Defining Multi-Resolution Networks for Flow Contingency Management

Christine Taylor¹, Tudor Masek², and Craig Wanke³
The MITRE Corporation, McLean, VA 22102

Sandip Roy⁴
Washington State University, Pullman, WA, 99164

and

Yan Wan⁵
University of North Texas, Denton, TX 76210

This paper describes a network modeling approach developed to support Flow Contingency Management, a component of the strategic traffic flow management system in the Next Generation Air Transportation System. The overall concept and associated modeling framework described in this paper provide a set of requirements for defining the network structure. Specifically, the network must be designed to allow a queuing model to propagate stochastic flows and analyze the impact of flow constraints as well as demand-shaping controls. In addition, the network topology must result in a computationally-tractable framework to support strategic timeframe decision making. To address these needs, a network model that uses multiple levels of resolution to represent various National Airspace System resources is proposed. Specifically, it is proposed that a boundary forming an area(s) of interest be defined, within which resources are represented at a greater level of detail than resources outside the area(s). Finally, an example problem, based on historic traffic and weather, is used to validate the effectiveness of using multiple levels of resolution within the network model and analyze the benefits and costs associated with proposing various boundaries on the area of interest.

Introduction

STRATEGIC Traffic Flow Management (TFM), as envisioned in the Next Generation Air Transportation System (NextGen), will better predict large-scale demand/capacity imbalances and provide decision makers with a coordinated response to better mitigate predicted congestion¹. In response to this objective, an operational concept for Flow Contingency Management (FCM)²,³ was proposed that aims to define an aggregate flow management strategy in response to likely future weather outcomes. Specifically, the concept defines a capability that can simulate the response of an aggregate flow to predicted weather impact, capture and design congestion management controls, both available now and envisioned in the NextGen environment, and measure the effect of these strategies using a set of metrics representing a variety of stake-holder interests.

Models of TFM systems can generally be classified as either flight-based or flow-based. Flight-based models simulate the movement of flights through the network, where individual airports and even specific routes are modeled as discrete elements in the network. Such flight-based models are often used to optimize the schedule of

¹ Lead Simulation Modeling Engineer, M/S 450, AIAA Member.
² Senior Operations Research Analyst, M/S 450.
³ Senior Principal Simulation Modeling Engineer, M/S 450, Senior Member AIAA.
⁴ Associate Professor, School of Electrical Engineering and Computer Science, and AIAA Member.
⁵ Assistant Professor, Department of Electrical Engineering, and AIAA Member.

American Institute of Aeronautics and Astronautics
individual aircraft in response to deterministic en-route capacity constraints\textsuperscript{4}, incorporating the capability to define ground delays and rerouting\textsuperscript{5}, as well as en-route holding\textsuperscript{6}.

However, flight-based models are not necessarily suitable for strategic TFM as they often do not provide a computationally-efficient framework to analyze problems of interest that will occur 2 hours or more in the future. Recognizing this issue, Reference 7 distinguishes between the needs of strategic and tactical TFM decision support tools by arguing that aggregate models are better suited to the strategic timeframe environment. Following this, Reference 7 builds upon the work presented in Reference 6 to define a flight-specific network only in areas of interest, where trajectories are represented as connections between these areas, as opposed to the contiguous sectors used in References 4-6.

In contrast, flow-based models aggregate the traffic flow through the National Airspace System (NAS) in order to simulate larger-scale phenomena, such as sector congestion or aggregate delays. Reference 8 proposes a deterministic multi-commodity time-expanded flow network to provide multiple routing and delay options for flows impacted by either nominal capacities or deterministic weather-impacted capacities. A different approach to constructing a flow network was defined in Reference 9, which uses a cell transmission model to track the number of flights at each position in the graph, as opposed to the progression of flow through the network. Reference 10 extends this methodology by defining a multi-commodity flow network in order to specify O-D pair rerouting in response to deterministic capacity constraints.

