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I. Introduction

A primary function of air traffic flow management is to strategically shape traffic demand to match capacities (e.g., airport arrival/departure rate limits and Sector capacities), without imposing excessive delay. In the current United States National Airspace System (NAS), the disruptions modulating capacities and hence traffic management are predominantly weather events, including convection, winter weather, and high winds. However, during the next 15 years and beyond, it is likely that the air traffic system will be increasingly subject to man-made disruptions that impact traffic management, including 1) a growing frequency of cyber- and physical-world security incidents, 2) commercial space operations, and 3) integration of high-altitude unmanned aircraft. Disruptions of these types have already begun to impact traffic control and management: for instance, the insider attack on the Chicago Air Route Traffic Control Center (ZAU) communication equipment during October 2014, and several recent commercial space launches and UAS-integration test scenarios. To date, such non-weather disruptions have had relatively contained and limited impact on air traffic system operations, but they will undoubtedly incur greater impact and cost in the near future as the airspace system becomes increasingly heterogeneous and cyber-enabled. In consequence, paradigms for traffic management that account for non-weather disruptions will be needed in the near future.

The management of air traffic flows in the face of severe weather alone is a hard problem. However, because of the predominance of weather impact, traffic managers are experienced in characterizing the impact of weather on capacities, and in shaping flows to match capacity requirements. Also, the managers have available a number of tools which assist in decision-making at several time/spatial scales, and additional decision-support capabilities are under development [1,2]. Addressing non-weather disruptions in air traffic management entails several new challenges:

1) These disruptions may cause drastic recurring long-duration and/or recurring reduction in airspace capacity. For instance, space operations can require complete closure of multiple Sectors over the countdown/launch duration, and will have regular impact when commercial space operations become common. Likewise, security incidents may cause closure of major airports or even Center offices. Because of their severity, the disturbances can have NAS-wide impact on traffic.

2) Predicting capacity reduction profiles due to non-weather disruptions is challenging. On one hand, these disruptions may be pre-planned and have highly structured impact which allow for nearly deterministic models. On the other hand, however, operators have limited experience with the potential impacts, and formal models for capacity-reduction impacts may be unavailable. Also, the events themselves are often rare, and may involve uncertainties that do not easily admit statistical models (e.g., the possible delay in a launch countdown, the time required to recover equipment after a cyber-attack, or the trajectory of a high-altitude drone that has become disabled). Thus, non-weather disturbances entail structured unmodeled uncertainties.
3) As non-weather disturbances become more frequent, operators will need to manage concurrent impacts from heterogeneous disturbances. For instance, on a given day, NAS flows may be impacted by a planned space launch or landing, statistically-modeled convective weather events, and a completely unexpected UAS failure. The possibility for heterogeneous impacts means that the air traffic command center will need to integrate data from diverse sources (weather forecasts, updates from space-launch personnel), and may significantly complicate decision-making procedures.

New decision-support solutions are needed to address these challenges, and so to provide operators with workable traffic flow management strategies for a future cyber-enabled National Airspace System with high-frequency space-vehicle and UAS operations. Per the challenges listed above, these capabilities must be able to address the drastic impacts and un-modeled characteristics of non-weather disturbances, and to integrate weather-based and other impacts. We anticipate that a mixture of proactive and reactive approaches will be needed, to 1) re-plan traffic flows ahead of time for regular scheduled events (like space-vehicle re-entries) and 2) strategize traffic management initiatives to address uncertain impacts (e.g., uncertainty in space-vehicle launch, unexpected impact from a security violation) at a look-ahead of one to several hours, respectively. At its essence, both proactive and reactive decision-making will require operators to re-orient traffic flows across a wide area, to robustly prevent congestion in the face of the disturbances, while avoiding delay. These regional flow-design tasks naturally require models for air traffic at the resolution of major traffic flows; several such models have been developed in recent years, to allow strategizing of traffic management in the presence of weather uncertainty. Here, we will explore via an illustrative example and basic formal analysis how a flow-level model of the NAS—specifically, a queueing-network model for flow contingency planning [3,4]—can be used for proactive and reactive management under non-weather disturbances to the NAS.

