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A Framework for Flow Contingency Management

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This paper presents an operational concept and corresponding framework for flow contingency management, a component of strategic traffic flow management in the Next Generation Air Transportation System. The concept and framework described in this paper aim to address the lack of information, and simulation and evaluation capabilities provided to decision makers in today’s strategic planning process. Specifically, the proposed concept explicitly models the uncertainties present at longer look-ahead times and provides quantitative analysis tools to evaluate the impact of proposed congestion-mitigation actions. This paper develops the overall concept and defines the associated modeling framework which specifies the flow of information throughout the decision making process. An example weather and traffic situation, taken from historic data, is simulated to illustrate the concept.

I. Introduction

THE Next Generation Air Transportation System (NextGen) Mid-Term concept seeks to address a major obstacle in current traffic flow management (TFM) operations, namely the often overly conservative actions taken when demand exceeds capacity in predicted or impending operations. The current approach to strategic TFM planning faces a number of challenges. Specifically, in today’s operation, decision makers are faced with enacting plans that are based on limited analytical information regarding future operating conditions. In addition, limited simulation capabilities are provided to analyze and evaluate potential plans developed. As such, decision makers must rely on experience to interpret the limited data and devise plans of action. This requires decision makers to balance uncertainty, which is not well understood or captured in today’s information, with the risk of inaction. Thus, in order to maintain safety, potentially over-reactive and redundant traffic management initiatives (TMIs) are implemented, which reduce system efficiency.

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”.¹ 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 predicted 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.

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 individual aircraft in response to deterministic en-route capacity constraints⁵, incorporating the capability to define ground delays and rerouting⁶, as well as en-route holding⁷.

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However, flight-based models are not necessarily suitable to strategic TFM as they often do not provide a computationally efficient framework to examine the more relevant problems of interest to decision makers 2 hours or more in the future. Recognizing this issue, Reference 5 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 5 builds upon the work presented in Reference 4 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 2-4.

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 6 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 7, 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 8 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 9 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 10 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, Reference 11 uses a stochastic flow model to analyze the impact of a single rate restrictions, such as Miles-In-Trail (MIT) or Minutes-In-Trail (MINT) imposed at ARTCC boundaries, on an uncertain flow. Reference 12 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 Reference 13 to capture how individual flight reroutes and delays can be assigned under uncertain weather. Reference 14 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, Reference 14 provides a significant step towards the development of a decision support tool compatible with the NextGen strategic TFM needs.

The FCM concept proposed in this paper extends these ideas to develop a NAS-wide strategic TFM decision support system that directly captures the uncertainties inherent in both weather and traffic predictions at longer look-ahead times (LATs). Using a framework that realistically captures flow routing and represents both operational constraints and TMIs, a simulation and design capability is proposed to enable decision makers to evaluate potential responses to predicted large scale demand capacity imbalances. The strategic plans developed through this process will provide a coordinated and efficient management response, effectively meeting the goals defined in the NextGen strategic TFM vision.

In the following section, a thorough description of the operational concept for FCM is presented. Section III presents the framework proposed to realize the operational concept and provides a discussion on each component. Section IV uses a traffic and weather example, taken from historic data, to illustrate the FCM concept more concretely. Based on the analysis results, Section V highlights areas of future work to achieve the overall FCM decision support system goals.

II. Proposed 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. Strategic operations are actions taken two or more hours in advance to mitigate the impact of congestion, resulting from either weather or another off-nominal event. Given that FCM is operating many hours in advance of any situation, there is a significant amount of uncertainty in both the capacity and demand
estimates that determine the predicted congestion. As such the goal of FCM is to provide 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.

To accomplish this task in a scientific manner, we propose using formal analysis methods that capture uncertainty in the available data in order to produce accurate plans that can be understood and utilized effectively by decision makers. The plans developed are based upon aggregate demand, or flows instead of flights, which is consistent with the information accuracy at longer LATs. As such, these plans provide high-level control strategies to address large scale demand capacity imbalances, leaving the details of exactly which flights are impacted to decision support systems that analyze and help implement these decisions at a local level. The overall concept has three stages: predicting weather impacts, developing mitigation approaches, and defining a strategic operations plan. Figure 1 depicts the envisioned decision making process.

The first planning steps are the simulation of weather impact and the generation of representative weather impact scenarios. Weather impact predictions are essentially propagations of TFM impacts due to weather, or any other event that limits the available capacity\textsuperscript{15,16}. We propose that by predicting the range of possible weather impact we can better understand how an event may evolve and disrupt TFM operations. As such, our operational concept begins by analyzing how flows are potentially impacted by reductions in capacity and how this capacity reduction propagates through the system. 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\textsuperscript{17}.