One issue with the previous models is their ability to capture the stochastic nature of the strategic TFM problem, where predictions of demand and capacity constraints are inherently uncertain. To address this issue, Reference 11 defines a center-level model of the NAS and propagates an uncertain demand through the network using a Poisson distribution, while assuming a stochastic transit rate to predict counts within each Air Route Traffic Control Center (ARTCC). Reference 12 modifies this formulation to directly account for the departure time uncertainties, as opposed to the overall demand uncertainty, to better capture actual departure rate behavior. Although these preliminary efforts are promising, significant research questions remain regarding how to appropriately model demand stochastics at the strategic time horizon and how to incorporate weather-propagation uncertainties into a dynamic flow model.

Furthermore, in order to provide a strategic decision support system capable of evaluating strategic TFM plans, it is necessary to also capture the impact of Traffic Management Initiatives (TMIs) on flows. Research in this domain is sparse, and only recently have a few works addressed this issue. Specifically, Reference 13 uses a stochastic flow model to analyze the impact of a single rate restriction, such as Miles-In-Trail (MIT) or Minutes-In-Trail (MINIT) imposed at ARTCC boundaries, on an uncertain flow. Reference 14 incorporates ground delay as well as boundary rate restrictions in an analysis of stochastic flow impact and permits some analysis of networked flow constructions. However in order to meet the needs of the envisioned FCM concept it is necessary to expand this type of analysis to capture multiple TMIs and their impact on an integrated flow network.

The network model proposed in this paper addresses the needs of the FCM modeling framework by incorporating the following properties directly into the network definition. First, as a strategic TFM decision support tool which models predicted congestion two hours or more in the future, it is desirable that the model represent the data accuracy available at this timeframe. At longer look-ahead times (LADs), the inherent uncertainties in both demand and capacity estimates, especially in the presence of predicted convective weather, argue for the development of a stochastic flow network model, as opposed to a deterministic flow model or flight-specific model. As such, the FCM network model is designed to represent aggregate flows traveling across the NAS, where routes through the network are defined as sector transits, as opposed to jet routes and fixes.

Furthermore, as the goal of FCM is to provide decision makers with the ability to assess the impact on flow in response to both constraints and controls, it is necessary that the network model be designed to capture both types of demand-shaping events. In the network model proposed, resource constraints, such as sector capacity or airport rate constraints, are naturally imposed on the flow by associating network routes with sectors and defining airports that are subject to capacity constraints. To effectively capture controls, such as ground delay programs (GDP), MIT/MINIT, or rerouting, the FCM network is represented as a multi-layer network, where each individual layer defines the network connecting a specific origin–destination (O-D) pair. The nodes in each O-D sub-network are further defined to align with natural control points to facilitate implementation of control. The resulting network model can then be used within a stochastic queuing model to simulate the uncertain response of the flow to both the controls and constraints.

Finally, in order to provide an effective decision support tool, it is necessary that the network provide a computationally-tractable framework. As such, we propose that the network represent NAS resources at varying levels of resolution, where areas of interest are more accurately captured, providing a more precise framework to capture constraints and controls. However, areas outside the area of interest are represented in the network as
aggregate resources, reducing the problem size while retaining the aggregate flow structure. By defining a connected network that seamlessly simulates the response of the flow to constraints and controls throughout different areas of the NAS in a computationally-tractable environment, we obtain a suitable framework for the development of a FCM decision support tool.

This paper begins with a discussion of the requirements of FCM and a brief description of the proposed FCM concept, to motivate the network modeling approach presented in this research. Following this, Section II provides a detailed description of the network components and captures the inherent relationships between the NAS resources and captures the inherent operational constraints and control points in the system. The specific definition of this modeling framework is the focus of this paper.

The predictive scenario generation, shown in orange, has two components, namely weather impact prediction and demand prediction. The weather impact model utilizes the weather forecast data, as well as configuration data to define areas of the NAS that will be (potentially) impacted by weather. The demand estimation model uses current flight plans as a basis to estimate the demand for the NAS resources captured in the network model. The predictive scenario information, in conjunction with the network model, is provided to the contingency plan development component, shown in blue.

