Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013)

Designing Coordinated Initiatives for Strategic Traffic Flow Management

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***Abstract*— This paper develops an approach for automation-assisted design of strategic traffic management strategies. The goal of strategic traffic flow management is to develop traffic management initiatives that mitigate potential large-scale congestion in the future when the imbalance cannot be effectively managed with tactical measures. Thus, despite the inherent uncertainties in the demand and capacity forecasts at longer look-ahead times, decisions regarding National Airspace-wide behavior are necessary. As such it is desirable to develop a decision support system that provides quantitative feedback on predicted traffic impact and aids in developing effective solutions. This paper proposes a framework to address this need by simulating and evaluating the effectiveness of proposed strategies across a variety of metrics. Using a realistic example taken from historic data, we explore the traffic management design space by varying the parameters associated with different management initiatives. The results are compared to those obtained using a naïve heuristic optimization approach and recommendations on requirements for future design approaches are provided.**

Keywords- Traffic flow management; decision support; strategic planning; congestion mitigation

I. INTRODUCTION

Strategic traffic flow management (TFM) involves planning large scale traffic management initiatives (TMIs) that re-shape the demand to better match predicted capacity, potentially reduced due to severe convective weather. Planning at longer look-ahead times (LATs) is a challenge as significant uncertainties exist in both weather and traffic forecasts. These challenges are exacerbated by the fact that in today's strategic planning process, insufficient information is provided in an integrated format and no decision support tools (DSTs) are present to aid in the development of these complex plans. The Next Generation Air Transportation System (NextGen) identifies Flow Contingency Management (FCM) as a critical component of the envisioned strategic TFM system that will identify and resolve large-scale congestion impacts [1].

The goal of FCM is to provide decision support capabilities that aid decision makers in developing effective and efficient TMIs to manage potential congestion. Although many decision support capabilities have been developed to aid TFM decision making, few address the requirements of strategic planning. Specifically, strategic TFM requires a computationally-efficient framework to examine National Airspace System (NAS)-wide congestion 2-24 hours in the future and capture the impact on the system from both limited capacity as well as the TMIs used to mitigate the congestion. Models that capture the behavior of individual flights [i.e., 2, 3, 4] are not suitable for this analysis as they require accurate flight plans, which are not normally available for many flights at this time horizon, assume deterministic capacity estimates, which in reality, are highly uncertain at these LATs, and can be computationally-prohibitive to use in a real-time decision making context. To address the computational issue, Churchill et al. [5] developed mixed flow-flight models that specify detailed flight propagation only in critical areas, capturing the remaining connectivity as aggregated flows.

Flow-based models, such as [6], [7], and [8] have further improved the computational performance of the simulations; however these models do not consider the forecast uncertainty and therefore are limited to examining the impact of a known strategy under known conditions. Queuing models capture the effect of uncertain demand propagation [9] and demand initialization [10]. However, these models do not consider weather-propagation uncertainties in the dynamic flow model.

Furthermore, a decision support system for strategic planning must capture the impact of TMIs on demand. Research in this domain is sparse, and only recently has this issue been explored in depth. Specifically, Moreau and Roy [11] uses a stochastic flow model to analyze the impact of a single rate restriction, such as Miles-In-Trail (MIT) or Minutes-In-Trail (MINIT) imposed at Air Route Traffic Control Center (ARTCC) boundaries, on an uncertain flow. Yan and Roy [12] incorporates ground delay as well as boundary rate restrictions in an analysis of stochastic flow impact. A probabilistic scenario tree approach is used in [13] to capture how individual flight reroutes and delays can be assigned under uncertain weather. Cook [14] describes the development of a decision support system that integrates the stochastic weather and traffic forecasts to provide decision makers a Ground Delay Program evaluation capability; however the scope is limited to forecasts of fog lifting at San Francisco International Airport (SFO).

Recent investigations by Clare et al. [15] highlight the current research interest in this difficult problem. In this research, developed under the SESAR[1] program, techniques of Model Predictive Control with Disturbance Feedback are used to capture the effect of uncertainty on the design of air traffic management strategies and further integrate the plans with models of airline operations recovery. Using a mixed integer optimization algorithm, optimal solutions developed under uncertainty can be derived for air traffic management (ATM) strategies and further translated into operational plans for flights. However, given different operational requirements of European and United States airspace regarding traffic demand uncertainty and user-provided information as well as the size and scope of the problems being addressed, this paper explores an alternative approach.

The FCM DST proposed in [16] provides a NAS-wide strategic TFM decision support system that directly captures traffic and weather uncertainties. Using a flow-based multi-commodity queuing network model, both operational constraints and TMIs are simulated to 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 work is to explore how to use simulation-based search and design procedures to analyze the option space and ultimately provide automation-derived suggestions regarding the specific implementation of proposed TMIs. In order to simulate the impact on the traffic resulting from a TMI, many TMI-specific parameters need to be defined. In situations where multiple TMIs are desired, the number of parameter combinations can quickly become exponential. We propose that the an appropriate division of workload allows decision makers to structure the solution and define the metrics that assess quality, while permitting automation to explore the vast number of parameter combinations, returning solutions that best meet the defined goals.

In this work we have applied a "design-through-simulation" framework to the design space exploration problem. Specifically, the MITRE Elastic Goal Directed Simulation Framework (MEG) [17], provides a large computing cluster and parallelization middle-ware to enable a stand-alone simulation, such as the FCM DST, to evaluate a large number of design combinations quickly, without the overhead required to develop the interface systems. In this work, MEG was used to perform a parameter sweep over a large number of TMI parameter combinations and record the performance of each combination for a variety of metrics. Next a basic Genetic Algorithm (GA), provided by the MEG framework, was employed to determine the suitability of employing heuristic search procedures for identifying quality solutions.

The paper is organized as follows. In the following section, a brief description of the operational concept is presented in order to provide a high-level description of the multiple components and interactions with operations. Section III provides a brief description of the various components in the simulation. Section IV defines the metrics utilized in this analysis. Section V uses a traffic and weather example, taken from historic data, to explore how different TMIs impact the defined metrics. Section VI highlights areas of continuing research.

II. Operational Concept and Framework

The FCM operational concept focuses on providing personnel at the Federal Aviation Administration's Air Traffic Control System Command Center (FAA ATCSCC) with the relevant information necessary to identify potential future congestion and simulate and evaluate proposed responses prior to implementation. The challenge of strategic TFM decision making is the uncertainty present in estimates of demand and capacity 2-24 hours in the future. Given this uncertainty, the FCM concept employs aggregate models to predict the range of possible congestion scenarios. By employing aggregate models, we can quickly simulate the overall response of the system to a variety of off-nominal conditions and to the TMIs proposed to mitigate the resulting congestion. 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, highlighting the flow of information. We discuss the envisioned decision making process in this section and provide brief details on the underlying models in the next section.