It is important to note that although we begin with weather impacts, FCM is not limited to evaluating congestion in the presence of weather. Congestion or capacity-reduction caused by other factors (e.g., other environmental factors like volcanic dust, or operational factors impacting capacity) could be similarly translated into this framework for analysis. As the uncertainty inherent in forecasting weather is often much greater than other capacity-reducing sources, we focus here on weather-impact modeling, but note that similar techniques could be applied to other sources.

The next component of the FCM operational concept develops mitigation plans linked to the weather impact forecasts. Mitigation plans comprise the set of TMIs, or control actions, such as ground delays, sector or flow controlled area rate restrictions, rerouting, or other necessary initiatives that must be taken to alleviate the congestion due to an imbalance between predicted capacity and predicted demand. A mitigation plan outlines where, when and which actions are to be implemented and how to best capture use of available capacity to reduce the overall impact on the system. Referring back to Figure 1, we observe that an input into this process is the definition of the evaluation metrics, which places a requirement on decision makers to analyze the weather-impact scenarios and based on experience and priorities, and to define performance metrics to assess the quality of proposed contingency plans. When developing the mitigation plans, metrics of utility such as throughput or delay are assessed to ensure that the contingency plans provide efficient congestion mitigation controls.
The FCM concept proposes that mitigation strategies can be designed by automation, defined by decision makers, or both. In a design mode, the automation would construct a contingency plan that best meets the evaluation metrics provided. Alternatively, decision makers could manually define congestion mitigation responses and utilize the simulation and evaluation capabilities to assess, modify and ultimately construct the contingency plans. Ultimately, it is envisioned that the decision maker will utilize the automation-designed contingency plans as a preliminary solution, which they can modify as necessary to address operational realities not captured in the model.

However, as there are multiple weather impact outcomes, there are multiple mitigation plans and integrating these multiple plans into a single strategic plan is the final step in the FCM process. The strategic plan reflects both the likelihood of the different weather-impact outcomes developing and their associated mitigation strategies being necessary, as well as input from both National Airspace System (NAS) users and service providers as to the relative priority of disparate goals, given the situation. In order to capture the complexity inherent in this decision making environment, a formal risk management decision framework will be developed that can capture and assess the benefits, costs, probabilities, and value of different actions to determine the strategic plan.

The strategic plan provided from this analysis will be 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. 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 schedules, fuel or other planning parameters to provide flexibility as they see fit. 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 Framework

The operational concept presented in Section 2 provides a descriptive overview of how FCM will aid decision making in the strategic timeframe. As is evident from the discussion, the operational concept relies on a set of intertwined analyses. In order to better understand how the concept envisioned for FCM will be realized, it is necessary to more concretely define the contents and relationships of the analysis components in a formal framework.

The FCM framework, shown in Figure 2, consists of four components: modeling framework definition, 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. 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\(^{15,17}\). 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\(^\text{18}\), 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 2, 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 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. The remainder of this section will provide a more detailed description of each of these components.
A. Modeling Framework

The FCM modeling framework provides the underlying flow topology for the simulation and analysis required to develop the contingency plans. To capture the connectivity of flow through the NAS and the impact on the flow due to both nominal and weather-induced constraints as well the congestion-mitigation controls, 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.

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 using a multi-resolution network model\textsuperscript{19}, 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 control, which require a higher level of modeling fidelity, and then discuss the aggregation methods used outside the area(s) of control.

For a given O-D pair network, the origin node and destination node represent the airports where the flow enters and leaves the network, respectively. Within the area(s) of control, we define the origin and destination nodes to represent individual airports and 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). The arcs connecting the nodes in a given O-D pair network are derived from an analysis of historic sector crossings, or more specifically, historically-used sector triplets\textsuperscript{5}. Using sector triplet data, we can reasonably limit network size by only representing realistic flow patterns across sectors, as illustrated in Figure 3. In addition to the sector list, sector entry

\textsuperscript{5} A “sector triplet” is simply a sequence of three sectors traversed by a flight, which is typically enough to identify a specific flow through the middle sector of the triplet.

Figure 2. FCM Framework Flow Diagram
times are recorded, from which the sector transit time for each flight is computed. The sector transit time for a given triplet is then defined as the average sector transit time for all recorded flights using the particular sector triplet in the given O-D network formulation.

Defining the network components in this manner 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 in the simulation is included as part of the discussion on the development of contingency plans (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 is associated with a specific sector. Controls affecting a single node, such as a miles-in-trail (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 specific networks, control actions that target only a subset of the traffic, such as a ground delay program (GDP), can be readily imposed.

Outside of the area(s) of control, 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 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. Outside the control area, 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.