The development of flow contingency plans requires that system constraints and congestion mitigation actions be defined and provided to a queuing model, which simulates the response of the flow to constraints imposed by nominal operating conditions, weather-impacted resources, as well as the congestion mitigation controls defined. The aggregate response to the constraints can then be used to evaluate the performance metrics defined. It is important to note here that the feedback loop between the queuing model and definition of the control actions can either be a manual feedback loop, with decision makers supplying the suggested controls, an automation-designed response, or a combination of both. Whichever path is chosen, the result of this process is the definition of contingency plans for the representative scenarios.

In order to develop a strategic plan, shown in red in Figure 1, the multiple contingency plans must be synthesized into a single strategic plan. In the proposed FCM concept, a formal risk analysis framework will be utilized to aid decision makers in negotiating and selecting the appropriate response for mitigating the predicted congestion. The resulting strategic plan consists of the Current Decision Point Plan (CDPP), which defines the set of controls to be enacted, and the advisories, which provide situational awareness to users of additional actions that may be implemented in the future.

Viewing Figure 1, we see that the modeling framework, or network model, is a critical component over which the entire decision support tool is developed. As such, defining a network model that can adequately represent the weather-impact, queuing model, and capture the control actions necessary to develop the contingency plans is critical to the success of FCM.

I. Flow Contingency Management Operational Concept

To motivate the development of the network model, we begin by briefly overviewing the proposed FCM concept and discussing the greater research effort that this work is a part of. The proposed FCM concept is motivated by the desire to provide a scientific basis for strategic operational decisions. Given the inherent uncertainty present 2 hours or more in advance of an event, the goal of FCM is to provide guidance on how to resolve significant discrepancies between capacity and demand, using a coordinated and integrated approach. Essentially, FCM aims to construct a solvable problem in the future by defining the system constraints necessary to do so, assessing degrees of freedom for creating a course of action, and building a mitigation plan while deferring the details until the situation evolves. For a more detailed description of the concept, please see References 2 and 3.

Associated with the overall FCM concept is a specific FCM framework, shown in Figure 1, which defines the flow of information and decisions through the strategic TFM decision process. Figure 1 highlights four components of the FCM framework: modeling framework description, predictive scenario generation, flow contingency plan development, and strategic plan development. The modeling framework component, shown in green, defines the FCM network model, which represents the connectivity between the NAS resources and captures the inherent operational constraints and control points in the system. The specific definition of this modeling framework is the focus of this paper.

The predictive scenario generation, shown in orange, has two components, namely weather impact prediction and demand prediction. The weather impact model utilizes the weather forecast data, as well as configuration data to define areas of the NAS that will be (potentially) impacted by weather. The demand estimation model uses current flight plans as a basis to estimate the demand for the NAS resources captured in the network model. The predictive scenario information, in conjunction with the network model, is provided to the contingency plan development component, shown in blue.

The development of flow contingency plans requires that system constraints and congestion mitigation actions be defined and provided to a queuing model, which simulates the response of the flow to constraints imposed by nominal operating conditions, weather-impacted resources, as well as the congestion mitigation controls defined. The aggregate response to the constraints can then be used to evaluate the performance metrics defined. It is important to note here that the feedback loop between the queuing model and definition of the control actions can either be a manual feedback loop, with decision makers supplying the suggested controls, an automation-designed response, or a combination of both. Whichever path is chosen, the result of this process is the definition of contingency plans for the representative scenarios.

In order to develop a strategic plan, shown in red in Figure 1, the multiple contingency plans must be synthesized into a single strategic plan. In the proposed FCM concept, a formal risk analysis framework will be utilized to aid decision makers in negotiating and selecting the appropriate response for mitigating the predicted congestion. The resulting strategic plan consists of the Current Decision Point Plan (CDPP), which defines the set of controls to be enacted, and the advisories, which provide situational awareness to users of additional actions that may be implemented in the future.

Viewing Figure 1, we see that the modeling framework, or network model, is a critical component over which the entire decision support tool is developed. As such, defining a network model that can adequately represent the weather-impact, queuing model, and capture the control actions necessary to develop the contingency plans is critical to the success of FCM.
II. Development of the Network Model

The FCM modeling framework provides the underlying topology for the simulation and analysis required to develop the contingency plans. In this section, we define the network modeling components highlighting how the definition facilitates the inclusion of both constraints and controls. We begin by first defining the network model representation in the area of interest, and then discuss the representation outside this area, where more aggregated structures are defined.