Very recently, several studies have begun to envision traffic management for a more heterogeneous NAS, particularly to address commercial space vehicle launches and landings [5-9]. Several of these efforts envision frameworks for incorporating space traffic into the NAS at a high level. Other studies discuss possible impacts on aviation of space-vehicle operations, including in the case of catastrophic failure of the space vehicle. Scoping studies of flow management in a future NAS with high-altitude UAS traffic, and of security challenges to flow management, have also been undertaken. Relative to these studies, our focus here is on exploring model-driven approaches for regional planning of traffic management capabilities for both routine and unexpected disruptions. By taking a model-driven approach, we intend to develop explicit procedures and strategies for regional- and national-level flow management, which can readily be incorporated into the current traffic-management system. This initial study will focus on using the flow-level model to simulate impact of potential non-weather disturbances on NAS congestion, and exploring flow design for these disturbances.

The NAS-scale queueing-network model developed through our earlier efforts is well suited for this study. In particular, rather than tracking each individual aircraft, the model is composed of aggregated origin-destination sub-flow-networks that are layered upon each other (see Figure 1 for illustration of the model). The model integrates various data/resources such as traffic demand and capacity reduction forecasts to track the propagation of aggregated traffic flow in these layered networks, given a plan of traffic management initiatives across the NAS. As such, the model can quickly evaluate the impacts of capacity reduction and strategic traffic management initiatives on NAS-wide traffic performance, and permit evaluation of which major traffic flows and airspace regions are subject to congestion and delay. Another feature of the model is its flexibility to integrate heterogeneous data resources for decision-making in the presence of uncertainties. The model also allows explicit representations of management capabilities, and hence allows the real-time design of management initiatives at a NAS-wide scale using
a combination of numerical approaches and control-theoretic techniques. The model has been prototyped for strategizing NAS-wide traffic management in the face of weather uncertainty, see Figure 1 for results from a case study focused on a long-duration tropical-weather event in the Southeastern United.

In this study, we will develop insights on the impact of non-weather disturbances to regional and NAS-wide traffic performance through simulation of the queuing-network model. We will then give some preliminary insight into the design of management initiatives (particularly, rerouting), to manage non-weather disturbances proactively. Specifically, the following results will be described:

1) For a case-study day, congestion and delays incurred by potential non-weather disturbances, which lead to severe capacity reduction of unknown duration in a swath of airspace, will be explored.

2) Advance re-design of major traffic flows for proactive management of planned non-weather disruptions (specifically, with known location and nominal event time) will be discussed. The simulation studies will be extended to study rerouting-based solutions for alleviating congestion. Also, the re-design task will be abstracted to a routing-fraction (rerouting) design problem for the queueing-network model, and formal analyses of effective designs will be obtained for a canonical example with a single re-routing waypoint.

II. Modeling for Evaluation, Proactive, and Reactive Design

Non-weather or man-made disruptions are a particular concern for air traffic management because they can incur wide-area long-duration impacts on traffic. For example, the security attack on Chicago Air Route Traffic Control Center (ARTCC), or ZAU, in 2014 restricted most over-flight traffic over the entire ZAU airspace, over a period of several weeks. This restriction led to delays of several hours for cross-continental and other air traffic in the United States, particularly on days with severe convective weather. Likewise, space-vehicle launches and landings may lead to the complete closure of multiple Sectors in one or more Centers, for a period of several hours. To evaluate and mitigate the NAS-wide impacts of the man-made disruptions, models of appropriate resolution are needed that permit fast wide-area analysis of traffic. Specifically, models are needed that capture traffic in sufficient detail to allow practical wide-area insight into traffic characteristics and to simplify computation.

This paper takes the perspective that multi-resolution flow-level models are appropriate for evaluating and designing against man-made disruptions. We believe that flow-based models for traffic are apt for
several reasons. First, evaluation and mitigation of man-made disruptions largely will be undertaken at longer look-ahead horizons of hours (reactive) to days/months (proactive). At these look-aheads, traffic demand and weather are subject to significant uncertainties which preclude accurate modeling of individual aircraft. Second, the need for wide-area analysis dictates using flow-based models, both because operators strategize traffic at the resolution of flows at the NAS-wide scale and because of the computational challenges associated with NAS-wide design. Third, the traffic management initiatives that can be brought to bear to resolve man-made disruptions (preferably rerouting, but also ground delay programs and airspace flow programs) are naturally modeled as acting on flows rather than individual aircraft.