The planning process starts with the ATCSCC Planner viewing an integrated picture of the weather and demand forecasts which highlights areas predicted to have high resource demand and potential weather impact. The Planner, in coordination with the ATCSCC National Operations Manager (NOM), National Aviation Meteorologists (NAM), and traffic managers at other facilities, selects regions that warrant further investigation. We term this the "area of

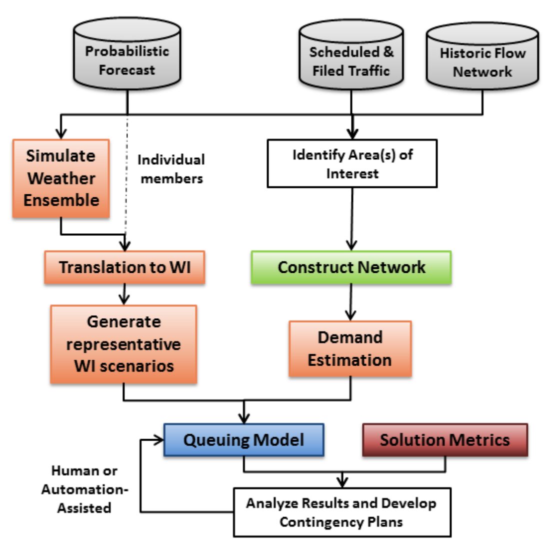

Figure 1. Flow Diagram of FCM

[1] SESAR is the Single European Sky ATM Research program that investigates a multitude of advancements to the European airspace system

interest" (AOI). The definition of the AOI results in the specification of the NAS representation used for the network model.

Once the AOI is selected, the weather-impact forecasts are defined by translating weather-forecast outcomes into TFM-relevant quantities, such as sector or airport capacity loss. These representative weather-impact scenarios represent possible futures of the propagation of weather-impact, and are defined by grouping individual weather-impact forecasts together based on metrics that highlight the commonality of forecast features. The simulation the propagates the demand forecast under various representative weather-impact scenarios to define the potential congestion.

Problems of this type are addressed in today's operation by the Strategic Planning Team (SPT) via teleconferences held every two hours. The SPT includes FAA traffic managers from many facilities as well as airline and military planners. The FCM-provided congestion predictions associated with various weather-impact scenarios would be used by these decision makers, in addition to other information, to determine what, if any, TMIs should be enacted to alleviate the predicted congestion. The resulting strategic plan includes both TMIs that should be enacted immediately and advisories for TMIs that *may* be enacted, depending on how the situation evolves. Thus, the FCM framework is not envisioned to change the current strategic planning process, but to inform it by providing provision of quantitative information and automation support for selection of efficient solutions.

The focus of this paper is on the process of defining the specifics of the TMIs for a given congestion mitigation scenario. The FCM DST captures the impact of Ground Delay Programs (GDPs), Airspace Flow Programs (AFPs) and strategic pre-departure rerouting. We note that this does not represent the exhaustive list of TMIs available or that can be captured within the model; however this set represents the critical TMIs under investigation in the strategic planning process. Depending on the TMIs chosen, the definitions can include specifying the implementation time, duration, rate and scope. The FCM framework enables these parameters to be defined by decision makers in a what-if scenario capacity; however, this process can be extremely time-consuming. Furthermore, as multiple representative weather impact scenarios exist, multiple plans may need to be created. As such, we explore how to evaluate the decision space and the impact on critical metrics and derive quality solutions quickly. The result is that FCM can define coordinated and effective solutions while providing feedback on the potential costs and risks of various plans prior to implementation, thereby providing a critical capability unavailable in today's strategic planning process.

III. FCM Simulation Framework

The FCM operational concept depicted in Figure 1 introduces a set of interconnected capabilities for predicting traffic flow management impacts. Specifically, the FCM simulation includes the development of the network modeling framework, the prediction of demand and weather-impact scenarios and the simulation of congestion via a queuing model. In this section we briefly describe these models. Further details on the model specifics can be found in [16] or in the referenced works in each section.

A. Network Model

The underlying flow topology for the simulation is captured using a multi-commodity network where each layer of the network is defined by an origin and destination pair (O-D pair). Within each O-D layer, the set of flow options are defined as 'routes', where a route specifies the flow through a set of resources [18]. Specifically, an Origin-Destination-Route (O-D-R) formulation captures the transition of flow from an origin node, through the en-route resource nodes, to the destination node. The network model defines origin and destination nodes as airports and the en-route resource nodes as sector transitions.

The historic network is generated from pre-departure filed flight plans taken from a single adaptation cycle. However, for a given simulation, only the portion of the network that is used to represent the demand prediction is simulated. The remaining network provides additional rerouting options for TMIs, if desired.

For a given simulation, the network can be further simplified based on the area of interest (AOI). Inside the AOI, the network is constructed as described above, allowing the model to capture airport departure and arrival rates and en-route sector throughput constraints effectively. However, outside the AOI, less detail is needed and operational constraints are not applied. Specifically, origin and destination nodes within the same ARTCC are clustered to minimize the amount of un-captured traffic and en-route resource nodes are represented by ARTCC transitions. Using this heterogeneous representation, we can capture the overall NAS-wide dynamics and impact of the TMIs while reducing the computational burden. Details on the specific network development can be found in [19] and [20].

B. Demand Forecast

FCM requires demand estimates in 15 minute time bins for each O-D-R. However, given the LAT of interest, these estimates are subject to significant uncertainties. Even ignoring effects of departure time uncertainty, demand forecasts in the 2-24 hour time horizon are complicated by the fact that much of the scheduled demand has not filed an intended route and a non-negligible fraction has not even scheduled intent for departure. In Wanke, et al. [21] models for predicting demand were explored that showed promise for capturing estimates of O-D-R demand. However, finalizing and implementing these models for a NAS-wide system is an active area of research. For the purpose of this paper, we utilize historic demand data to provide the traffic scenario under investigation.

