A Decision Support Tool for Flow Contingency Management

Christine Taylor\textsuperscript{1}, Craig Wanke\textsuperscript{2}

\textit{The MITRE Corporation, McLean, VA 22102}

Yan Wan\textsuperscript{3}

\textit{University of North Texas, Denton, TX 76210}

Sandip Roy\textsuperscript{4}

\textit{Washington State University, Pullman, WA, 99164}

This paper describes a prototype capability for Flow Contingency Management, a component of strategic Traffic Flow Management decision making in the Next Generation Air Transportation System. The Flow Contingency Management concept and associated capabilities described in this paper aim to address current shortfalls in today’s strategic planning process, namely the lack of integrated information, simulation and evaluation capabilities provided to decision makers. Specifically, the proposed prototype integrates the traffic and weather forecasts and further translates these predictions into forecasts of system impact, addressing a gap in today’s operating environment. Viewing the integrated forecast, decision makers can simulate and evaluate proposed congestion-mitigation strategies prior to implementation and quantitatively compare different options before enacting a given plan. As such, the prototype provides an integrated problem identification and quantitative what-if analysis capability for strategic traffic flow management. The paper reviews the overall concept and associated modeling framework, highlighting aspects of the model that address difficulties inherent to traffic flow management planning in the strategic timeframe. To illustrate the proposed decision making process, an example weather and traffic situation, taken from historic data, is simulated and the results highlight the envisioned operational benefits for strategic traffic flow management decision making.

I. Introduction

The Next Generation Air Transportation System (NextGen) Mid-Term concept seeks to address the current shortfalls in today’s traffic flow management (TFM) operations, namely the lack of integrated information, simulation and evaluation capabilities provided to decision makers [FAA, 2009]. Today, traffic manager’s decision support tools (DSTs) are generally disparate systems that provide individualized deterministic solutions. In strategic flow planning as it exists today, there is a gap in the ability to help TFM identify and minimize the impact of potential congestion. In addition, a capability that gathers potentially useful information and formulates this into an integrated National Traffic Management solution is required.

A component of the NextGen Mid-Term concept developed to address this need is Flow Contingency Management (FCM), defined as “the process which identifies and resolves congestion or complexity resulting from blocked or constrained airspace or other off-nominal conditions”[FAA, 2009]. The goal of FCM is to provide decision support capabilities that aid decision makers in developing effective and efficient strategies to manage potential congestion, especially resulting from severe weather. In addition, FCM informs users of likely upcoming management strategies to increase situational awareness and enable users to best meet their individual goals within the system constraints.

\textsuperscript{1} Lead Simulation Modeling Engineer, M/S 450, AIAA Member.

\textsuperscript{2} Senior Principal Simulation Modeling Engineer, M/S 450, Senior Member AIAA.

\textsuperscript{3} Assistant Professor, Department of Electrical Engineering, and AIAA Member.

\textsuperscript{4} Associate Professor, School of Electrical Engineering and Computer Science, and AIAA Member.
Although a multitude of decision support capabilities, both proposed and in operation, have been developed to aid TFM decision making, few address the requirements of FCM. Specifically, strategic TFM requires a computationally-efficient framework to examine the more relevant problems of interest to decision makers 2 hours or more in the future. As such, flight-based models that optimize the schedule of individual aircraft in response to deterministic en-route capacity constraints [Bertsimas, 1998], ground delays and rerouting [Bertsimas, 2000], as well as en-route holding [Bertsimas, 2008], are computationally prohibitive. Recognizing this issue, [Churchill, 2009] 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 and defines a hybrid representation of the model developed in [Bertsimas, 2008] where a flight-specific network is only defined in areas of interest and connections between these areas are represented using an aggregate flow-based model.

In order to simulate larger-scale phenomena, such as sector congestion or aggregate delays, flow-based models that aggregate the traffic flow through the National Airspace System (NAS) are typically utilized. [Myers, 2008] proposed to capture these impacts using a multi-commodity time-expanded flow network model. An alternative formulation used in [Menon, 2004] represents the problem using a cell transmission model that captures the number of flights as opposed to individual flight position. [Sun, 2008] extends this research to a multi-commodity formulation in order to capture origin-destination specific routing.

Another requirement of FCM is the ability to capture the stochastic nature of the strategic TFM problem as predictions of demand and capacity constraints are inherently uncertain. To address this issue, [Roy, 2003] 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). [Sridhar, 2006] 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 a few works have addressed this issue. Specifically, [Moreau, 2005] uses a stochastic flow model to analyze the impact of a single rate restriction, such as Miles-In-Trail (MIT) or Minutes-In-Trail (MINT) imposed at ARTCC boundaries, on an uncertain flow. [Wan, 2008] incorporates ground delay as well as boundary rate restrictions in an analysis of stochastic flow impact and permits some analysis of networked flow constructions. A probabilistic scenario tree approach is used in [Hoffman, 2007] to capture how individual flight reroutes and delays can be assigned under uncertain weather. [Cook, 2010] describes the development of a decision support system that integrates the stochastic weather and traffic forecasts to provide decision makers a TMI evaluation capability. Specifically, the model estimates when the fog will lift at San Francisco International Airport (SFO), and is used to assess how a ground delay program should be used to limit arrivals. Although limited in scope, [Cook, 2010] provides a significant step towards the development of a decision support tool compatible with the NextGen strategic TFM needs.