A. Network Model within the Area of Interest

The FCM modeling framework is a multi-commodity network model, where each origin-destination (O-D) pair forms a layer in the network. The origin and destination nodes used to define each layer represent individual airports or potentially a Terminal Radar Approach Control (TRACON), in which a small number of airports are located in close proximity and are operated in a coordinated manner. The origin and destination nodes define the points where the flow enters or exits the network.

To define the remaining nodes in the network, we analyze historic flight plans and updates from a specified time period to define the flight plan for each unique flight as a list of sector crossings with their associated crossing time and location. For each sector crossing pair, a node is defined that represents the existence of a directional crossing between two sector boundaries. Thus, for a sector pair that has historic flow in both directions, two nodes are defined. This distinction of crossing direction is not necessary to capture flow patterns but is a valuable modeling tool for defining controls, which are discussed later in this section. The locations of the sector crossing nodes are defined using the average crossing location; however this definition is only important for visualization purposes and does not affect the network model.

Figure 1. FCM Framework Flow Diagram
The arcs in the network are defined for each O-D layer individually. For a given O-D layer, we determine the list of sector crossings or more precisely, sector triplets used by each flight associated with the O-D pair. Using sector triplet data, we can reasonably limit network size by only representing realistic flow patterns across sectors. Furthermore, the estimate of transit time is improved as it is the average transit time for all flights transiting that specific connection for that O-D pair. Figure 2 illustrates the transformation of the historic flight plans into the FCM network definition.

Figure 2. Illustration of Sector Transit Representation

The above choices for the network representation were defined, in part, by the need to easily capture the constraints and controls in the network in order to measure the impact of these events on the flow as it is propagated through the queuing model. For details on the implementation of these constraints and controls within the queuing model, please see Reference 18; however here we briefly describe the model as relevant for the network definition. Specifically, the queuing model defines the movement of flow through the network, subject to rate constraints, which limit the amount of flow that can transit through different nodes in a time period. When the flow entering a node is in excess of this limit, backlog is generated at the node, which can be used to identify areas of congestion and compute delay metrics.

The constraints considered in this analysis are airport rate constraints and sector capacity constraints, as illustrated in Figure 3. The airport rate constraints provide a limit on the departure and arrival rate at each airport, and are directly applied as a throughput rate limit to or from these nodes. To accommodate this constraint, the network model is augmented, by appending a source node to each airport where flow originates and a sink node to each airport where flow terminates. Examining Figure 3, we see that the airport departure rate limits the demand into Airport 1 (A1), while providing unrestricted access to the following sector. This modeling formulation is necessary when limiting departure rates out of an airport for flows travelling into different en-route sectors and also provides an operationally-consistent approach since flights do not depart airports if they cannot enter into the en-route airspace. Furthermore, this approach can be easily extended to accommodate airports within a TRACON. Similarly, the airport arrival rate is imposed at the boundary to the sector/airport node, as shown in Figure 3. Again, by including a sink node after Airport 2 (A2), all arrival delays are incurred en-route, which is operationally-consistent. Again, this formulation permits a straightforward extension to TRACON arrivals.

Figure 3. Imposing Constraints in the FCM Network
Figure 3 also shows that capacity constraints are applied in the network model as throughput rate limits at sector boundary nodes. As the arcs are defined as sector transit arcs, we can associate each arc in every O-D network with a corresponding sector. Furthermore, every boundary node is associated with the upstream sector. By computing the total flow on each arc in the sector and the total backlog generated at each out-bound boundary node, we can calculate the total occupancy within a sector and further restrict the occupancy to be below a given capacity threshold. However, as each O-D network propagates flow through individual rate restrictions, it is necessary to ration the overall throughput limit to each O-D network. References 18 and 19 describe this calculation.