B. Predictive Scenario Generation

As a strategic TFM decision support tool, FCM is envisioned to aid decision makers in assessing and mitigating potential congestion problems 2 hours or more in advance. In this timeframe, significant uncertainties exist in both the weather and traffic predictions. Thus for FCM to provide useful information to decision makers it is necessary to develop methodologies that can accurately capture both the probabilistic weather impact predictions and the probabilistic demand profile.

1. Generating Weather-Impact Predictions

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 is being developed, whose primary purpose is to generate probabilistic scenarios (trajectories) of weather-impact on NAS constraints for use in the queuing-model-based analysis/design of contingencies. 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. 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 parameters of the influence model - which govern initiation, movement, and decline of convective weather events - can be selected so that probabilities of convective weather in individual grid squares match probabilistic weather forecasts at snapshot times. The parameterization of the model requires data from current probabilistic weather forecasts for the desired simulation duration (the planning horizon). Such probabilistic forecasts (including ensemble forecasts) are typically physics-based models that produce probabilities of sensible weather (e.g., rain) in individual grid squares at snapshot time. The models can be post-processed so that the probabilistic forecasts match the expected frequency of occurrence at the snapshot times (i.e., the forecasts are statistically reliable), and also allow realistic spatial and temporal interpolation between the snapshot times. The influence model can be parameterized (as described in Reference 16) so that generated weather trajectories statistically match the probabilistic forecasts at the snapshot times, but also have realistic spatial and temporal correlation and interpolate between snapshot times. In our initial efforts, we have used the convection probability forecast from the Short Range Ensemble Forecast (SREF) system as an input into our influence model.

Upon parameterization, the influence model can be used to rapidly generate trajectories (scenarios) of weather propagation. In turn, each influence-model-generated trajectory can be translated to a weather-impact scenario capturing evolution of NAS constraints (Sector capacities, AARs, etc.), using existing research on the impact of weather on these constraints. Once built, the WI simulator permits 1) fast generation of a large number of weather-impact scenarios; 2) generation of a few representative scenarios with associated probabilities; 3) analysis of temporal and spatial correlations in weather impact among other statistics; and 4) interface with the queuing model for traffic flow.

For FCM, the generation of representative scenarios with associated probabilities using the WI simulator is of particular importance, because these special scenarios can potentially guide the design of contingencies. With this motivation in mind, we have put significant effort into developing solutions for the representative-scenario-selection problem. A fruitful approach is to first pursue clustering of scenarios according to one or metrics that that are germane to NAS performance/management (e.g., capacity reduction at critical airports). Then, a representative element of each cluster can be selected as a representative scenario, with associated probability given by the fraction of all scenarios that are in the cluster. A point-selection technique that is traditionally used for numerical integration provides a particularly useful tool for clustering and finding representative scenarios in clusters. In addition to studying representative scenario selection, we have pursued temporal/spatial analysis of weather impact using moment-linearity properties of the influence model, and have begun to develop reduced-order models for critical weather impacts for interfacing with the queuing model.

The WI simulator is diagrammed in Figure 4. It is worth noting that, although we have here advocated generating a weather simulator from available forecasts and then translating weather trajectories to weather-impact ones, the alternate approach of translating weather forecasts to weather impact forecasts first and then directly generating a weather-impact forecast is also feasible. Both approaches are diagrammed in the figure.

2. Estimating Demand

For FCM to predict congestion, especially resulting from predicted weather impact, it is necessary to capture the future demand for NAS resources. However, given the LAT of interest, significant uncertainties exist in the estimation of demand from the filed flight plans. Specifically 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 schedule data. Although simplistic, it has been shown to capture demand well and therefore provides a convenient first approach for generating stochastic demand estimates. However, additional fidelity in the estimates is desirable.

More complicated stochastic demand models can also be obtained and parameterized based upon the current demand level, flight schedules, and uncertainties reflected from past data. Ongoing research is investigating how to leverage this additional information to develop an O-D (Origin-Destination) specific demand prediction model. By capturing aspects such as specific airport characteristics, trends in schedules, etc., we aim to more accurately represent the demand and thereby decrease the overall uncertainty in the model.

C. Flow Contingency Plan Development

In order to permit systematic evaluation and design of traffic flow management at a multi-Center or NAS-wide spatial scale and at the LAT of interest to FCM, we need a simulation and analysis framework that can 1) tractably represent traffic-flow dynamics in the NAS, 2) capture flow-management capabilities, and 3) account for the significant uncertainties present in the information available in the timeframe. We propose that queuing network models serve these needs as they naturally capture the uncertainties in traffic flow, the impact of operational constraints and control actions on flows, and the aggregation of flows and control actions.