The FCM concept proposed in previous research [Taylor, 2011a] extends these ideas to develop a NAS-wide strategic TFM decision support system framework that directly captures the uncertainties inherent in both weather and traffic predictions at longer look-ahead times (LATs). Using a modeling framework that realistically captures flow routing and represents both operational constraints and TMIs, a simulation and design capability was proposed that could predict large scale demand and capacity imbalances and evaluate the effectiveness of proposed congestion mitigation strategies. The strategic plans developed through this process aim to provide a coordinated and efficient management response, effectively meeting the goals defined in the NextGen strategic TFM vision.

The purpose of this paper is to define a decision support system structure for FCM that provides a problem identification and what-if analysis capability for National Airspace (NAS)-wide strategic TFM. The FCM operational concept and corresponding prototype described in this paper aim to alleviate some of the current shortfalls present in today’s operating environment. Specifically, an integrated interface is proposed to facilitate access to relevant information regarding traffic and weather. Furthermore, the FCM prototype utilizes the integrated information to simulate and evaluate potential TMI implementations, effectively providing a what-if analysis capability for strategic TFM planning.

In the following section, a description of the operational concept for the FCM DST is presented. Section III discusses the simulation models used within FCM to integrate the available information and provide predictions of delay and congestion to decision makers. Section IV uses a traffic and weather example, taken from historic data, to illustrate the potential benefits of the proposed FCM DST. Based on the initial analysis results, Section V highlights
II. Operational Concept for FCM

The FCM operational concept proposed in this paper is motivated by the desire to provide a scientific basis for strategic operational decisions. Specifically, the goal of FCM is to address the current challenges faced in the today’s strategic planning environment by providing decision makers, specifically, traffic flow managers at the Federal Aviation Administration’s Air Traffic Control System Command Center (FAA ATCSCC), with the relevant information necessary to identify potential future congestion problems and simulate and evaluate proposed responses prior to implementation.

Strategic TFM for the NAS at the ATCSCC level involves actions that must be taken two or more hours in advance to mitigate the impact of large-scale congestion, resulting from either weather or another off-nominal event. The inherent challenge of decision making at these time horizons arises from the significant uncertainties in both the capacity and demand estimates used to predict congestion. As such, the models utilized are based upon aggregated representations of NAS flow, as opposed to flights, which is consistent with the information accuracy at longer LATs. The result is that FCM provides guidance on how to resolve significant discrepancies between capacity and demand, using a coordinated and integrated approach. In essence, 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. Figure 1 illustrates the envisioned decision making process.

Figure 1. Flow Diagram of FCM Decision Making Process
The process begins with the ATCSCC Planner viewing an integrated picture of predicted future events that may potentially create congestion, such as forecasted convective weather or special events that create high demand for resources as well as current operating conditions. Using this information, the Planner, in coordination with the ATCSCC National Operations Manager (NOM), will define and select regions that warrant further investigation, or areas of interest. The National Aviation Meteorologists (NAM) at ATCSCC may assist in the definition of the area of interest in cases where predictions of convective weather are the predominant constraint.

Given the area of interest, the simulation constructs the underlying modeling formulation. The first step is to define the network model, which provides the underlying structure for the problem. Specifically, a multi-commodity route network is constructed, where each layer of the network represents an origin-destination pair and the origin and destination nodes are connected by a set of ‘routes’, or more specifically connected NAS resources [Tien, 2011].

The next step in the FCM simulation is to predict future demand and capacity. Demand predictions are based upon aggregated representations of NAS flow, as opposed to flights, which is consistent with the information accuracy at longer look-ahead times (LATs). As such, two quantities must be predicted, namely demand counts and route usage. The counts are predicted from a combination of historical demands, scheduled demands and filed flight demands for each origin-destination pair. The route utilization prediction is derived from historic usage as well as predicted winds and filed flight plans. Together, these components provide the definition of the predicted traffic within the model.

The predicted capacity is taken from the nominal airspace operating constraints and augmented by predictions of capacity reduction due to weather. Weather impact predictions are essentially propagations of TFM impacts due to weather, or any other event that limits the available capacity [Roy, 2010], [Xue, 2011a]. We propose that by predicting the range of possible weather impacts we can better understand how an event may evolve and disrupt TFM operations, greatly reducing the need for decision makers to mentally project how the forecasted event translates into a reduction in capacity. Representative weather impact scenarios are aggregated from the set of potential outcomes, with associated statistics, to inform decision makers on the likely outcomes arising from an event [Xue, 2011b]. Using the predicted demand and capacity estimates, the queuing model simulates the impact of the operating constraints on the flow and predicts the congestion at various NAS resources and the associated delays resulting from the congestion [Wan, 2011], [Tien, 2011].

The predicted congestion associated with various weather impact scenarios is then viewed by the Planner, the NOM, and the ATCSCC National Traffic Management Officers (NTMO) for En-route and Terminal, who will be referred to as the decision makers for the remainder of the paper. The decision makers will determine what, if any, TMIs should be enacted, based on the location, duration and severity of the predicted congestion. The NAM may assist in gauging the likelihood of various weather-impact outcomes in order to focus planning efforts. Together, they will develop and define the TMIs, with the associated rates, scopes and implementation times, and the queuing model is then used to simulate the response of the flow to both the constraints and the TMIs. The FCM framework is designed to capture currently utilized TMIs, such as ground delay programs (GDPs), Airspace Flow Programs (AFPs), MIT/MINIT, and pre-departure rerouting; however this is not an exhaustive list of controls that could be captured within the model. The resulting analysis, which highlights congestion and delays, differentiated by cause (i.e. caused by constraint or a specific TMI) is returned for refinement. As such, FCM provides feedback on the potential costs and risks associated with a set of TMIs prior to implementation, providing a critical capability unavailable in today’s strategic planning process.

