and control strategies within ZTL. To evaluate the effectiveness of the network abstraction and queuing network setting in capturing the traffic trend, the proposed model uses the nominal capacity values for ZTL sectors, assuming no weather impact, and propagates demand from origins to destinations by using the observed route demand fractions observed on August 30, 2010 and the apportioning method formulated in Section III.B. The step size for the simulation is 15 minutes. The arrival counts at ATL from simulation and historical observation are thus compared. As can be seen from the comparison in Figure 6, the simulation results resemble the actual traffic counts, despite the significant abstraction in the network structure.

The main reason for not having an exact match is the estimation of arc transit time and thus route transit time. For each O-D network, the transit time of an arc is the average of travel time between paired sector/center boundary points for which the arc represents. It can be expected the transit time across an enroute center has a larger variance than across a sector. For a fair comparison of the results of control strategies, the route transit time in this paper is then obtained from aggregating all the arc transit times on that route. Further improvement on the accuracy of flow propagation can be done via estimating arc transit time for individual routes.

V. Scenario Analysis and Numerical Results

A. Design of Mitigation Plan

The mitigation control plan associated with the weather scenario is generated in order to explore how TMI are used today to impact the traffic flows in Atlanta ARTCC (ZTL) when airspace is constrained by weather. In this example, we analyze the development of an action plan during the strategic planning teleconference at 1115Z (0715 EDT). Since low ceilings and rain are forecasted to impact ZTL and the Atlanta Airport (ATL), the agreed strategy is to move the arrival and departure flows to avoid the predicted convective activity during 1800-2400Z and to implement a GDP for ATL of 96 arrivals per hour for arrivals at and after 1730Z at 1500Z. Mile-In-Trail is also proposed on four ATL arrival fixes during 1800-2400Z at the rate of 8 aircraft per 15 minutes. As the day progresses, an increase in convective activity on the southeast arrival fix, CANUK, is expected, and it would require flights from the MCO cluster to be routed to the southwest arrival fix, HONIE and flights from the DFW cluster to the northwest arrival fix, ERLIN. This reroute begins at approximately 1800Z and lasted until the thunderstorms moved out of the area at 2400Z. During this time period the arrivals were only using three of the four arrival fixes. Figure 7 illustrates the timeline of all the proposed control actions.
The described control plan is intended to mimic what subject-matter experts would propose to mitigate potential capacity-demand imbalance due to weather. With a proper translation of the control plan into proper model inputs, the proposed FCM queuing model is capable of simulating the impact of various control actions in a coordinated fashion. There are several types of variables to be set to implement all the TMIs in the control plan, regarding departure rate, demand split fraction, and location-specific service rate. For the GDP control, the OD-specific departure rate is apportioned by the demands, and the local start time, which is no earlier than 1500Z is determined based on the average flight time to ATL as the GDP only applies to the arrivals after 1730Z. In Table 5, the number of control variables for GDP is no different for both models because the arc transit time is not route-specific. For the MIT control, the service rate at the four arrival fixes is the same in both models. For the reroute control, the demand assignment logic aims to avoid the constrained routes and redistribute demand proportionally to the available routing options. The number of split fraction variables of the route-based model is much fewer than that of the arc-base model because the route-based model only needs to control the flow at the origin airports at the reroute start time while the arc-based model requires the determination of timing and new fraction rates at each flow-splitting location. Table 5 illustrates the scale of the number of variables that need to be adjusted in order to implement the control strategy for the route-based and arc-based formulations. As illustrated in the motivational example, when implementing actions related to demand redistribution, such as reroute, having the route-based control requires less variables to set, and redistributing demand at the origin airports may be more intuitive to the decision makers.

Table 5. Summary of Control Variables Set in the Queuing Model

<table>
<thead>
<tr>
<th>Control Type</th>
<th>Variable Type</th>
<th>Number of Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Route-Based Model</td>
</tr>
<tr>
<td>GDP</td>
<td>Departure rate</td>
<td>478</td>
</tr>
<tr>
<td>Mile-In-Trail</td>
<td>Service rate</td>
<td>100</td>
</tr>
<tr>
<td>Arrival Reroute</td>
<td>Demand split fraction</td>
<td>530</td>
</tr>
<tr>
<td>Departure Reroute</td>
<td>Demand split fraction</td>
<td>403</td>
</tr>
</tbody>
</table>

B. Result Interpretation

At each network node and each time period we calculate the delay using the formula in Section III.C and assign it to a single delay category in a preferential order of MIT, GDP, weather-induced, and congestion delay, so if a node has multiple controls, its delays would not be double counted. For example, if a node has capacity limit of weather and MIT control, its delay is considered MIT delay. The weather-induced delay refers to the delay accumulated at nodes where weather impact is the only limiting factor, and no control has been proposed. Additionally, if a node has no control or weather impact, its delay is simply due to a demand-capacity imbalance and is categorized as congestion delay. Congestion delay could also be an indirect consequence of applied control, since the delays accumulated at a node might be due to controls placed at upstream nodes. As the overall impact of individual reroute actions cannot be easily isolated, reroute delay discussed here only includes the estimated
schedule delay (or extra flight time) due to reroutes, as the route-based model can directly estimate it with demand distribution information using Eq. (7).