To this end, we have developed a dynamical queuing network model and used the model to simulate NAS dynamics. The model has the following features that make it promising for FCM: 1) interfaces with the weather-impact model and allows the evaluation of dynamical uncertain weather-impact; 2) captures the impact of a series of management actions in practice today or envisioned in the NextGen environment such as Miles-in-Trail (MIT)/Minute-in-Trail (MINIT), Ground Delay Program (GDP), Time-based Metering (TBM), Routing, and Airspace Flow Program (AFP); 3) represents traffic as stochastic flows while capturing realistic route structure, and 4) reasonably interfaces with operational practice and therefore can be easily parameterized from data.

Using the FCM network model described in Section III.A, stochastic flows originate at the origin nodes, traverse the sector boundary nodes, 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 airport arrival rates, 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.

We modeled five control actions that are currently in practice or potential for use in NextGen, including MIT/MINIT, routing, time-based metering, 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 between the various sector boundary nodes. Other management actions such as TBM and AFP are also modeled as rate controls that limit the flow rate at a sector boundary node.

As the simulation of the model 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 flow, crossing flow, 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, which can give decision makers a quick sense of the performance of proposed congestion mitigation strategies in the presence of uncertain weather. In addition, metrics may be aggregated based on various performance areas so that decision makers would be well informed of possible impacts and their causes. For example, it is crucial for decision makers to know whether delay at an airport or in a sector is caused by capacity reduction due to weather or by the control actions in a mitigation strategy, so that the effectiveness of control actions can be distinguished. Mitigation strategies can thus be modified or synthesized accordingly.

Moreover, the uncertainty of demand and weather impacts complicates the decision making process. The risk of congestion and the robustness of control actions are also of decision makers’ concerns. Given the stochastic nature of the FCM network model, the uncertainty can be quantified to help understand the disturbance due to imperfect prediction on weather impact and demand. Lastly, the spatial and temporal variation in demand makes it challenging to find a balance between congestion mitigation and equity. Equity metrics can thus be formed to quantify the proportionality of delay allocated to each observation subject, such as airports, Origin-Destination pairs, centers/sectors, user categories, geographical locations, etc. The ultimate goal of the FCM metrics is to provide decision makers necessary but not overwhelming information of predicted NAS performance and strategy effectiveness; hence, potential congestion mitigation strategies can be explored and evaluated via either manual or automation-based approaches with adequate human involvement. Future research will explore these issues.

D. Strategic Plan Development

After flow contingency plans have been developed for a set of likely weather-impact scenarios, a plan of action needs to be formulated. This plan has two components. The first includes actions that need to be defined and executed immediately, referred to here as the current decision point plan (CDPP). The second component is comprised of potential future actions (advisories) to allow airspace users to do their own flow contingency planning. This high-level description is unchanged from how the Strategic Plan of Operations (SPO) is expressed today. However, the availability of quantitative flow contingency plans will greatly improve the effectiveness of the planning process.

Figure 5 illustrates the FCM planning process, given flow contingency plans as previously described. Each flow contingency plan represents a response to one of the weather-impact scenarios with an associated probability of occurrence. Each plan is defined at a minimum by two, time-varying vectors of metrics: (1) a set of TMIs, with start times, durations, and other parameters, and (2) a set of impact metrics, describing the effect of the plan on airspace users and the NAS.

In Figure 5, TMIs associated with each flow contingency plan are drawn as two time segments. The magenta segment represents the lead time required to implement the TMI, which is assumed to be in effect during the blue time segment. The scenarios in Figure 5 represent three weather scenarios of varying intensity. Scenario B has the most severe weather, requiring more TMIs for congestion management. Scenario A has almost no significant weather, requiring very little control, and Scenario C falls between them.

One key element of FCM planning is the use of incremental decision-making to manage uncertainty. Decisions made now are made knowing that the problem will be periodically revisited and the strategy adjusted. For Figure 5, it is assumed that the next decision point is 60 minutes in the future. Thus, all TMIs that would need to be initiated before that time must be considered as part of the CDPP. Scenarios B and C both have TMIs in this category. If these TMIs are similar, e.g., a departure rate control to the same group of airports, then a rational CDPP is to implement some form of that TMI, as Scenario B and Scenario C together have a 70 percent probability of occurrence. The remaining TMIs in the flow contingency plans do not need to be executed before the next decision point. Thus, they can form the basis for a strategic plan describing potential future actions, probability of action, and expected impact of those actions.

Of course, there are many factors which affect TMI choices, including those that the automation is not aware of. The automation may provide some support for “what-if” planning, but it is envisioned that the final plan is
composed by human decision makers. The major question, then, is: precisely how should the plan be formed, given the tools envisioned in this concept? Several research issues arise:

- What formal decision-making approaches are applicable to this problem?
- What role do humans play in the process, and via what kind of interfaces?
- How can we quantify the TFM system goals such that mathematical decision-making approaches can be applied?
- How do airspace users participate in the process?