Once the decision makers define a satisfactory set of TMIs, and consult with the Supervisory Traffic Management Coordinators (STMC) at the ARTCCs impacted by the TMIs, it is necessary to formulate the strategic plan. In cases where multiple weather impact outcomes are generated, the decision makers may formulate multiple contingency plans and integrating these multiple plans into a single strategic plan is the final step in the FCM process. The strategic plan should reflect both the likelihood of the different weather-impact outcomes developing and their associated mitigation strategies being necessary, as well as incorporate input from both National Airspace System (NAS) users, and STMCs as to the relative priority of disparate goals, given the situation. The integration process would be similar to the negotiations in today’s strategic planning process; however by utilizing FCM, a more accurate picture of the implications of enacting a specific contingency plan is provided to inform decision making.

The strategic plan developed is segmented into the Current Decision Point Plan (CDPP), which defines the necessary actions that should be settled upon now, and a list of advisories, which consist of actions likely to be recommended for implementation later. Determining which actions are included in the CDPP or the advisories is part of the negotiation process, but is aided by the probabilities, costs, and timing of actions, which is supplied by FCM to decision makers. It is important to note here that the CDPP represents the agreed upon plan of action; however it is possible and even likely that the actions included in the CDPP at a given time will not be enacted until
later and simply represent impending actions. Airspace users, empowered with both the knowledge of impending actions, as defined in the CDPP, as well as the advisories, can adjust their fueling requirements and other planning parameters to provide predictability and ultimately maintain the integrity of their flight schedules. The updated demand information, in combination with updated capacity predictions derived through the evolving weather impact updates, are then used to repeat the strategic decision process.

III. FCM Simulation

The FCM simulation described in Section II introduces a number of interconnected capabilities for predicting traffic flow management impacts. Specifically, the FCM simulation includes the development of a modeling framework, the generation of predictive scenarios, and the simulation of congestion using a queuing model. In this section we describe these models in greater detail.

A. Modeling Framework

The FCM modeling framework provides the underlying flow topology for the simulation. To capture the connectivity of flow through the NAS, a multi-commodity network is proposed. Specifically, the FCM network is defined as a series of overlapping networks, where each origin and destination pair (O-D pair) defines a single layer of the network [Wan, 2011].

Defining a network model that captures the structure required to simulate and design control actions while providing a computationally-tractable framework is a challenge. As such, we propose a multi-resolution network model [Taylor, 2011b], where the network nodes represent various aggregations of NAS resources and where the selection of the appropriate level of aggregation is determined by the modeling fidelity necessary to capture the control actions. As such, we first develop the network topology within the area(s) of interest, which require a higher level of modeling fidelity, and then discuss the aggregation methods used outside the area(s) of interest.

For a given O-D pair network, the origin and destination nodes represent the airports where the flow enters and leaves the network, respectively. Within the area(s) of interest, we define the origin and destination nodes to represent individual airports which 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). Figure 2 illustrates how the sector boundary nodes are defined. The routes connecting the nodes in a given O-D pair network are derived from an analysis of historic routes which are converted to sector entry lists with associated sector entry times. For each route with an identical sector entry list, we define the sector transit time as the average transit time, which results in an averaged route transit time. Figure 2. Illustration of Sector Transit Representation

For a given O-D pair network, the origin and destination nodes represent the airports where the flow enters and leaves the network, respectively. Within the area(s) of interest, we define the origin and destination nodes to represent individual airports which 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). Figure 2 illustrates how the sector boundary nodes are defined. The routes connecting the nodes in a given O-D pair network are derived from an analysis of historic routes which are converted to sector entry lists with associated sector entry times. For each route with an identical sector entry list, we define the sector transit time as the average transit time, which results in an averaged route transit time. Outside of the area(s) of interest, the network model represents NAS resources as aggregated clusters of individual resources. Specifically, the origin and destination nodes in the network represent multiple airports...
clustered together and the associated demand between the node pair corresponds to the total demand between the airports represented in the clusters. 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 [Wang, 2011], 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. 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. As the multiple aggregation levels are simply represented as nodes and arcs within the network, an integrated modeling framework is developed that reduces network size, yet provides the detail desired in the areas of interest to simulate and evaluate flow impact.

Defining the network using an Origin-Destination-Route (O-D-R) formulation, as proposed in [Tien, 2011], provides a convenient representation of the flow for the purpose of capturing the impact of resource constraints and congestion-mitigation controls. A description of how the constraints and controls are implemented is included as part of the discussion on the queuing model development (Section III.C); however, here we highlight how the network model formulation is purposely constructed to easily facilitate the capture of this information. Specifically, airport rate constraints on departures or arrivals can be applied to the specific nodes representing the affected resource. Constraints limiting sector throughput can be easily applied as each arc in a route is associated with a specific sector. Controls affecting a single node, such as a MIT, can be applied to a directional sector crossing node so that only flow in the specified direction is subjected to the restriction. Furthermore, by defining O-D-R specific networks, control actions that target only a subset of the traffic, such as a GDP, or an AFP can be readily imposed.

B. Predictive Scenario Generation

Predictive scenario generation, shown as orange boxes in Figure 1, 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 [Roy, 2010], [Xue, 2011a], [Xue, 2011b]. The demand estimation model uses historic traffic and current flight plans as a basis to estimate the demand for the NAS resources captured in the network model. This section describes the models used to generate the components of the scenario.