C. Weather-Impact Predictions

The weather impact model utilizes long range ensemble forecast data to define areas of the NAS that will be (potentially) impacted by weather. Ensemble forecast products, such as those provided by the Short Range Ensemble Forecast (SREF) [22] or generated from the SREF Calibrated Thunder Forecast using a method developed by our collaborators Professor Sandip Roy and Mengren Xue at Washington State University and described in [23] and [24], are utilized to provide trajectories of weather futures which are more suitable to the types of decisions being simulated in FCM. By translating the convective weather ensemble members into sector coverage and then ultimately capacity reduction, using a translation method such as the 2-D coverage model in [25], we define an ensemble of potential weather-impacts. Incorporating airport impact predictions is a focus of ongoing research [26] [27]; however, these results are still preliminary. Therefore, this analysis considers only ensembles of en-route weather-impacts.

Given the weather-impact ensemble, it is important to group these various scenarios into a small set to facilitate planning. Grouping scenarios requires defining metrics of similarity and in this work we utilize the aggregate demand over capacity when comparing the similarity of ensemble members. The ensembles are then grouped using a Gaussian Quadrature method, as described in [28] in order to define a small set of representative weather-impact (WI) trajectories that provide the capacity reduction scenarios along with the associated grouping metric value. Furthermore, assuming all ensemble members are equally likely, we can infer the probability of occurrence for each representative scenario.

Figure 2 highlights the process for developing the representative weather-impact scenarios used in this research; however it is worth noting that alternative formulations, such as those proposed in [29] could also be used.

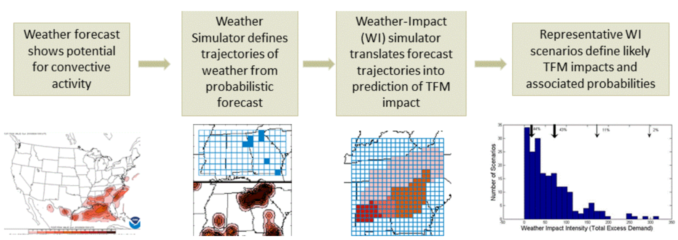

Figure 2. Generation of Representative Scenarios

D. *Queuing Model Simulation*

Simulation of the impact due to nominal and weather-impacted capacity as well as the TMIs used to mitigate congestion is conducted using a queuing model, which was developed by our collaborators Professor Yan Wan and Robert Xue at the University of North Texas [30]. This model 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 GDPs, AFPs and pre-departure rerouting.

Using the FCM network model described in Section III.A, stochastic flows originate at the origin nodes (for pre-departure demand), traverse the sector boundary nodes along each route, and terminate at the destination nodes. Active demand is populated on the arcs in the network at the start of the simulation. Propagation of the flow through the network is subject to operational constraints on the system, which include airport departure rates (ADRs), airport arrival rates (AARs) and capacity constraints at the sector boundary entry locations.

The TMIs captured in the model modulate demand propagation as follows. For GDPs, the impacted departure demand is subjected to a different departure rate, than the remaining departure flow, and accumulates ground backlog, or ground delay. A similar mechanism exists for AFPs; however these target O-D-Rs that pass through the defined AFP. Strategic rerouting shifts the demand between specified O-D-Rs, changing the shape of the flow through the network. Details on the implementation of these models can be found in [31].

The operational constraints and the TMIs reduce the rate of flow propagation, 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 locations at a later time, if the locations are instead en-route. For the purposes of this analysis, ground delay and air delay should be viewed as representing the severity of the congestion and therefore indicate the scale of the strategic and tactical responses required to mitigate the situation.

IV. FCM Evaluation Metrics

The simulation tracks the flow propagation and therefore can measure the delays occurring at all resource nodes throughout the network. From this data, simple metrics such as accumulated ground delay or air delay, as defined above, can be computed. However, the mitigation strategies may not simply alleviate delay, but shift uncontrolled congestion into a controlled delay response. Therefore, we further seek to distinguish the behavior of TMIs by considering the delay distribution across various resources and also the temporal distribution of delays. This section elaborates on the metrics considered and defines an objective function to compare the various strategies proposed.

A. *Delay Metrics*

Ground delay and air delay metrics are calculated by summing the total backlog at each time step and multiplying by the step duration (namely, 15 minutes) across all resource nodes and are distinguished only by whether the resource represents an origin node (ground delay) or an en-route resource node (air delay). En-route delays can be further classified as weather delays or congestion delays, where weather delays are defined as backlogs occurring in sectors with weather-impact. We note that congestion delays are often a product of weather delays resulting in a loss of capacity that propagates through the system. Ground delays can also be segregated by whether the delay is due to a TMI that impacts the departure airport (TMI delay) or the delay is due to a lack of available capacity in the immediate departure sector.

Note that the queuing backlog for flights entering a congested sector is not meant to represent what would actually happen in operations: presumably, some short-range TFM or ATC action would be taken to avoid large numbers of holding flights. But it is a useful metric to quantify where such action would be needed, and ideally, avoided.

B. *Reroute Metrics*

Strategic pre-departure reroutes can reduce overall delay in the system by removing the demand from congested sectors to sectors with available capacity. However, as reroutes modify the original intent, we define a metric to penalize flow on these reroutes. Defining an appropriate penalty is a subjective matter; however based on subject matter expert (SME) discussions, we selected a value of 15 per unit of demand in order to encourage demand experiencing less than 15 minutes of delay to stay on their intended route. In addition, for reroutes with longer transit times than the original route, we add a penalty equivalent to the transit time difference. We note that reroutes with shorter transit times are not rewarded.

C. *Concentration Metrics*

The ground and air delay metrics provide insight into the overall performance of a particular set of TMI parameters but do not describe the temporal aspect of the delays. As NAS disturbances propagate temporally as well as spatially, capturing the temporal delay distribution can provide additional insight.

To measure the temporal distribution of delay, we define a concentration metric, as shown in Equation 1

$$\text{TCM} = \sqrt{V \cdot (\boldsymbol{\delta} + \boldsymbol{I}) \cdot V^T} \quad (1)$$

where the row vector $V = (v_1, \ldots, v_T)$ provides the time series data of delays summed over all resources of interest at each time period $t = 1, .., T$. We note that we distinguish the airport resources and sector resources to provide two separate metrics, namely TCM_G for ground resources and TCM_S for sector resources. The matrix $\delta = \{\delta_{i,j} | i, j = 1, \ldots, T\}$ defines the adjacency of time periods such that

$$\delta_{i,j} = \begin{cases} 1, \text{ for } j = i+1 \text{ } or \text{ } j = i-1 \\ 0, \text{ elsewhere} \end{cases} \quad (2)$$

and $\boldsymbol{I}$ is a $T \times T$ identity matrix.