The network model is also defined to facilitate the capture of control actions, namely a ground delay program (GDP), an Airspace Flow Program (AFP), a Ground Stop (GS), Miles-In-Trail (MIT) or Minutes-in Trail (MINIT) restrictions, and rerouting, as shown in Figure 4. Examining Figure 4 we see that controls on the departure rate of an airport can be applied in response to a GDP, AFP or a GS. As the network is O-D specific, this limit will affect only origin airports subject to the restriction and only flows at these airports destined to the impacted airport.

Rerouting, is defined by the fraction of flow travelling along each sector boundary pair, as shown in Figure 5. A nominal fraction for each route is defined by the fraction of flow historically travelling along each arc. However, if it is desirable to control the direction of the flow, modifications to these fractions can be imposed. For example, if in Figure 5, all 4 routes are equally likely in an O-D pair, ¼ of the flow will be directed from S2, through S1, to each of the sectors S3 – S6. However, if it is desirable to prohibit any flow into S3, the fraction of flow travelling from S2 through S1 to S3 (r23) could be set to 0 and the total incoming flow from S2 to S1 would be distributed among the remaining 3 connections. Details on the implementation of this control can be found in Reference 19.

B. Network Structure Outside the Area of Interest

The previous section described the modeling approach employed to provide the greatest representation accuracy; however the level of detail required by such a formulation would be computationally-intractable for FCM as a decision support tool. As such, we propose that only certain areas of the network be captured at this resolution, namely regions within the area of interest. The remainder of the network, outside the area of interest, is defined to represent larger areas and more aggregate representations of the NAS. Furthermore, outside the area of interest, no
constraints can be applied and only controls generated in response to impacts within the area of interest can be imposed. The remainder of this section describes this aggregated representation.

A major obstacle to modeling a multi-commodity network is the number of origin-destination pairs that exist in the NAS. To limit the number of origin and destination nodes, and therefore reduce the number of O-D subnetworks in the FCM model, we cluster multiple airports together into a single node. To define an appropriate clustering, suitable for the overall FCM modeling framework, a hierarchical airport clustering method, called Split by City-Pair (SPC) is proposed. As described in greater detail in Reference 20, SPC leverages the flow structure patterns of the NAS by employing a top-down mechanism to split clusters into sub-clusters based on historic city-pair traffic. Compared with previously proposed clustering methods, the SPC method can achieve smaller network sizes with similar cluster numbers, while capturing a higher percentage of overall NAS traffic flow. The proposed clustering defined in Reference 20 is shown in Figure 6, where no area of interest is assumed. We further note that the proposed clusters represent over 93% of traffic in the network.

![Figure 6. Airport clustering proposed in Reference 20](image)

Outside the area of interest, the origin and destination nodes are connected by a series of Air Route Traffic Control Center (ARTCC) boundary nodes and ARTCC triplets. The definition of the ARTCC triplets, and the associated transit times, and routing fractions are determined in the same manner as described in the previous section for sector triplets.

Outside the area of interest, there are no constraints imposed on the system since defining a departure or arrival rate for a cluster of airports or a capacity of an ARTCC does not provide a meaningful constraint. Furthermore, given the aggregated nature of the flow representation, no controls are generated in these areas; however controls generated within the area of interest may be applied to areas outside the area of interest. Specifically, limits on departure rates due to GDPs, AFPs, or GSs, can be used to limit the overall cluster departure rate to the affected airport. Similarly, reroutes that are imposed to address the flow of traffic into the area of interest can be applied to the aggregate flows from clusters or through ARTCCs in order to meet the requirements of the reroute control enacted. However, boundary rate controls between ARTCCs are not imposed as the level of aggregation would not provide a sensible limit to the flow, nor would it be possible to translate such an action into a real TMI.

C. Defining the Area of Interest

Given the network definition within and outside the area of interest, it is necessary to appropriately define the boundary of the area of interest. Specifically, since only areas within the area of interest capture constraints and provide locations to control the traffic, it is necessary to include areas of weather-impact inside the area of interest. Furthermore, in order to seamlessly integrate the two different network representations proposed, the area of interest must be defined to align with ARTCC boundaries. Taken together, we define the area of interest to at least include...
the ARTCC(s) with weather-impact; however the number of surrounding ARTCCs to be included in the area of interest warrants further exploration. Specifically, as each ARTCC contains a number of sectors and airports, the size of the resulting network increases with every ARTCC included, but by including additional ARTCCs within the area of interest, the fidelity of the results will increase. As such, the remainder of this paper will explore this trade-off for a single example.