1. Generating Weather-Impact Predictions

Given that a significant portion of congestion can be attributed to convective weather, it is necessary that the FCM simulation predict the impact of weather, or other uncertain capacity-reducing events, in a manner consistent with information requirements for strategic planning. Specifically, FCM requires weather-forecasting capabilities at a 2-24 hour time horizon that can 1) characterize the impact of convective and winter weather on NAS resources such as sector capacities, or Airport Arrival Rates (AARs); 2) capture the significant uncertainty in weather-impact evolution at this time-horizon, so as to permit generation of possible weather-impact scenarios and allow calculation of weather-impact statistics; 3) permit fast (computationally-efficient) simulation and analysis, as well as interfacing with traffic flow models. As current or envisioned weather products are not computationally-tractable for fulfilling this need, a weather-impact (WI) simulator has been developed, whose primary purpose is to generate probabilistic scenarios (trajectories) of weather-impact on NAS constraints. Within the scope of the FCM capability, the WI simulator will input data from current probabilistic forecasts, and output representative WI scenarios (trajectories) as well as relevant statistics on weather-impact over the planning horizon of interest.

A promising architecture for the WI simulator, along with a means for building (parameterizing) the simulator from existing forecast products, has been proposed [Xue, 2011a]. In particular, we advance the influence model, a stochastic network model that describes propagation of discrete-valued quantities on a graph, as a means for capturing propagation of convective and other weather on a grid. The influence model is promising for representing weather and weather-impact propagation, in that it can naturally represent complex temporal propagations of statuses in a way that permits both fast simulation and significant analysis. The parameterization of the model requires data from current probabilistic weather forecasts for the desired simulation duration (the planning horizon) so that the predicted trajectories have the same statistics as the forecasts and produce realistic spatial and temporal correlations of weather trajectories.

Upon parameterization, the WI simulator can be used to rapidly generate trajectories (scenarios) of weather propagation which can then be translated into a weather-impact scenario capturing evolution of NAS constraints (Sector capacities, AARs, etc.), using existing research on the impact of weather on these constraints. Given that the WI simulator can generate a large sample of WI trajectories quickly, it is desirable that the samples be further classified using metrics of interest to decision makers and return a small sample of representative WI scenarios with
associated probabilities [Xue, 2011b]. For FCM, the generation of representative scenarios is of particular importance, because these special scenarios can potentially guide the design of contingencies. To define representative scenarios it is necessary to first select one or more metrics of classification that are germane to NAS performance/management (e.g. capacity reduction at critical airports). Once classified into scenarios, a particular WI scenario is chosen from the cluster of scenarios as representative of the WI trajectory. Figure 3 illustrates this approach.

![Figure 3. Flow Diagram for Representative Weather-Impact Scenario Generation](image)

2. Estimating Demand

The second component of the predictive scenario generation task in FCM constructs estimates of demand in 15 minute time bins for each O-D-R; however, given the LAT of interest, significant uncertainties are associated with these estimates. Airport departure demands are difficult to predict because of departure time uncertainty, which can be influenced by a multitude of factors, such as previous arrival flight delays, abnormal surface events (runway and taxi way closures, obstructions on runways or taxiways, snow and/or ice removal, de-icing operations, runway direction reversals), unavailable gates, unscheduled flights, the effects of adverse weather, and accidents/incidents. As such, it is desirable to define a stochastic demand flow which has the capability of capturing uncertainty, is more reflective of reality, and can result in the design of flow management strategies that operate well under such uncertainties.

The Poisson flow model is the most typical stochastic flow model used to represent demand in queuing network models for air traffic as it is defined by its (possibly time-varying) flow rate, which can be obtained from an estimate of predicted counts. Although simplistic, it has been shown to capture demand well and therefore provides a convenient first approach for generating stochastic demand estimates. To estimate demand counts, we propose a model that will be a blend of operational and historical data to provide a real-time, problem-specific demand forecast for evaluating and designing flow management actions. At a particular LAT, the demand for an O-D pair can be split into three components:

- **Filed** traffic includes airborne IFR flights and pre-departure flights which have an active flight plan.
- **Scheduled** traffic includes flights which have a schedule entry for this day in the Official Airline Guide, but do not yet have an active flight plan.
- **Unknown** traffic includes those flights that will depart during the planning period of interest, but about which we have no information at the time of the prediction.

Given that the unknown demand is the most difficult to predict, the initial model we are proposing in [Wanke, 2012] defines a non-homogenous Poisson process at each prediction hour that is a function of the known demand, prediction time, and LAT associated with the departure time of the prediction. Using historic data of scheduled flights, filed flight plans and actual departures, an initial analysis shows potential for accurately predicting demand between airport pairs and the airport clusters defined outside the area control.

For an O-D-R model, it is necessary to predict not only the demand for an O-D pair but the demand along each route (i.e. the fraction of flow traveling along each route in the O-D-R network). We propose that the estimate of route utilization can be decoupled from the estimate of overall O-D demand and combined during the simulation to
predict the total flow on each route for each prediction time. Route utilization is dependent on many factors, including winds aloft, congestion, airline scheduling preferences, equipage, etc.; however to best capture the intent of the airlines, we will use historic distributions along routes and augment the usage fractions based on predictions for the day’s operations. The initial model proposes presented in [Wanke, 2012] considers the historic flow fraction, the relative route transit times, adjusted for wind, and the previously filed flight plans and the results show promise for developing a route utilization prediction capability.