The TCM defined in Eq. 1 can be viewed as a variant of the Hierfindahl-Hirshman Index [32], which is commonly used for measuring market share concentration and extends the spatial concentration indices proposed in [33] to the temporal dimension. Using this metric, we can distinguish between proposed TMI responses that concentrate delays temporally or spread them out in time.

D. *Objective Function Definition*

We define an objective function to compare the results of the parameter sweep and ultimately provide a goal function for the genetic algorithm. The objective function is composed of four terms: ground delay, air delay, rerouting penalty and rerouting transit time. We utilize the traditional rule-of-thumb that en-route delay is twice as expensive as ground delay. We augment this sum with the transit time and rerouting penalty, also in a 2 to 1 ratio. The components of ground delay and sector delay as well as the TCM metrics will be used to further analyze the solutions, but are not explicitly considered in the objective function.

V. Automation-Assisted Design Example

To evaluate the need and benefit of automation-assisted design, we defined a realistic example, derived from historic traffic and weather data. In this section, we briefly describe the example problem and analyze the predicted congestion we seek to ameliorate. Following this, we define the TMI design space and explore how the different TMI parameter values impact various metrics. Finally, we utilize a naïve GA to more quickly navigate this space, using the objective function defined, and evaluate the performance.

A. *Example Problem*

In this example, we consider the prediction of severe weather as the planning event under investigation. Specifically, we use the SREF calibrated thunder forecast at 00:00Z on 26 September 2010 to illustrate the predicted weather, where Figure 3 shows the probabilistic forecast for 4, 8, 12, and 16 hours in the future.

In order to obtain representative weather-impact forecasts, we utilize the method described in [28] to create a synthetic ensemble of weather-impact forecasts and classify four representative weather-impact scenarios based on the criteria of nominal demand over weather-impacted capacity. The last image in Figure 2 shows the distribution of outcomes for weather in terms of capacity reductions in ZTL sectors.

In order to develop a comprehensive strategic plan, all four scenarios would need to be evaluated; however for the purpose of illustrating the design space and automation-assisted contingency plan development, we will focus on the most severe example, the very-high weather-impact (VH-WI) scenario, as it would be the most challenging to solve. Figure 4 shows the corresponding ZTL sector capacity reductions for the forecast at 4, 8, 12, and 16 hours in the future, where darker red areas signal greater capacity reductions. Based on this capacity-reduction forecast, we define the AOI to include ZTL, as well as Jacksonville ARTCC (ZJX), Houston ARTCC (ZHU), and Memphis ARTCC (ZME).

Our initial demand is taken from 30 August 2010, which

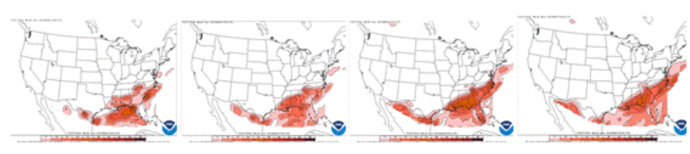

Figure 3. SREF forecast on 9/26/10 at 00:00 Z for 4, 8, 12, and 16 hours LAT

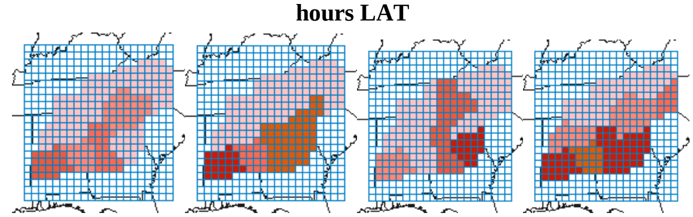

Figure 4: Snapshots of Sector capacity reductions for the VH-WI Scenario at 4, 8, 12, and 16 hours LAT

was relatively free of both weather and TMIs, and thus can be assumed to represent the nominal traffic flow without impact. By employing the queuing model to simulate the impact on the traffic from the VH-WI scenario capacity reductions, we can evaluate the predicted congestion.

The total sector delay predicted under the VH-WI scenario is 429,543 minutes. Figure 5 shows the distribution of the accumulated delay by sector, where darker sectors have higher delays. Examining Figure 5 we see that ZTL11 and ZTL20 have the most congestion. The sector delay can be further decomposed into weather-impact delay and resulting congestion delay, where the distribution of delay is 116,151 minutes and 313,392 minutes, respectively. We note that almost 80 percent of the weather-impacted delay occurs in ZTL11 (51,936 minutes) and ZTL20 (40,729 minutes). We also observe from the queuing analysis that 83,010 minutes of delay occurs on flows destined to ATL and 74,988 minutes of delay occurs on flows departing ATL.

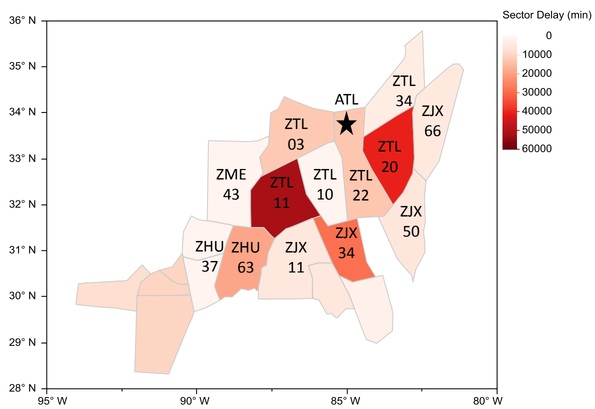

Figure 5. Delays by Sector for VH-WI Scenario

B. *Structuring the Contingency Plan*

Based on the predicted congestion, we structure the contingency plan to contain a GDP for ATL, an AFP for the southern edge of ZTL and reroutes for ZTL11 and ZTL 20.

1) *GDP Definition*

As a significant portion of the delay can be attributed to ATL-bound flights, a GDP would reduce this flow and potentially mitigate the congestion. The automation-assisted design process requires that decision makers define the GDP destination (ATL), as well as desirable parameter ranges for four GDP parameters.

- Rate: The permissible arrival rate per hour. This rate is translated to an associated departure rate for flights within the GDP scope.
- Scope: The scope defines the ARTCCs whose airports are subject to the GDP rate. This can be based on a mileage or ARTCC definition. Here, we define the scope based on ARTCC connectivity where a scope of 0 implies only ZTL airports are not exempt; a scope of 1 implies airports in all neighboring ARTCCs as well as ZTL are not exempt, etc.
- Start time: The start time of the GDP defines the local start time at the destination airport. The time of application at affected departure airports is calculated using the O-D-R transit times.
- Duration: The duration of the GDP is in hours.