III. Evaluating the FCM network

In this section, we evaluate how modifying the boundary of the area of interest impacts both the accuracy of the resulting simulations and the computation effort required for a single example problem taken from historic data.

D. Example Problem

The example problem used to evaluate the network model examines the impact of weather within Atlanta ARTCC (ZTL) on September 26, 2010. In the FCM framework, weather-impact is defined using the methodology proposed in Reference 17. Briefly, the weather-impact model provides probabilistic trajectories (scenarios) of weather-impact based on the given probabilistic weather forecast. To generate the forecast, a prototype WI simulator was developed that tracks convective weather-impact in ZTL at 15-minute intervals and then translates the predicted coverage into capacity reduction. To define the representative weather-impact scenarios, 200 simulations were run to construct the ensemble of weather-impact trajectories and the resulting trajectories were clustered together based on the total amount of good-weather traffic that would be in excess of capacity in ZTL. Based on this analysis, four representative weather-impact scenarios denoted as “very-low impact (VL-WI)”, “low impact (L-
“Very high impact (VH-WI)” were defined. Figure 7 displays four time snapshots for each scenario at LATs of 4, 8, 12, and 16 hours where areas shown in darker shades of red signal areas with a higher percentage of capacity reduction. We note here that although convective weather was forecasted outside of ZTL, only weather within ZTL was considered in this analysis.

As the corresponding traffic on September 26, 2010 was obviously impacted by the weather event, we instead utilize the traffic from August 30, 2010, a date with low weather coverage and few TMIs, to provide the demand in the example. Specifically the actual departure times were collected for each airport in 15-minute intervals. For airports assigned to clusters outside of the area of interest, the total departure rate for the cluster is the accumulated departure rate for each airport. The demand profile is generated using a Poisson distribution\(^{18}\) where the mean flow rate is defined as the departure rate for each airport or cluster, as appropriate.

In order to best represent the actually-flown traffic options, the network definition was also derived from the traffic on August 30, 2010. Based on the area of interest selected, the network was defined using the methodology described in Section II. It is envisioned that the network will be derived from multiple days, likely months of traffic. However, a single day of traffic is deemed to be sufficient for this analysis.

E. Defining the Area of Interest

Defining the boundary for the area of interest determines the resulting network size as well as the level of accuracy of the flow network. From the perspective of reducing computation effort, it is desirable to limit the area of interest. However, to define effective controls and predict the impact of these controls on the flow, it is necessary to capture a sufficiently-large area to obtain the desired accuracy. As such, we begin by defining different areas of interest and examine the resulting network size.

In the example problem described above, only sectors within ZTL are impacted by weather and thus are subjected to capacity reductions. In order to capture the impact of the capacity reductions on the flow, ZTL must be included within the area of interest. Figure 8 depicts the network model when ZTL is defined as the area of interest and the resulting network is denoted as N1.

Alternatively, it may be desirable to expand the area of interest to encompass sectors surrounding ZTL. Referring back to Figure 7, we notice that in each weather-impact scenario except VL-WI, the weather-impact is concentrated in the southern part of ZTL, bordering Jacksonville Center (ZJX). In order to capture the impact on the flow in response to the weather impact or enact controls in ZJX, we define the area of interest to encompass both ZTL and ZJX. Figure 9 depicts the corresponding network model, denoted as N2. Finally, in order to capture and control the impact on flow in all ARTCCs adjacent to ZTL, we define a network (N3) to have an area of interest encompassing ZTL, ZJX, ZHU, ZME, ZID, and ZDC, as shown in Figure 10.

For each of the three networks defined, we analyze the number of nodes as well as the number of constraints and control points generated, as shown in Table 1. Examining Table 1, we see that as the boundary of the area of interest grows, the network size grows significantly. Comparing N1 and N2, we see that if we expand the area of interest to include ZJX the number of O-D sub-networks increases by 23% and the total number of arcs increases by

---

Figure 8. Depiction of N1
28%. Comparing N1 to N3, we see that if we expand the area of interest to encompass ZTL and all the surrounding centers, the number of O-D sub-networks more than doubles and the number of arcs increases by 167%.