C. Queuing Model Simulation

The simulation of the impact on demand from the capacity constraints, as well as congestion mitigation controls, is performed using a queuing model [Wan, 2011], [Tien2011]. A queuing model was selected as the simulation logic as it provides a tractable approach for representing traffic flow dynamics in the NAS, accounts for the significant uncertainties present in the information available in the timeframe, and captures the impact of a series of constraints and flow-management actions in practice today or envisioned in the NextGen environment such as MIT/MINIT, GDP, Rerouting, and AFP.

Using the FCM network model described in Section III.A, stochastic flows originate at the origin nodes, traverse the sector boundary nodes along each route, and terminate at the destination nodes. However the propagation of flow through the network is subject to the operational constraints on the system, such as AARs, sector capacities, etc. as well as the weather-impacted restrictions defined by the weather-impact scenarios. Furthermore, the set of congestion mitigation controls proposed to manage the flow are represented by changes in the flow propagation. Specifically, these constraints and controls reduce the rate of flow (number of aircraft per unit time) leaving the constrained/controlled locations, while introducing accumulated aircraft at the entrances of these locations. In reality, the accumulated aircraft represent the number of aircraft being held from taking-off, if the locations are on the ground; and undergoing vectoring, holding, or speed reduction so as to reach the constrained/controlled locations at a later time, if the locations are instead en-route.

Currently, the queuing model captures four control actions that are in practice including MIT/MINIT, routing, GDP, and AFP. Specifically, a MIT/MINIT restriction is captured by a deterministic service time queuing model: each aircraft in the coming flow takes a fixed service time to pass a flow-restriction location. The service time equals the duration of the MINIT restriction, and therefore guarantees the minimum separation distance or travel time between neighboring aircraft. GDP is modeled as an exponential service queue to the flow at a departure airport and destined to an airport with arrival rate constraints. Rerouting is modeled as changing the fraction of flow travelling along each route in an O-D-R network. AFPs are modeled similarly to GDPs, but are only applied to flows on routes that are impacted by the AFP. As each of these actions defines an aggregate rate that must be distributed between the different flows, disaggregation approaches [Tien, 2012] have been developed to both mimic current operations and increase the likelihood of achieving the overall program rate.

As the simulation tracks the flows coming to, getting delayed at, and crossing management points at discrete time steps, a direct output is the time-course statistics of arriving flows, crossing flows, and flows delayed at all management points in the network. These statistical data values capture the transient dynamics of the NAS in response to dynamical weather uncertainties. From this data, basic metrics such as airport delay, airport throughput, sector count, and sector delay can be easily summarized to provide decision makers an accurate picture of the predicted impact. Based on these results decision makers can develop informed congestion management strategies, which can then be simulated and evaluated for refinement. Furthermore, as the queuing model analysis distinguishes between the impacts caused by constraints and the congestion management controls, decision makers are provided additional information regarding the effectiveness of their proposed responses.

IV. Analysis of FCM as a DST

To illustrate the concept presented in Section II, we utilize a realistic traffic and weather example, derived from historic data. Specifically, we begin by viewing the weather forecast within a proposed graphical user interface (GUI). The initial GUI is designed to provide decision makers with the information necessary to conduct the specified functions defined in Section 2, namely defining the area of control, evaluating the resulting congestion and developing congestion mitigation responses. In addition, a discussion of the modeling assumptions and simulation results will be presented. Through this example, we illustrate how FCM can provide decision makers with improved information regarding the response of the system to a constrained weather event. We emphasize here that the results presented in this section are illustrative of the capabilities envisioned by the FCM decision support system proposed and do not represent definitive responses to the traffic and weather situation under examination. Furthermore, the initial prototype has not been refined to optimize human-automation interaction. As such, the interface presented.
should be viewed in the context of the types of information and capabilities envisioned by the decision support system and not the final product.

A. Identify the Area of Interest

In this example, we consider the prediction of severe weather as the planning event under investigation. Specifically, we use the Short Range Ensemble Forecast (SREF) probabilistic convective weather forecast at 00:00Z on September 26, 2010 to illustrate the predicted weather, where Figure 4 shows the probabilistic forecast for 4, 8, 12, and 16 hours in the future.

Figure 4. SREF forecast on 9/26/10 at 00:00 Z for 4, 8, 12, and 16 hours LAT

Figure 5 shows a single snapshot of the forecasted weather provided by the Corridor Integrated Weather System (CIWS) forecast within the GUI interface proposed for the initial problem identification task. Although the details of the proposed functionality of the GUI are still under investigation, we highlight here that the decision maker can view an integrated picture of the weather forecast with the airspace definition at multiple times, resolutions and with varying levels of detail presented. Using this interface, the decision maker will select the area of interest to explore.

Figure 5. Forecasted weather and Airspace Configuration in GUI

Figure 5 shows a single snapshot of the forecasted weather provided by the Corridor Integrated Weather System (CIWS) forecast within the GUI interface proposed for the initial problem identification task. Although the details of the proposed functionality of the GUI are still under investigation, we highlight here that the decision maker can view an integrated picture of the weather forecast with the airspace definition at multiple times, resolutions and with varying levels of detail presented. Using this interface, the decision maker will select the area of interest to explore.

5 The CIWS weather forecast is utilized in the GUI instead of the SREF forecast as a result of data availability issues and connectivity requirements within the initial prototype. It is envisioned that the final prototype GUI will have the ability to display a variety of different forecasts, which the user can select from, to identify the area of interest.
further. In this example, given the prediction of persistent and severe convective weather in Atlanta ARTCC (ZTL), we select ZTL as the area of interest.

B. FCM Simulation

Given the definition of the area of interest, the FCM simulation is run to define the network model, generate the predictive scenarios, and estimate areas of congestion and the magnitude of the impact. In this section, we explore the development of each of these components for this example.