Table 1 defines the parameter evaluation options considered.

Table 1. GDP Parameter Ranges

Parameter	*Min. Value*	*Max. Value*	*Increment*
Rate (flights/hour)	70	100	10
Scope	0	2	1
Start Time (UTC)	16:00	19:00	90 min
Duration (hours)	0	9	3

We note that a duration of zero implies that the GDP is not included in the contingency plan.

2) *AFP Definition*

In addition, or as an alternate to a GDP, an AFP may be valuable for controlling the flow directly into ZTL for the most impacted sectors. To define an AFP, the decision maker must define the boundary of the FCA as well as the parameter ranges for rate, start time, and duration.

The FCA is defined by denoting the (directional) resource node boundaries through which the flow is restricted. Figure 6 shows the restriction assumed for this example.

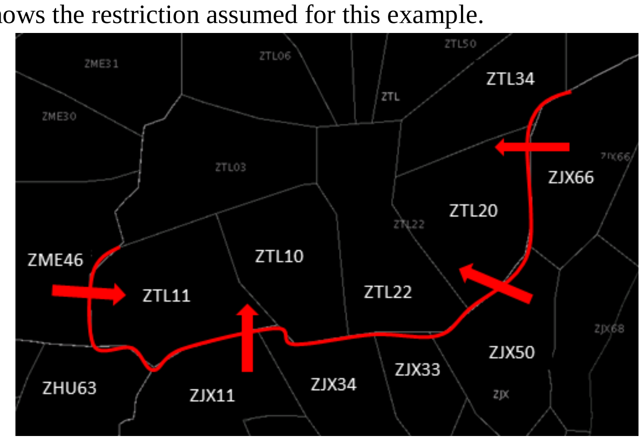

Figure 6. FCA Definition

The parameters defined for an AFP are similar to those of a GDP.

- Rate: The permissible arrival rate per 15 minutes across the defined boundary. This rate is translated to an associated departure rate for every impacted O-D-R.
- Start time: The start time of the AFP defines the local time of application. Departure times for impacted flows are pre-calculated using the O-D-R transit times.
- Duration: The duration of the AFP is in hours.

Based on the congestion, we define the following options for evaluation in Table 2, where again a duration of zero implies that the AFP is not part of the plan.

Table 2. AFP Parameter Ranges

Parameter	Min. Value	Max. Value	Increment
Rate (flights/15 m)	6	12	3
Start Time (UTC)	16:00	19:00	90 min
Duration (hours)	0	6	3

3) Reroute Definition

Based on the congestion profile, we define sets of reroutes for each of the most severely impacted airspaces, namely ZTL11 and ZTL20. The decision makers would define the specific flows to be rerouted and the associated parameter ranges for both the start time and duration. The flows are then distributed among available reroutes that avoid the impacted areas.

The following three flows will be rerouted out of ZTL11 as the delays on these flows represent 18 percent of the total ZTL11 delay.

- Dallas Fort Worth Airport (DFW) Cluster to ATL
- Pensacola Airport (PNS) to ATL
- Louis Armstrong New Orleans Airport (MSY) to ATL

The parameter ranges considered for this set of reroutes are provided in Table 3.

Table 3. ZTL11 Reroute Parameter Ranges

Parameter	Min. Value	Max. Value	Increment
Start Time (UTC)	17:00	19:00	2 hours
Duration (hours)	0	9	3

In addition, the following four flows will be rerouted out of ZTL20 as the delays on these flows represent 40 percent of the total ZTL20 delay.

- Miami Airport (MIA) Cluster to ATL
- ATL to Raleigh-Durham Airport (RDU) Cluster
- RDU Cluster to ATL
- Orlando Airport (MCO) to ATL

The parameter ranges considered for this set of reroutes are provided in Table 4.

Table 4. ZTL20 Reroute Parameter Ranges

Parameter	Min. Value	Max. Value	Increment
Start Time (UTC)	19:00	21:00	2 hours
Duration (hours)	0	9	3

C. Impact on Metrics from TMIs

A full combinatorial sweep of the above TMIs results in 82,038 evaluations (assuming the remaining parameters for a TMI with zero duration are not enumerated). The average evaluation time for a single run on the MEG computing cluster is approximately 90 seconds. For the parameter sweep, we utilize 60 processors simultaneously, resulting in a total evaluation time of approximately 35 hours.

Using the metrics and objective function defined in Section IV, we can analyze the sensitivity of the design space to changes in the TMI parameter values. The range of objective function values is from 142,551 to 980,099 and Figure 7 shows the distribution of solutions across this range. The objective function value corresponding to the original congestion problem is 859,087, and is contained in the set

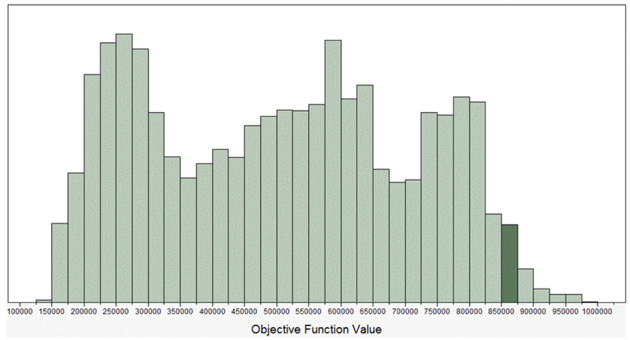

Figure 7. Distribution of Solutions by Objective Function

highlighted in darker green. Viewing Figure 7, we see that there are significant opportunities to reduce the congestion; however doing so without a thorough analysis could impact the system negatively.

1) The Minimum Cost Solution

The minimum cost solution corresponds to a contingency plan with the following TMI parameters.

- GDP: Rate = 90, Tier = 2, Start time = 19:00, Duration = 9h
- AFP: Rate = 6, Start time= 19:00, Duration = 6h
- ZTL11 Reroutes: Star time = 17:00, Duration = 9h
- ZTL20 Reroutes: Start time =19:00, Duration = 9h

Using all four TMIs at the maximum duration available provides the best solution, but the implementation times differ. Specifically, both sets of reroutes are implemented as early as possible, allowing the GDP and AFP to be implemented as late as possible. Also, the AFP uses the lowest available rate while the GDP rate is set higher and over the largest scope.

The overall sector delay for this solution is 56,083 minutes, of which 42,001 minutes is in weather impacted sectors. Using this set of TMIs removed 63% of the weather-impacted delays but also reduced the congestion delays by over 95%. Figure 8 illustrates that this plan is projected to remove all of the delays in many sectors, and significantly reduce the most severe congestion in ZTL11 and ZTL20. This TMI parameter combination does produce 28,674 minutes of ground delay, where 13,636 minutes are a direct result of the TMIs and the remaining 15,037 minutes are due to congestion.