IV. Concept Illustration by Example

To more concretely illustrate the concept presented in Section III, we utilize a realistic traffic and weather example, derived from historic data. Through this example, we explore how the different components of the FCM concept are used to generate strategic TFM responses to predicted weather. Specifically, we will begin by defining the initial weather and traffic problem, and then explore the development of the network, and the estimation of both weather-impact and demand. Following this, we will define the control scenarios considered and evaluate their impact on the traffic as simulated by the queuing model. Finally, we will explore how the plans can be integrated into a single strategic TFM response. We emphasize here that the results presented in this section are illustrative of the capabilities envisioned by the FCM framework proposed and do not represent definitive responses the traffic and weather situation under examination.

A. Example Problem

The example problem used to illustrate the FCM concept is derived from historic traffic and weather within Atlanta ARTCC (ZTL) on September 26, 2010. The SREF probabilistic convective weather forecast at 0500 EDT is provided as an input to the weather-impact model. Figure 6 shows the probabilistic maps taken at 5AM for time horizons of 4, 8, 12, and 16 hours in the future. We note that although convective weather is predicted to occur outside of ZTL, we only consider the portion within ZTL in this example.
Figure 7 illustrates the combination of the SREF thunderstorm forecast, at the forecast LAT times provided in Figure 6, and historical air traffic data to provide a thunderstorm impact prediction. This was accomplished by gridding the aircraft position data to construct various composites that are then integrated with the SREF output as described in Reference 21. The illustrations are based on the composited aircraft location and the SREF probability of a thunderstorm being independent, where the product of the two represents a first-order proxy for the gridded probability of en route aircraft encountering thunderstorms.

As the corresponding traffic on September 26, 2010 is obviously impacted by the weather event, we instead utilize traffic predictions from a date with relatively little weather-impact. To identify such a day, we analyzed the period 6/1/2010 to 8/31/2010 and assessed both the weather coverage and number of TMIs issued each day, as shown in Figure 8. Examining Figure 8, we see that on August 30, 2010, the average weather coverage is extremely low and there are few TMIs, which have little impact on traffic in ZTL. As such, traffic from August 30, 2010 provides the demand in this example.
B. Network Definition

The network representation is derived from the filed flight plans for August 30, 2010. We note that this date was purposely chosen to coincide with the traffic day selected for the analysis in order to best represent the actual flown traffic options. It is envisioned that the network will be derived from multiple days, likely months of traffic; however for this initial example, a single traffic day was selected.

To define the level of aggregation for the different NAS resources, we selected ZTL as the area of control. As such, all origin and destination pairs outside of ZTL are aggregated into clusters, and the individual airports within ZTL are represented as individual nodes, as shown in Figure 9. We highlight here that cluster nodes are denoted by the airport with the largest number of operations within the cluster. Figure 9 defines the location of a few specific clusters and airports which are chosen as they will be referred to later within the analysis.

Outside of ZTL, the transit nodes are represented as connecting ARTCC boundaries and within ZTL sector transit nodes are defined. Using the approach described in Section III.A, we construct the relevant connections for
each O-D layer of the network in order to define the entire network shown in Figure 10. Table 1 provides the corresponding details on the network size.

<table>
<thead>
<tr>
<th>Network Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of O-D Networks</td>
<td>2995</td>
</tr>
<tr>
<td>Number of Airports</td>
<td>22</td>
</tr>
<tr>
<td>Number of Sectors</td>
<td>45</td>
</tr>
<tr>
<td>Number of Nodes</td>
<td>1506</td>
</tr>
<tr>
<td>Number of Arcs</td>
<td>48924</td>
</tr>
</tbody>
</table>

C. Predictive Scenario Generation

To generate a prediction of the scenarios we must first estimate the future weather-impact and traffic demand, as described in Section III.B. This section outlines the methodology used to generate four representative weather-impact scenarios as well as the demand estimates for the queuing model.

1. Weather-impact

The weather-impact module provides probabilistic trajectories (scenarios) of weather-impact based on the given probabilistic weather forecast shown in Figure 6. To generate the forecast, a prototype WI simulator was developed that tracks convective weather-impact in ZTL at 15-minute intervals over a 19-hour time horizon (0500-2400EDT) on September 26, 2010. Specifically, the influence-model stochastic simulator tracked the presence or absence of convective weather in grid-squares measuring 40 km by 45 km. 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

\[ C_s = C_n(1 - 2 * f_w) \]

where \( C_s \) is the sector capacity for that interval, \( C_n \) is the nominal capacity of the sector (estimated as the 95\(^{th}\) 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. Reference 22). 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 distribution of metric values over the ensemble of weather-impact trajectories is shown in Figure 11.