1. Modeling Formulation

Given the definition of ZTL as the area of interest, we define the network using the method described in Section III.A. Specifically, we cluster all airports outside ZTL, while the airports in ZTL are represented as individual nodes in the network. Outside ZTL, the en-route transit nodes are represented as connecting ARTCC boundaries and within ZTL sector transit nodes are defined. Using the database of historically flown routes, we apply this aggregation and define the O-D-R network of interest. Figure 6 depicts the user interaction pane for defining the network and the areas of interest (left) as well as the resulting integrated picture of the CIWS weather forecast overlaid on the definition of all O-D-R routes into (pink) and out of (green) Atlanta Hartsfield Airport (ATL) for the selected area of interest (right). We note that area of interest selection can also be accomplished by clicking on the map directly.

![Figure 6. Area of interest selection and forecasted weather integrated with O-D-R routes for ATL](image)

2. Predictive Scenario Generation

Given the identification of the area of interest, the next step of the FCM simulation is the generation of the predictive scenarios. This section outlines the methodology used to generate the representative weather-impact scenarios as well as the demand estimates for the queuing model.

a. Weather-impact

The WI simulator provides probabilistic trajectories (scenarios) of weather-impact based on the given probabilistic weather forecast shown in Figure 4. Specifically, the WI simulator tracked the presence or absence of convective weather in grid-squares measuring 40 km by 45 km at 15-minute intervals over a 19-hour time horizon. The generated weather trajectories were then translated into weather-impact measures needed in FCM. In this example, we computed the high-altitude sector capacities for each time interval based on a simple coverage estimate, namely

\[ C_S = C_N (1 - 2 \times f_W) \]

where \( C_S \) is the sector capacity for that interval, \( C_N \) is the nominal capacity of the sector (estimated as the 95\textsuperscript{th} percentile sector crossing flow as determined from the traffic data used to develop the network), and \( f_W \) is the
fraction of 2-D coverage (see e.g. [Mitchell, 2006]). The simulator was parameterized using hourly SREF probabilistic-weather forecasts, and 200 simulations were run to define an ensemble of weather-impact trajectories.

In order to define representative weather-impact scenarios, it is necessary to define one or more performance metrics to compare the individual ensemble members and generate statistics of likelihood for each representative scenario. For this example, the metric used was the total amount of good-weather traffic that would be in excess of capacity in ZTL over the duration of the simulation. The representative WI scenarios are displayed in the GUI, as shown in Figure 7. Viewing Figure 7, we see that the top of the interface provides the distribution of metric values over the ensemble of weather-impact trajectories. Specifically, the distribution is categorized into four representative scenarios, which are classified as “very-low weather-impact (VL-WI)”, “low weather-impact (L-WI)”, “high weather-impact (H-WI)” and “very-high weather-impact (VH-WI)”. The distribution provides a reasonable approximation of the uncertainty in weather-impact trajectories where the metric values for the four representative scenarios are shown, and the probabilities assigned to each scenario, are provided at the top of the distribution.

The GUI also summarizes the severity and likelihood of each scenario directly in order to provide decision makers the ability to more closely examine the predicted WI evolution in time for a given scenario. This information is shown at the bottom of Figure 7 for the VH-WI Scenario for four time snapshots, namely at LATs of 4, 8, 12 and 16 hour from 00:00Z. Viewing Figure 7, we see that darker shades of red signal sectors with a higher percentage of capacity reductions. The four WI scenarios are compared at these time snapshots in Figure 8 and each WI scenario is provided as an input to the queuing model in order to estimate the impact of the predicted weather on the traffic.

b. Demand

Given the uncertainty inherent with demand estimation at this LAT, significant estimation research is required to adequately predict traffic levels based on flight plans. The research results presented in [Wanke, 2012] detail the initial approach for demand prediction currently under investigation. However, as this work is still in the preliminary stages, results presented here are provided using actual historic traffic demand for August 30, 2010. This date was chosen because it had low weather coverage and few issued TMIs, in order to provide an approximate estimate of demand to ZTL unaltered by weather.
The demand estimates are derived from the actual departure rate for each O-D pair from the Enhanced Traffic Management System (ETMS) data for every 15 minute time bin. The number of departures was then used to define the mean flow rate for the Poisson distribution, enabling us to still represent demand uncertainty, albeit with an accurate initial input. To estimate O-D-R demand, we need the additional estimate of route utilization. Ongoing research is in the process of developing a methodology for route utilization prediction; however, for this analysis, we simply utilize the corresponding fractions of flow for the filed flight plans on August 30, 2010.

In addition to the demand originating at departure airports, there are flows present in the network at the beginning of the analysis. Estimating the flow present on each arc is a continuing area of research. As such, we instead assume that there are no flights in the network at the beginning of the analysis, which is a reasonable estimate if the analysis begins at 00:00Z and we seek estimates of traffic impact hours into the simulation, where flows are more accurately represented.

3. Queuing Model Simulation and Analysis

The queuing model described in Section III.C simulates the response of the predicted demand to the nominal and weather-impacted capacity constraints for each WI scenario. The output of the model is then translated into an estimate of delay at the various departure nodes, as well as the en-route sector congestion in ZTL. This information is then displayed in the GUI for each scenario. Specifically, by selecting a specific WI scenario, for example the VH-WI scenario as shown in Figure 9, a decision maker is provided with a summary of the WI statistics as well as time snapshots of the WI trajectories. The bottom of Figure 9 provides a summary of the delays predicted by sector, where darker sectors indicate higher levels of delay.
Figure 9. VH-WI Scenario information for contingency plan development

The map, shown in Figure 10 displays the sector and airport impacts over time for this scenario, where the sector impact is color-coded to represent less than 15 minutes of expected delay (green), 15 – 30 minutes of expected delay (yellow) and greater than 30 minutes of expected delay (red). Airport impacts are viewed as semicircles where the left semi-circle represents arrivals and the right semi-circle represents departures. Furthermore, the size of the semi-circle displays the relative demand to capacity ratio. By clicking on the semi-circles, a time history of the information is displayed for the selected airport.