2) The Maximum Cost Solution

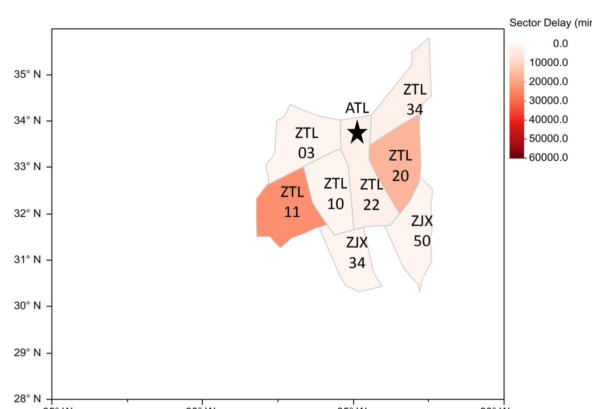

Figure 8. Delays by Sector for Best TMI Parameters

The highest cost solution was obtained using the following TMI parameters.

- GDP: Rate = 70, Tier = 0, Start time = 16:00, Duration = 9h
- AFP: Rate = 6, Start time= 16:00, Duration = 3h
- No ZTL11 or ZTL20 Reroutes were implemented.

Using this combination of parameters, the total ground delay is 25,466 minutes, with 11,797 minutes resulting from the TMIs. However the application of these TMIs actually increases the total sector delay to 477,316 minutes, with 129,140 minutes of delay in weather-impacted sectors and 358,176 minutes resulting from congestion. Viewing the solution in greater detail we note that without the reroutes, all demand is scheduled to travel through the most severely congested regions and by ending the AFP early, we effectively release the demand into the weather-impacted sectors during this critical time.

3) Sensitivity of the TMI Parameters

Examining the best and worst solutions highlights the importance of the reroutes in the overall solution, as well as the timing of the GDP and AFP. In order to understand the sensitivity of the solution to these parameters and other interaction effects, we explore the variation of GDP and AFP times. For this analysis, we assume that both sets of reroutes are implemented at the earliest time and for the longest duration. All other parameters, other than those examined, are left free in order to highlight the distribution of responses.

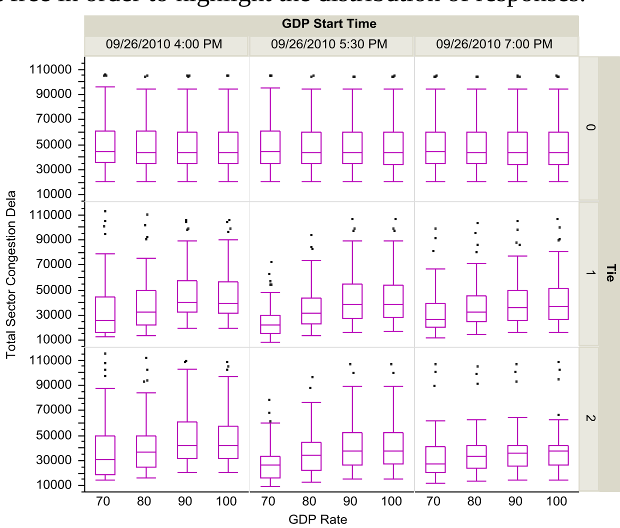

Figure 9. Sensitivity of Sector Congestion to GDP Parameters

Figure 9 shows the variation in sector congestion as a function of the TMI parameters. Examining Figure 9, we see that there is little variation due to start time or rate if Tier 0 is selected; however the delay is very sensitive to both the start time and rate when a larger scope is applied. Furthermore, we see that for Tier 2 and the latest start time, the GDP rate doesn't affect the sector delay significantly.

Figure 10 shows the sensitivity of sector weather and congestion delay as well as ground delay to the AFP parameters. Examining Figure 10 shows that starting the AFP at the later time and implementing a longer duration reduces

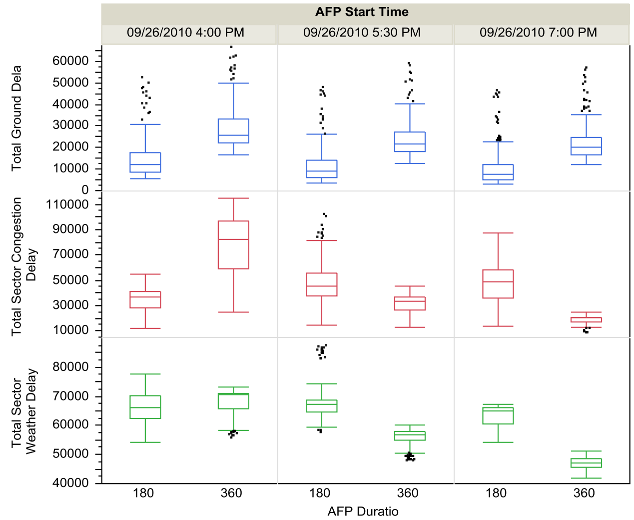

Figure 10. Sensitivity of Delays to AFP Parameters

the mean and spread of both sector and weather delays. We also note that these reductions are much larger than the corresponding increase in ground delay.

4) Characteristics of the Top Ten Solutions

Although optimal solutions are convenient, it is often beneficial to provide multiple good quality solutions. If we consider the top 10 solutions generated for this objective, all within 1% of optimality, we notice some interesting similarities, namely the start time and duration for the AFP and reroutes are identical as well as the duration of the GDP. The only variations are in the GDP start time (17:30 or 19:00), GDP rate (80, 90, 100), GDP tier (1 or 2) and AFP rate (6 or 9). Reviewing Figures 9 and 10, we see that the congestion is insensitive to these changes.