Table 6 summarizes the delay statistics before and after implementing the control plan. The payoff of the control plan looks promising. The reduction of weather-induced is 3,614 minutes, whereas the total delay caused by control actions is 782 minutes. Figure 8 shows the temporal distribution of weather delays, where the proposed control plan is well synchronized with the weather impact, reducing the times of highest weather delay. The additional benefit associated with ground delay as opposed to airborne delay is reflected as the weather-induced delay begins to decrease approximately 1 hour after the GDP start time.

<table>
<thead>
<tr>
<th>Category</th>
<th>Before Controls</th>
<th>After Controls</th>
<th>Delay Savings</th>
<th>MIT</th>
<th>GDP</th>
<th>Congestion</th>
<th>Reroute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delay Minutes</td>
<td>48,476</td>
<td>44,862</td>
<td>3,614</td>
<td>495</td>
<td>287</td>
<td>64</td>
<td>119</td>
</tr>
</tbody>
</table>

Figure 8. Temporal Distribution of Weather Delays

The goal of traffic flow management is to create a workable problem for the air traffic controller. Another consideration in evaluating the effectiveness of a control strategy is whether the control is reducing the delays in the weather-impacted sectors. As weather-impacted sectors have reduced capacity, their ability to manage any increase in volume is limited and as such it is desirable to target these sectors for reduced delays. Figure 9 compares the weather impact delays in the four impacted sectors, namely ZTL10, ZTL20, ZTL22, and ZTL34. Examining Figure 9, it is observed that the control strategy effectively reduces the weather impact in ZTL10, ZTL20, and ZTL22, but slightly increases the weather delay in ZTL34. However, as ZTL34 nominally has the lowest weather delays and the overall decrease in weather delays is significant, the proposed control plan does provide a positive response to the weather impact scenario.
C. Discussion

We have demonstrated the FCM modeling framework using the proposed route-based model on performing the evaluation of the weather impact and its associated control plan. To show the modeling equivalency of the route-based model to the arc-based one, Figure 10 compares the simulated arrival counts at ATL of using two models. Since both models use the same scenario of weather impact, demand profile, control strategy, and network definition, two arrival profiles are nearly identical. In particular, for a fair comparison, the arc transit time is not treated as route-specific. This intends to emphasize that the route-based model has achieved equivalent performance as the existing arc-based model in terms of flow propagation.

VI. Conclusions and Future Works

Traffic flow management nowadays uses many resources to obtain an accurate portrayal of the NAS in an attempt to know where and when it is necessary to exert controls to balance aircraft demand when airspace becomes constrained. The FCM framework offers the possibility that both demand and available airspace be viewed and controlled within a single resource. Incorporating route information into the FCM framework provides a viable option to addressing the modeling challenges encountered in the FQN of Ref. 4. The route-based formulation possesses several desirable features for FCM. First, it allows direct estimation of scheduled delays, which will help FCM address a similar performance goal currently evaluated in NAS operations. In addition, because routes are known a priori in this formulation, the proposed model can identify a particular flow heading towards a capacity-constrained area and thus implement reroute or a rate control on that flow. Lastly, constrained resources of interest may be translated into a set of routes, which provides a straightforward approach for identifying demand-capacity imbalances.

Future research focus will fall upon using route traffic management assists the decision making process. With a realistic-size route set, the route-based model is expected to provide a wider range of demand distribution alternatives. As the size of its formulation may grow with the number of routes considered, the tradeoff between the richness of routing options and computational complexity at a strategic timeframe should be further analyzed. Also,
it is expected that under the multi-resolution network of FCM, employing route-specific arc transit time would better address flow propagation and thus benefit the prediction of the spatial and temporal effect of weather impact and control actions.

![Figure 10. Equivalency of Control Performance of Route-based and Arc-based Formulations](image)

**Acknowledgements**

The authors would like to thank Tudor Masek, Mary Hokit, Philip Brown, Dr. Lixia Song, and Stephen Zobell, of The MITRE Corporation and Dr. Sandip Roy of Washington State University for their valuable suggestions and insights.

**NOTICE**

This work was produced for the U.S. Government under Contract DTFWA-10-C-00080 and is subject to Federal Aviation Administration Acquisition Management System Clause 3.5-13, Rights In Data-General, Alt. III and Alt. IV (Oct. 1996).

The contents of this document reflect the views of the author and The MITRE Corporation and do not necessarily reflect the views of the FAA or the DOT. Neither the Federal Aviation Administration nor the Department of Transportation makes any warranty or guarantee, expressed or implied, concerning the content or accuracy of these views.

© 2011 The MITRE Corporation. All Rights Reserved.

**References**

This article has been cited by:


2. Yi Cao, Dengfeng Sun. 2015. Migrating Large-Scale Air Traffic Modeling to the Cloud. *Journal of Aerospace Information Systems* 12:2, 257-266. [Abstract] [Full Text] [PDF] [PDF Plus]