Detailed information regarding the specific flows involved in the sector congestion and the associated time periods of delay can also be viewed by selecting a sector of interest from a drop-down menu in the GUI. Figure 11 shows the predicted impact for ZTL20 under the VH-WI scenario, where the bottom right picture in Figure 11 highlights the contribution to the delay in time by each O-D pair and the bottom left picture shows the top seven flows, which account for more than half of the delays in ZTL20. Using this information, decision makers can determine which O-D pairs are experiencing the greatest impact and when and where the severe congestion is occurring, which can inform the development of contingency plans.

C. Impact Analysis and Contingency Plan Development

Using the information provided, the decision maker can construct a contingency plan to mitigate the predicted congestion and using the GUI define the TMIs, rates, and implementation times to evaluate the impact of the proposed plan. For the VH-WI scenario, the decision makers see that ZTL20 is the most impacted sector, predicted to have severe and sustained delays beginning at 12:00Z and dissipating around 21:00Z. Furthermore, we see in Figure 11 that only a few O-D flows contribute to the majority of the congestion in ZTL-20 and these consist of both arrivals into ATL as well as over flights.

Considering the impact in ZTL20 and to a lesser extent the impact across all southern sectors in ZTL, the following TMIs are constructed using the GUI interface. Specifically, a GDP is defined to reduce the arrival rate into ATL using the following rates, imposed for all ATL-bound arrivals.

- At 10:00Z the arrival rate is lowered from a nominal rate of 136 flights/hour to 110 flights/hour.
Figure 10. Time snap-shot of predicted traffic impact for the VH-WI scenario

Figure 11. Predicted impact by O-D flow over time in ZTL20 for the VH-WI scenario
- At 12:00Z the arrival rate is reduced to 98 flights/hour
- At 18:00Z the arrival rate is increased to 110 flights/hour and remains in place until 20:00Z

An AFP is defined to control volume through the heavily impacted sectors on ZTL’s southern boundary. Specifically, the AFP will target flows from ZME, ZHU, and ZJX into ZTL10, ZTL11, ZTL20, and ZTL22, where Figure 12 shows the flows affected by this AFP. The rate selection was based on guidance from [FAA, 2011] which recommends a 30-35% rate reduction from the peak demand. Using the information provided by FCM, the four highest peak demand periods yield an average of approximately 12.2 flights per 15 minutes. As such, the AFP rate is defined as 8 flights per 15 minutes. The time period for AFP implementation is chosen to correspond with the peak congestion periods for the sectors involved, namely 1530Z to 2400Z.

![Figure 12. Visualization of AFP impacted flows](image)

To further mitigate some of the impact, reroutes are defined by the O-D pair, sector(s) (or centers) to avoid, timeframe, and the fraction of flow to be moved. The flows on all routes that meet the criteria are rerouted evenly across alternate routes for the O-D pair. Table 1 lists the reroutes defined in this example and Figure 13 illustrates the selection of a reroute for the MIA-cluster to ATL. Examining Figure 13, we see all O-D-R routes available in the network for the MIA-cluster to ATL including the alternate route that moves the flow through ZTL10 as opposed to ZTL20.

<table>
<thead>
<tr>
<th>Origin</th>
<th>Destination</th>
<th>Avoidance Area</th>
<th>Begin</th>
<th>End</th>
<th>Fraction of Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCO-cluster</td>
<td>ATL</td>
<td>ZTL19</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
<tr>
<td>MIA-cluster</td>
<td>ATL</td>
<td>ZTL19</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
<tr>
<td>ATL</td>
<td>RDU-cluster</td>
<td>ZJX</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
<tr>
<td>DFW-cluster</td>
<td>ATL</td>
<td>ZTL09</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
<tr>
<td>RDU-cluster</td>
<td>ATL</td>
<td>ZTL19</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
<tr>
<td>IAD-cluster</td>
<td>ATL</td>
<td>ZTL19</td>
<td>12:00Z</td>
<td>21:00Z</td>
<td>100</td>
</tr>
</tbody>
</table>
The above controls are provided as input to the queuing model simulation, which is re-run to compute the impact of the contingency plan on the traffic in the VH-WI scenario. The GUI, depicted in Figure 14, shows the overall sector delay at the bottom as well as the list of TMIs developed in the center. Viewing the summary delays by sector at the bottom of Figure 14 shows a significant delay reduction for ZTL20 and a small delay reduction for ZTL11. Comparing the predicted delay in each of these sectors confirms that the ZTL20 has a 75% reduction in delay and ZTL11 has a 13% reduction in delay. Importantly, we see no increase in delay in any sector in ZTL, and therefore the en-route congestion has not been moved to another sector in the weather-impacted region. The overall en-route delay was reduced from 52,666 minutes to 18,758 minutes, corresponding to a 64% reduction.