The larger areas of control in N2 and N3 enable additional constraints to be captured, which increases the accuracy of the resulting simulation, and yields additional locations to apply control, which provides decision makers with increased flexibility when defining contingency plans. Examining Table 1, we see that between N1 and N2, the number of constraints captured increases by 88% while the number of control locations increases by 55%.

![Figure 9. Depiction of N2](image)

![Figure 10. Depiction of N3](image)

**Table 1. Comparison of Network Size vs. Accuracy**

<table>
<thead>
<tr>
<th>Network</th>
<th># of O-D Networks</th>
<th># of Clusters</th>
<th># of Airports</th>
<th># of Centers</th>
<th># of Sectors</th>
<th># of Arcs</th>
<th># of Constraint Points</th>
<th># of Control Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1</td>
<td>1,722</td>
<td>44</td>
<td>24</td>
<td>19</td>
<td>45</td>
<td>16,236</td>
<td>523</td>
<td>1,006</td>
</tr>
<tr>
<td>N2</td>
<td>2,124</td>
<td>43</td>
<td>48</td>
<td>18</td>
<td>87</td>
<td>20,926</td>
<td>985</td>
<td>1,556</td>
</tr>
<tr>
<td>N3</td>
<td>3,523</td>
<td>36</td>
<td>122</td>
<td>14</td>
<td>257</td>
<td>43,418</td>
<td>2,914</td>
<td>3,756</td>
</tr>
</tbody>
</table>

American Institute of Aeronautics and Astronautics
Between N1 and N3, the number of constraints captured increases 457% while the number of controls captured increases 273%.

F. Evaluating Simulation Accuracy

Given the trade-off in network size versus the ability to capture constraints and controls, it is necessary to further analyze how modifying the boundary of the area of interest impacts the computation effort and accuracy of the simulation. For the remainder of this analysis we focus on the results generated using the N1 and N2 network topologies.

To begin, we compare how well the two network topologies estimate arrival demand into Atlanta International Airport (ATL). To obtain the actual counts we can compute the actual arrival demand into ATL on September 30, 2010 and compare this to the simulated arrival profiles, in the absence of weather, for each network, as shown in Figure 11. Figure 11 also provides a moving average of the counts to smooth the arrival profiles. Examining the moving average curves in Figure 11, we see that both networks provide relatively accurate estimates of the arrival demand, however if we compute the root mean square (rms) of the error, we find that N1 has a slightly lower rms error than N2. Specifically, the rms error of N1 is 5.47 while the rms error of N2 is 6.28 and the difference, which can be seen in Figure 11, is likely a result of the slight shift to the right in the arrival demand estimate provided by N2.

The computation effort associated with the simulation results shown in Figure 11 is detailed in Table 2. Examining Table 2, we see that the computation effort is decomposed into the time to simulate and analyze the queuing model results, where it takes approximately 50% longer to perform each task when using N2 as opposed to N1 as the underlying network. We note here that the values shown in Table 2 were the result of a single simulation on a non-dedicated server where the code has not been optimized for performance. As such, the results shown should be interpreted as the likely increase in computation effort when using N2 versus N1 and not an absolute measure of the computation effort associated with the FCM simulation and analysis.

Table 2. Comparison of Simulation Times using N1 and N2

<table>
<thead>
<tr>
<th>Network</th>
<th>Simulation Time (min)</th>
<th>Analysis Time (min)</th>
<th>Total Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1</td>
<td>47</td>
<td>19</td>
<td>66</td>
</tr>
<tr>
<td>N2</td>
<td>71</td>
<td>29</td>
<td>99</td>
</tr>
</tbody>
</table>

Given that the two networks provide comparable simulation accuracy, but significantly different computation costs, we next examine how expanding the area of interest to encompass ZJX, and therefore increasing the number

American Institute of Aeronautics and Astronautics
of control locations, improves the prediction of weather-impact. Specifically, for each of the weather-impact scenarios shown in Figure 7, we compute the hourly delays incurred when utilizing N1 and N2, as shown in Figure 12.