Viewing Figure 11, we can see that grouping the ensemble into four representative scenarios, which we classify as “very-low weather-impact (VL-WI)”, “low weather-impact (L-WI)”, “high weather-impact (H-WI)” and “very-high weather-impact (VH-WI)”, provides a reasonable approximation of the uncertainty in weather-impact trajectories; the metric values for the four representative scenarios are shown, and probabilities assigned to each scenario, are provided at the top of Figure 11. The four scenarios are compared in Figure 12: in particular, sector capacity reductions are shown at four time snapshots, namely at LATs of 4, 8, 12, and 16 hours from the 0500EDT forecast for the four representative weather-impact scenarios. Viewing Figure 12, we see that darker shades of red signal areas with a higher percentage of capacity reductions. These four representative weather-impact scenarios will each be provided as inputs to the queuing model, which in turn will estimate the impact on the flow as a result of each predicted impact as well as the control scenarios proposed to mitigate the impact.
2. 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. Although this is an area of necessary research within FCM, for an initial proof-of-concept, we utilized the actual historic demands for August 30, 2010. Specifically, we analyzed the actual departure rate for each O-D pair from 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.

In addition to the actual demand originating at departure airports, there are flows present in the network at the beginning of the analysis. Defining estimates of the amount of 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 midnight and we seek estimates of traffic impact hours into the simulation, where flows are more accurately represented.

D. Contingency Plan Development

In order to develop contingency plans for each of the weather-impact scenarios described above, we define four control plan responses and evaluate the impact of implementing each control for each scenario as well as the impact of implementing no control.

1. Control Plans

The four control plans described in this section were developed by SMEs in response to the four weather-impact scenarios described above, assuming the weather-impact is measured beginning at 0500Z. A single iteration approach was deemed sufficient for the purposes of the proof-of-concept; however it is envisioned that these plans ultimately will be developed by SMEs in an iterative fashion, adapting plans in response to the predicted impact of the controls and evaluation metrics, or via an automation-designed approach.

Figures 13 through 15 display the four control plans which are derived from an analysis at 1115Z. Referring to Figure 13, which describes Control Plan 1, we see that a reroute to the north departure corridor is recommended for BOS-cluster bound flights departing Atlanta International Airport (ATL) between 1200Z-1500Z in response to the VL-WI scenario which shows an early reduction in the east departure corridor. We further highlight that the BOS-cluster contains the set of airports shown in Figure 9 and the reroute here applies to all flights destined for those airports. Figure 13 includes a depiction of the arrival airspace configuration to clarify the reroute control advised.
Figure 14 defines Control Plan 2 and corresponds to a potential response for the L-WI scenario. Examining Figure 14, we see that a MIT restriction for all arrival routes is suggested between 1700Z and 2000Z which limits the rate to 32 flights/hour for each of the four arrival routes. During the same time period it is recommended that all ATL-bound flights from DFW-cluster be rerouted to ERLIN (NW arrival route) in order to balance the predicted weather impact in the SW of ZTL.

Figure 15 defines Control Plan 3, corresponding to the H-WI scenario, which again suggests the MIT and ATL-bound DFW reroute of Control Plan 2 to begin at 1700Z, but continues these actions until 2330Z, as the predicted weather-impact is of longer duration. In addition, a GDP is also suggested for all ATL-bound flights beginning at 1500Z and lasting till 2400Z to reduce the arrival rate to 96 flights/hour into ATL.

Figure 16 describes Control Plan 4, corresponding to the VH-WI scenario. To manage the severe and persistent WI predicted in this scenario, a GDP is again suggested for ATL-bound flights from 1500Z until 2400Z and the MIT and DFW-cluster reroutes are extended until 2400Z. In addition, it is suggested that MCO-cluster bound departures out of ATL be rerouted to the west departure corridor and that MCO-cluster and MSY-cluster ATL-bound flights be rerouted to HONIE (SW arrivals into ATL).
Figure 13. Depiction of Control Plan 1 (VL-Control)

Figure 14. Depiction of Control Plan 2 (L-Control)

Figure 15. Depiction of Control Plan 3 (H-Control)
2. Evaluation of Controls

In order to evaluate the impact of each representative WI scenario and the above defined controls, we utilize the queuing model described briefly in Section III.C and in greater detail in Reference 18. Specifically, for each of the four representative weather-impact scenarios, we evaluate the delay incurred when no control is applied and the impact on delay as a result of applying each of the four controls plans. For a detailed description of the implementation of the controls within the queuing model the reader is referred to References 18 and 23.