As the primary controls utilized in this plan are GDP and AFP, the reduction in en-route delay has a corresponding increase in ground delay. Prior to the TMIs, the total ground delay was minimal, with Charlotte Douglas International Airport (CLT) having a total of 45 minutes of delay, resulting from the surrounding sector congestion. However, with both an AFP and GDP in place, the ground delay increases significantly to a total of 51,293 minutes. Given that ground delay is preferable to air delay, as it represents a controlled response as opposed to tactical maneuvering and avoids en-route holding, this increase is reasonable. Using the 2 to 1 ratio of air delay costs to ground delay costs, the total cost reduction for this control plan is 16%.

Figure 15 shows the distribution of ground delay across the clusters for all clusters with greater than 30 minutes of total delay. Although the ground delay for some clusters is extremely high, it’s important to recognize that each cluster contains multiple airports and the delay represents the accumulated delay across these airports and not the delay at a single airport. Examining Figure 15 shows that the clusters with the largest impacts are the MCO_cluster, MIA_cluster, and MSY_cluster. Using the GUI, we determine that many of the impacted flows at these origin nodes intersect the AFP, but are destined to airports outside of ZTL. For example, flows from the MCO_cluster through ZTL20 and ZTL11 to airports outside ZTL accumulate 8,087 minutes of delay. Thus, large reductions in ground delays are possible if additional reroutes enacted. Given that rerouting around AFPs is a standard practice to avoid delay, FCM enables both decision makers and users to gain insight into which flows will be most impacted and provides options for avoiding this impact in order to improve the performance of the system.

Figure 13. Depiction of O-D-R routes for MIA-cluster to ATL
Figure 14. VH-WI scenario with contingency plan evaluation

Figure 15. Departure delays due to AFP and GDP for origins with greater than 30 minutes delay
Given this analysis, decision makers can determine if additional controls are warranted or if modifications to the current control actions are needed. For example, viewing the ground delay predicted under this control plan, especially the large ground delays at clusters heavily impacted by the AFP, an alternate plan is constructed. The new contingency plan does not include the AFP, but instead defines a GDP with a lower arrival rate into ATL, specifically:

- At 10:00Z the arrival rate is lowered from a nominal rate of 136 flights/hour to 110 flights/hour
- At 12:00Z the arrival rate is reduced to 98 flights/hour
- At 14:00Z the arrival rate is further reduced to 84 flights/hour and remains in place until 20:00Z

In addition, we maintain the reroutes suggested in the first plan, as defined in Table 1.

Comparing the impact of this contingency plan to the impacts forecasted if no TMIs are defined, we see that the predicted delay in ZTL20 is reduced by 68%, the predicted delay in ZTL11 is reduced by 9%, and as with the previous control plan, no increase in air delay is generated in any ZTL sector. The overall en-route delay was reduced from 52,666 minutes to 21,676 minutes, corresponding to a 59% reduction. However, it is important to note that these predicted air delays are slightly higher than the delays generated under the previous control plan.

Examining the ground delay generated under with the second control plan shows a much different picture of delay. Specifically, the total ground delay predicted with this control is 3,831 minutes. Figure 16 shows the distribution of ground delay across the clusters for all clusters with greater than 30 minutes of total delay. Examining Figure 16 shows that the MCO_cluster is most severely impacted by this control plan, but the reduction in impact, as compared to the previous control plan, is significant. Using the 2 to 1 ratio of air delay costs to ground delay costs, the total cost reduction for this control plan is 55%.

Using FCM, decision makers can continue to modify the TMIs and create new contingency plans. Trade-offs regarding the increase in uncontrolled en-route sector delay vs. controlled ground delay can be discussed using a quantitative framework for comparison and evaluation. Once a contingency plan is finalized, further decision on what components of the plan should be included in the strategic plan are necessary, but would be driven by decision maker experience and informed by the information provided in the proposed decision support tool.

V. Continuing Work

This paper introduces a decision support tool for FCM that aims to address some of the current shortfalls in today’s strategic TFM operations. Specifically, the proposed concept provides decision makers with a planning tool for strategic TFM that integrates the weather and traffic information, while capturing the inherent uncertainty present at longer LATs, and simulates the impact of predicted events. By providing decision makers with detailed information regarding predicted severe congestion, the tool enables decision makers to analyze the problem in detail, develop specific mitigation plans, analyze the results, and revise plans as necessary. As such, the proposed FCM concept and decision support tool fills a critical gap in today’s current TFM planning environment.

Given the scope of the research effort required to define the underlying models and GUI interface for the FCM decision support tool, additional research is ongoing to refine these capabilities. Specifically, it is necessary to develop a demand prediction model that provides accurate forecasts of the spatial and temporal propagation of flows...
in order to predict congestion. In addition, the analysis of the TMI impacts highlighted the need to improve the underlying network model to capture additional routing alternatives. Although simply expanding the historic network time horizon can accomplish this task, computational efficiency would be traded. As such, future research will investigate how to dynamically add routing options to the network based on the utility of the routes for improving the network structure.

Finally, as a decision support system, the ultimate goal of FCM is to aid decision makers in the strategic traffic management process. As such, continuing research is exploring how FCM could provide insight into the selection of the area of interest as well as the TMI parameter values. Investigations into the area of interest definition are exploring how the underlying network structure as well as sensitivities inherent in the propagation of impact can be used to highlight areas of interest to decision makers based on the predicted weather impact. To address the TMI parameter optimization problem, we are exploring both stochastic and heuristic optimization approaches that will enable automation to suggest specific rates and implementation times for TMIs. Together these capabilities will improve the human and automation interaction, allowing decision makers to focus on the problem structure using experience and incorporating knowledge of the operation environment unknown to the automation while allowing the automation to effectively simulate and optimize the resulting problem.

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