As these ten solutions are similar in objective function value, we explore how the TMIs affect the temporal correlation metrics. Figure 11 shows the top ten solutions, denoted as red points within the red circle, within the overall distribution of these two metrics. Viewing the solutions in this space, we see that all ten solutions are clustered together at the lowest values of TCM_S but mid-way through the range of TCM_Gvalues. One reason for the larger spread in TCM_Gvalues

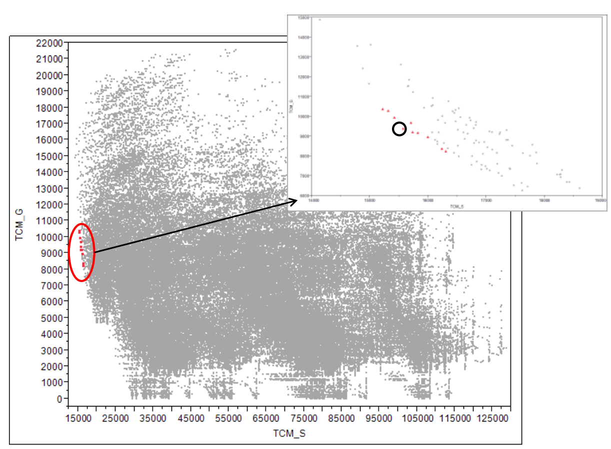

Figure 11. Ground vs. Sector TCM values with Top Ten Solutions Highlighted

is that the solution space contains contingency plans that produce little or no ground delay, but significant sector delay, while no contingency plan reduces the sector delay to zero. In the top right hand corner of Figure 11 is an insert showing more detail regarding these top solutions. Examining the insert, we see that all but one of the top 10 solutions lie on the Pareto front, with the optimal solution (circled) providing a good balance between the two concentration metrics.

D. Exploration of the Design Space using a GA

Exploring the design space by enumerating all possible parameter combinations provides useful information regarding the sensitivity to the various metrics; however the computational expense is prohibitive for strategic decision-making purposes. As such, we employ a naïve GA, which is a heuristic optimization approach readily available in MEG.

Heuristic optimization approaches, such as GAs, are often employed when optimizing a simulation-based model as more traditional methods may not be applicable to the structure of the problem. The goal of heuristic optimization algorithms is to guide the search to valuable areas of the design space, as determined by the objective function, while incorporating a degree of randomness, to find alternate and potentially better solutions. However, there is no guarantee of finding an optimal solution.

The MEG GA uses an algorithm similar to [34], described here briefly. A GA operates by defining a 'chromosome', where each chromosome specifies a specific value for each design parameter from the range provided. A population consists of the number of individual chromosomes created for a generation. To move to the successive generation, the current population is evaluated using a fitness function, or objective function. Based on fitness, parents are selected to populate the successive generation, where a pair of parents swap portions of their chromosomes (i.e., values of design variables). To induce randomness, mutations, or random re-sets of specific parameter values are permitted. The process continues until the specified set of generations has been evaluated.

Using the objective function defined in Section IV, we first explore how varying the number of searches performed affects the quality of the solutions returned. Specifically, we vary the number of generations considered and measure both the computation effort as well as the objective function value. For this experiment we utilize 50 processors, which correspond to the population size defined for a given generation. Table 5 shows the results.

Examining Table 5, we see that a naïve GA is able to find the optimal solution after only searching 3% percent of the solution space, reducing the computation time by 96%. Using 50 generations, we re-ran the GA 5 times and each time the optimal solution was obtained.

Table 5. Computation Effort verses Optimality for GA

# of Generations	*% of Design Space*	*Computation Time (min)*	*% over Optimal*
30	1.8	53.13	8%
40	2.4	69.08	2%
50	3.0	85.33	Optimal
60	3.6	102.46	Optimal

VI. CONCLUSIONS

Developing coordinated and effective congestion mitigation plans is a major challenge faced in today's traffic management system. This paper proposes a DST that addresses this need by enabling NAS-wide evaluation of mitigation plans prior to implementation. Using the FCM framework, we explored the TMI parameter design space, highlighting the significant opportunities available to reduce congestion, while also showing that improper coordination of TMIs could degrade the situation. Finally, we showed that employing a GA could yield the same quality solutions at a small fraction of the computation expense.

Although the initial results are extremely promising, much research remains. It is desirable to determine if the sensitivity relationships shown exist in general, as they can be used to reduce the design space complexity. The first step towards this goal is to continue to map the design space, aiming to capture the optimal TMI parameters within the space as opposed to at the edge. Given improved information regarding sensitivity, we can incorporate refinements into the GA, enabling faster computation, where the ultimate goal is to provide automation-derived solutions in a time span suitable for decision making. Finally, for automation-derived solutions to be useful for strategic TFM decision making, we must expand the set of metrics to encapsulate the various criteria relevant to decision makers.

NOTICE

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

ACKNOWLEDGMENT

The authors would like to thank all who helped with this work for their valuable insights, especially Rachel Ethier, Mary Hokit, John Huhn, Tudor Masek, Ali Rakei, Dr. Lixia Song, Dr. Alex Tien, and Kevin Workman, from the MITRE Corporation. The authors would also like to thank our collaborators, Professor Sandip Roy, Mengren Xue and Rahul Dhal from Washington State University, and Professor Yan Wan and Robert Zhou from the University of North Texas whose contributions were integral to this research.

REFERENCES

[1] FAA ATO NextGen and Operations Planning, June 30, 2009, *NextGen Mid-Term Concept of Operations for the National Airspace System*, Washington, DC.

[2] Bertsimas, D., and Stock, S., "The Air Traffic Flow Management Problem with Enroute Capacities," *Operations Research*, Vol. 46, No. 3, May–June 1998, pp. 406–422.

[3] Bertsimas, D., and Stock Patterson, S. "The Traffic Flow Management Rerouting Problem in Air Traffic Control: A Dynamic Network Flow Approach" *Transportation Science, 34* (3), 239-255, 2000.

[4] Bertsimas, D., Lulli, G., and Odoni, A. "The Air Traffic Flow Management Problem: An Integer optimization Approach" *13th International Conference, IPCO 2008* (pp. 34-46). Bertinoro, Italy: Springer.

[5] Churchill, A., Lovell, D., and Ball, M., "Evaluating a New Formulation for Large-Scale Traffic Flow Management" *Eighth USA/Europe Air Traffic Management Research and Development Seminar,* Napa, CA, July 2009.

[6] Myers, T., and Kierstead, D. "Network Model to Address Capacity/Demand Imbalances in the National Airspace System" *AIAA Guidance, Navigation and Control Conference and Exhibit.* Honolulu, Hawaii, August 2008.

[7] Menon, P. K., Sweriduk, G. D., and Bilimoria, K., "New Approach for Modeling, Analysis and Control of Air Traffic Flow," *Journal of Guidance, Control, and Dynamics*, Vol. 27, No. 5, 2004, pp. 737–744.

[8] Sun, D., and Bayen, A. M. "Multicommodity Eulerian–Lagrangian Large-Capacity Cell Transmission Model for En Route Traffic" Journal of Guidance, Control, and Dynamics , 31 (3), pp. 616-628. 2008

[9] Roy, S., Sridhar, B., and Verghese, G. C., "An Aggregate Dynamic Stochastic Model for Air Traffic Control," *5th USA/Europe ATM 2003 R&D Seminar*, Budapest, Hungary, June 2003.