Figure 17 defines the overall delay incurred under each WI scenario when no control and when each of the control plans is implement. Examining Figure 17, we see that the delays are categorized by cause. The primary cause of all delays is the weather (Wx), shown in pink, which defines the total delay accumulated as a result of the constraints, e.g. the sector capacity limits. As such, all delay present when no control is applied is weather delay. Congestion delay (cong), shown in blue, is any delay caused by a demand capacity imbalance that isn’t attributed to a weather or control delay. Congestion delays can also be an indirect consequence of a control (i.e. when delays are introduced elsewhere in the network as a result of applied control), for example additional en-route delays that propagate upstream of a MIT restriction. MIT delay, shown in green, represents the delays incurred when a MIT restriction is defined at a boundary crossing. Rerouting (rrt) delays, shown in purple, represent the congestion delays incurred by rerouting flows onto now-more-heavily-used routes. We note that rerouting may also incur delays associated with additional flying time; however these are not included in the analysis. Finally, GDP delay, shown in orange, represents the delays incurred at the airports and clusters in response to a GDP restriction limiting departures. As such, GDP delays measure ground delay minutes as opposed to airborne delay minutes.

Examining Figure 17, we see, as expected, that the weather delays are minimal in the VL-WI scenario and increase to significant levels in the VH-WI scenario. Examining the VL-WI scenario, we see that low weather delays are improved slightly by applying the VL control and that only a small amount of additional delay is incurred by applying the other control plans in this WI impact scenario. For the remaining three WI scenarios, we notice a consistent pattern of behavior in response to the application of the various controls. Specifically, VL-control provides no benefit but does not negatively impact the overall delay and L-control slightly reduces the overall delay. By implementing H-control, the delays actually increase, as compared to the L-control case. For the L-WI and VH-WI scenarios, this increase is mainly due to the implementation of the GDP, while in the H-WI scenario, the additional delay can be attributed to MIT delay. Finally, the VH-control provides the greatest reduction for each of these three WI scenarios, and in the case of the H-WI and VH-WI scenarios, the delay reductions are significant.

Reviewing the results of Figure 17, we note that the correct application of control can benefit the overall delays; however when control is applied inappropriately, delays can actually increase. To illustrate this point, Figure 18 shows the hourly delays accumulated in the VL-WI scenario under no control, VL-control, and VH-control. In Figure 18, the delays are further divided into the categories of “uncontrolled” delay and “controlled” delay, where weather and congestion delays are defined as uncontrolled delays and the delays that result from the application of MIT, rerouting, and GDP are defined as controlled delays. It is important to note that the uncontrolled and controlled delay charts are shown at very different y-axis scales. Examining Figure 18, we see that under VL-control, we reduce the weather delays (as compared to the no control case) while only incurring small amounts of control delay, and the controlled delay is synchronized with the weather impact. Alternatively, when applying VH-
control, the controlled delay is introduced later than needed, effectively providing no benefit on the weather induced delay and simply creating additional delay.

3. Analysis of the VH-WI scenario

In addition to overall delay, it is desirable to understand how the delays are incurred spatially and temporally. In the interest of simply illustrating the potential capabilities of the FCM analysis, we examine the VH-WI scenario under VH-control. We begin by comparing the time history of delays, as shown in Figure 19, where we see that the VH-control is well synchronized with the weather impact, reducing the times of highest weather delay. Furthermore, given the small amount of control delay incurred, the reduction in uncontrolled delays is significant. Furthermore, as much of the controlled delay is due to the GDP, we receive the additional benefit associated with ground delay as opposed to airborne delay.

The impact of the GDP delay on the various airports or clusters is shown in Figure 20. Examining Figure 20, we see that most clusters receive less than 10 minutes of accumulated GDP delay, which is negligible given the severity of weather-impact in this scenario, but a few airports/clusters receive significantly larger delays. Specifically, the MCO-cluster incurs over 70 minutes of GDP delay, however as almost 13% of the arrival demand at ATL is from the MCO-cluster, this large GDP delay is sensible.

Another consideration in evaluating the effectiveness of a control strategy is whether the control is reducing the delays in the weather-impacted sectors. As weather-impacted sectors have reduced capacity, their ability to manage any increase in volume is limited and as such it is desirable to target these sectors for reduced delays. Figure 21 compares the weather impact delays in the four impacted sectors in the VH-WI scenario, namely ZTL10, ZTL20, ZTL22, and ZTL34. Examining Figure 21, we see that the VH control strategy effectively reduces the weather impact in ZTL10, ZTL20, and ZTL22, but slightly increases the weather delay in ZTL34. However, as ZTL34 nominally has the lowest weather delays and the overall decrease in weather delays is significant, the VH control does provide a positive response to the VH-WI scenario.
Figure 18. Comparison of Control Strategies for VL-WI scenario.

Figure 19. Comparison of Control Strategies for VH-WI scenario.
Figure 20. Distribution of GDP delay by cluster/airport for VH-WI control in VH-WI scenario.