Examining Figure 12, we see that the closest agreement between the two network topologies is achieved when considering the VL-WI scenario. This is a sensible result since the minimal impact predicted by this WI scenario tends to be more concentrated north of ATL, further away from ZJX, and therefore little benefit would be realized by increasing the accuracy of the simulation in ZJX. Examining the L-WI scenario, we see that by using N2 we obtain a slightly higher estimate of delay, implying that N1 under-predicts the delay in this case; however the difference is extremely small. For the H-WI and VH-WI scenarios, this trend reverses and N1 slightly over-predicts the delays incurred, where the most noticeable difference is seen when considering the VH-WI scenario.

As the VH-WI scenario reveals the largest discrepancy in delays between the two networks, we analyze this case further to determine if utilizing N2 as opposed to N1 would provide decision makers with additional insight and additional control points of interest. Specifically, Figure 13 shows the delays incurred by sector when using N1 and N2. Examining Figure 13, we first see that only ZTL sectors are highlighted, meaning that even when using N2, no delays were accumulated outside ZTL. As such, expanding the area of interest to include ZJX does not provide additional insight into the problem. We further observe that ZTL20 has the only noticeable change in delay, where N1 over-predicts the delay for this case slightly. Examining Figure 14, which decomposes the delays by time, we see that this difference occurs between 2100 and 2400Z, which corresponds to the time showing the largest discrepancy in delay estimates in Figure 12.

By over-predicting the delay, unnecessarily conservative actions may be taken to mitigate the impact; however the delay prediction error in the VH-WI scenario is still relatively small at approximately 1.4%. Furthermore, as no delays are present in any sectors in ZJX, little additional insight is provided to decision makers by disaggregating...
ZJX and therefore the additional degrees of control freedom provided in N2 are not likely to be of value. However, by expanding the area of control to encompass ZJX, the computation time required to run N2 increases by about 50%. Therefore, the small accuracy gains obtained by using N2 are outweighed by the additional computation costs for this example.

![Figure 13. Comparison of Delays captured using N1 and N2 for VH-WI](image)

![Figure 14. Comparison of Delays Captured by Hour using N1 and N2 for VH-WI](image)
IV. Conclusions

This paper develops a network representation that fulfills the specific set of requirements for a network model in FCM. Specifically, a network that uses multiple levels of resolution is proposed in order to capture the necessary constraints and controls at locations of interest, while maintaining a tractable simulation framework. This paper provided a detailed description of how the various components of the network were defined within and outside the area of interest. To measure the costs and benefits associated with expanding the area of interest, an example problem was simulated using two different network topologies and showed that for the example, the expanded area of interest provided only modest improvements in accuracy while incurring significant computation costs.

The research presented in this paper provides an initial step towards developing a network model for FCM. Specifically, this paper analyzed the trade-off associated with expanding the area of interest for only a single example; however other examples may highlight the need to include alternate regions within the area of interest. Further research requires multiple instances of impact to be considered when developing heuristics to define the area of interest. In addition, it may be desirable to consider how expanding the area of interest to include only subsets of an ARTCC may benefit the performance.

The ultimate goal of the proposed network modeling methodology is to provide an automated network generation tool. Optimization methods that evaluate the inclusion of nodes in clusters and cluster definitions in the network are currently being reviewed for their applicability. Furthermore, as a decision support tool that evaluates congestion over long LATs, it is desirable that the network topology adapt to evolving situations. As such, a dynamic network modeling framework, that can be automatically generated, and provide the appropriate level of fidelity requires significant research advances.

Acknowledgments

The authors would like to thank all who helped with this work for their valuable insights, especially Philip Brown, Marky Hokit, John Huhn, Dr. Lixia Song, Dr. Alex Tien, Dr. Liya Wang, and Stephen M. Zobell, from the MITRE Corporation, Mengran Xue from Washington State University, and Robert Zhou from the University of North Texas.

NOTICE

This work was produced for the U.S. Government under Contract DTFAWA-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


14 American Institute of Aeronautics and Astronautics