[10] Sridhar, B., Soni, T., Sheth, K., and Chatterji, G., "Aggregate Flow Model for Air-Traffic Management," *Journal of Guidance, Navigation, and Control,* Vol. 29, No. 4, 2006,

[11] Moreau, D., and Roy, S., "A Stochastic Characterization of En Route Traffic Flow Management Strategies" *AIAA Guidance, Navigation and Control Conference*, San Francisco, CA., August 2005.

[12] Wan, Y., and Roy, S., "A Scalable Methodology for Evaluating and Designing Coordinated Air-Traffic Flow Management Strategies Under Uncertainty" *IEEE Transactions on Intelligent Transportation Systems,* Vol. 9, No. 4, December 2008.

[13] Hoffman, R., Krozel, J., Davidson, G., and Kierstead, D., "Probabilistic Scenario-Based Event Planning for Traffic Flow Management" *AIAA Guidance, Navigation, and Control Conference*, Hilton Head, SC, August 2007.

[14] Cook, L., "Ground Delay Program Parameters Selection Model (GPSM): SFO Field Evaluation Project (ZON 17, Segment 5) Engineering Evaluation Assessment Report" Mosaic ATM, December 17, 2010

[15] Clare, G., Richards, A., Escartin, J., Martinez, D., "Air Traffic Flow Management Under Uncertainty: Interactions Between Network Manager and Airline Operations Centre", 2nd SESAR Innovation Days, Braunschweig, Geremany, November, 2012.

[16] Taylor, C., Wanke, C., Wan, Y., Roy, S., "A Decision Support Tool for Flow Contingency Management", AIAA Guidance, Navigation, and Control Conference, Minneapolis, MN, August, 2012.

[17] Page, E., Litwin, L., McMahon, M., Wickham, B., Shadid, M., Chang, E., "Goal-Directed Grid-Enabled Computing for Legacy Simulations" 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing, Ottawa, Canada, May 2012.

[18] Tien, S-L., Taylor, C., Wan, Y., Zhou, Y., Wanke, C., "A Route-Based Queuing Network Model for Air Traffic Flow Contingnecy Management", AIAA Aviation Technology, Integration, and Operations Conference, Virginia Beach, VA, Sept. 2011.

[19] Wang, L., Taylor, C., and Wanke, C., "An Airport Clustering Method for Air Traffic Flow Contingency Management," AIAA Aviation Technology, Integration, and Operations Conference, Virginia Beach, VA, Sept. 2011.

[20] Taylor, C., Masek, T., Wanke, C., Roy S., and Wan, Y., "Defining Multi-Resolution Networks for Flow Contingency Management", AIAA Aviation Technology, Integration, and Operations Conference, Virginia Beach, VA, Sept. 2011.

[21] Wanke, C., Masek, T., Taylor, C., Roy, S., and Wan, Y., "Modeling Air Traffic Demand for a Real Time Queuing Network Model of the National Airpsace System," AIAA Modeling, Simulation and Technologies Conference, Minneapolis, MN, August 2012.

[22] Bright, D. and Nutter, P., "On the Challenges of Identifying the "Best" Ensemble Member in Operational Forecasting" in *Proceedings of the 84th AMS Annual Meeting,* Seattle, WA, January 2004.

[23] Roy, S., Wan, Y., Taylor, C., Wanke, C., "A Stochastic Network Model for Uncertain Spatiotemporal Weather Impact at the Strategic Time Horizon" in *Proceedings of AIAA Aviation Technology, Integration, and Operations Conference,* Fort Worth, TX. September 2010.

[24] Xue, M., Zobell, S., Roy, S., Taylor, C., Wan, Y., and Wanke, C., "Using Stochastic, Dynamic Weather-Impacted Models in Strategic Traffic Flow Management", in *Proceedings of 91st American Meteorological Society Annual Meeting*, Seattle, WA, January 2011.

[25] Mitchell, J. S. B., Polishchuk, V., and Krozel, J. "Airspace Throughput Analysis Considering Stochastic Weather," AIAA Guidance, Navigation, and Control Conference and Exhibit, Keystone, Colorado, July 2006.

[26] Xue, M., Dhal, R., Roy, S., Taylor, C., Wanke, C., Huhn, J., "Refinement and Enhancement of an Influence-Model-based Weather-Impact Simulator" *AIAA Modeling Simulation and Technology Conference,* Minneapolis, MN, August 2012.

[27] Roy, S., Dhal, R., Taylor, C., Wanke, C., Xue, M., Wan, Y., "Generating Representative Weather Impact Futures for Strategic Traffic Flow Management" in *Proceedings of 93rd American Meterorolgical Society Annual Meeting,* Austin, TX, January 2013.

[28] Xue, M., Roy, S., Zobell, S., Wan, Y., Taylor, C., Wanke, C., "A Stochastic Spatiotemporal Weather-Impact Simulator: Representative Scenario Selection", AIAA Aviation Technology, Integration, and Operations Conference, Virginia Beach, VA, Sept. 2011

[29] Steiner, M., Bateman, R., Megenhardt, D., Liu, Y., Xu, M., Pocernich, M., and Krozel, J., "Translation of Ensemble Weather Forecasts into Probalistic Air Traffic Capacity Impact." Air Traffic Control Quarterly, Vol. 18 Num. 3, 2010

[30] Wan, Y., Taylor, C., Roy S., Wanke, C., and Zhou Y. "Dynamic Queuing Network Model for Flow Contingency Management," AIAA Guidance, Navigation, and Control Conference, Portland, Oregon, Aug. 2011.

[31] Tien, S-L., Taylor, C., Wanke, C., "Modeling Departure Rate Controls for Strategic Flow Contingnecy Management", Submitted to the AIAA Guidance, Navigation and Control Conference, Minneapolis, MN, Aug. 2012.

[32] Hirschman, Albert O. "The Paternity of an Index" *The American Economic Review*, Vol. 54, Issue 5, pp.761, 1964

[33] Guimarães, P. E., Figueiredo, O., and Woodward, D. P., "Accounting for Neighboring Effects in Measures of Spatial Concentration" *Journal of Regional Science*, Vol. 51, Issue 4, pp. 678-693, 2011.

[34] Goldberg, G. Genetic Algorithms in Search Optimization and Machine Learning, Reading, MA: Addison Wesley, 2004.

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