Figure 21. Comparison of Weather delays by Sector for VH-WI scenario under VH-WI control.
E. Strategic Plan Development

The analysis in the previous section provides a wealth of information to decision makers as to the value of the relative control plans under each WI scenario; however given the various probabilities of occurrence for each WI scenario, and the associated effective strategies, additional analysis is needed to develop a single strategic plan. As such, in this section we illustrate how the above information can be coalesced into a CDPP and future advisories.

The first step in constructing the strategic plan is to define the objective function of the decision maker. In Section III.D, we discussed the various concerns of decision makers when developing a strategic plan, namely safety, throughput, equity, etc.; however defining these metrics in an appropriate manner for FCM is still an area of ongoing research. Therefore, for the purpose of this example, we assume that minimizing delay is the metric of concern.

In this example, the analysis time is 1115Z. As such, we can define the CDPP as being any action that needs to begin prior to the next analysis time, nominally 1315Z. Therefore when constructing the strategic plan, we define all actions commencing prior to 1315Z as part of the CDPP and all actions commencing later as part of the advisory.

To determine which control plans should be included in either component of the strategic plan we then examine the probability of occurrence, the reduction in delay achieved if the situation develops as predicted and the additional delay incurred if the situation develops other than planned. In this example, the VL-WI scenario has a 44% probability of occurrence, and therefore it is desirable to include a control strategy to manage this contingency.

In the previous section we showed that the VL-control provides the best option of the four considered for reducing delays in the VL-WI scenario and furthermore does not adversely impact the delays in the remaining WI scenarios. As such, the VL control is included in the strategic plan as part of the CDPP since the controls commence at 1200Z.

As the L-WI has a 43% chance of occurrence and the H-WI and VH-WI have a combined 13% chance of occurrence; it is necessary to include contingency plans that effectively manage these events in the strategic plan. In the previous section we showed that the VH-control plan was the most effective at managing each of these WI scenarios, but we previously highlighted that unnecessary delays would be incurred by implementing the VH control plan if the VL-WI scenario was realized. However, given that the controls included in the VH-control plan do not commence until 1500Z, it is desirable to include the VH-control plan as an advisory in the strategic plan.

The result is a strategic plan that enacts a reroute of the BOS-cluster bound departures out of ATL to the north departure gate at 1200Z. Furthermore, the strategic plan advises that additional actions including a GDP for ATL-bound flights at 1500Z and additional reroutes as well as MIT restrictions commencing at 1800Z may be necessary, however the need for such actions will be re-evaluated at the next planning horizon. As such, the resulting strategic plan provides the necessary actions to mitigate impending congestion, provides situational awareness among users of likely future actions, and maintains the flexibility to adapt to uncertain conditions.

V. Continuing Work

This paper introduces a concept and framework for FCM that aims to address some of the current shortfalls in today’s strategic TFM operations. Specifically the proposed concept provides a methodology that directly captures the inherent uncertainties present in the strategic timeframe by constructing representative weather-impact scenarios (and their associated statistics) and integrating these potential outcomes into a stochastic queuing model that captures the uncertainty in the demand as well as behavior of the system in response to constraints. Furthermore, the proposed concept provides a simulation framework to model potential congestion mitigation responses, in the form of control actions, thus enabling decision makers to evaluate the relative effectiveness of potential contingency plans and develop an integrated strategic plan. As such, the proposed concept improves the strategic TFM decision-making process by providing quantitate information about the likelihood of future events and a simulation and evaluation capability to aid in the development of appropriate mitigation responses.

Through an illustrative example, this paper highlighted how the envisioned capabilities could be integrated to define a strategic plan in response to a predicted weather event; however much research remains. Additional research is required to improve the definition of representative scenarios as well as develop appropriate demand prediction methods for FCM and both components must be validated for their prediction accuracy. Improvements to the queuing model center consist of expanding the set of TMIs represented within the model and ensuring that the translation from real-world TMIs to queuing model control actions is accurately captured. Furthermore, as the design of a reasonable contingency plan can be an arduous process, optimization techniques that can recommend a coordinated and efficient set of actions to decision makers is desirable. Finally, given that multiple weather-impact scenarios of varying likelihood will be generated with potentially very different proposed responses, ongoing research will examine formal decision making approaches that can balance the costs and risks associated with
defining a strategic plan and leverage incremental decision making techniques in order to maintain flexibility and improve efficiency of NAS resource utilization.

As a simulation and evaluation tool, the FCM framework must also capture the various objectives associated with mitigating congestion and developing a strategic plan, recognizing that the resulting metrics must be represented using decision variables within the model in order to provide differentiation between options. Specifically, continuing research will focus on defining alternate metrics such as throughput, safety, etc. in order to develop contingency plans that match desired goals. Strategic plan metrics may differ in scope, focusing on equity, robustness, etc., and defining these goals in a concrete manner will be a challenging research area.

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