During the last 10 years, a number of flow-level models for air traffic have been developed, primarily to assist in strategizing traffic management at a NAS-wide scale in the face of severe weather (convection, winter weather, high winds, etc) [3,10,11]. As an initial effort in this direction, a number of Eulerian models for air traffic were proposed, which track and allow forecasting of aircraft counts in airspace partitions [10,11]. Eulerian models of several resolutions have been developed, with the coarsest tracking traffic counts in Centers and the finest capturing Sectors and even sub-regions within Sectors. More recently, network models which represent aggregated directional flows have been proposed [3,12,13]. Relative to the Eulerian models, these flow-network models have the benefit of 1) allowing representation of traffic management initiatives as queueing elements and 2) distinguishing congestion impacts on traffic for different origin-destination pairs. At the same time, they are sufficiently aggregated to allow fast simulation of NAS-wide flows and congestion under uncertain weather features, and provide simple structural insights into congestion and its resolution using TMIs.

In this paper, we will draw on a multi-resolution flow-network and queueing model for the NAS, which was developed for strategic traffic management under weather uncertainty [3,12], see Figure 1. This flow- and queueing-network model is the main analysis engine for the Flow Contingency Management (FCM) Tool, which allows evaluation and design of traffic management initiatives for the entire NAS over a full day, across severe weather futures derived from an ensemble weather forecast [3,4,12,14]. Several studies have validated that this flow-network model permits effective forecasting of NAS-wide traffic flows, and evaluation/design of TMIs within a region of interest [15]. The FCM tool with the model embedded is currently being prototyped at the ATCSCC, as a decision aid for resolving severe-weather impact in the air transportation network. The flow-network model is promising for the proposed evaluation of man-made disruptions, because it allows analysis of the propagative impact of disruptions on flows across the NAS, and the resolution of disruptions using heterogeneous management capabilities. For this reason, we are motivated to use the flow-network model to evaluate and design against man-made disruptions.

A complete formulation of the flow- and queueing-model can be found in [3]. Briefly, the network model represents directional traffic flows at two resolutions: capturing traffic densities between high-altitude Sector boundaries and centroids within a region of interest (typically 2-3 Centers), and at the level of Centers outside the region of interest. The traffic flows are assimilations of traffic among multiple overlaid origin- and destination- (OD) networks, each of which uses a probabilistic description of traffic routing from an origin airport (or airport group) to a destination airport (or group). The demand for each OD network is modeled as having a deterministic piece which captures filed and nominal scheduled traffic, and an added stochastic piece which captures deviations from schedule as well as “pop-ups” (unmodeled freight and general-aviation traffic) [16]. Capacitations of airspace regions or airports, whether at nominal levels or at reduced levels due to weather, are represented as a queueing actions on flows entering the regions (or on arrivals and departures at the airport). The changes in airport and airspace capacities due to severe weather are extracted from ensemble forecast products,
using rubrics for capacity reduction due to weather [16]. Specifically, forecast futures for these capacity reductions are developed from the ensemble members, and are then used to drive the flow-network model. Meanwhile, TMIIs that restrict traffic flows (such as GDPs, AFPs, and MINIT) are also represented as queueing actions, while re-routing is modeled as modifying flow fractions for multiple OD pairs, see [3] for details.

The flow and queueing model can be used for evaluating and designing against non-weather disruptions to the airspace system, but with some modifications. First, proactive evaluation and design requires application of the model at much longer look-ahead horizons (months to years, perhaps). At these look-aheads, demand and weather impact do not admit models based on current forecast data or known weather/traffic conditions. Instead, archived historical data must be used to derive statistical distributions for demands and nominal routing fractions. Meanwhile, in evaluating weather impact, either nominal (good-weather) conditions must be assumed, or representative scenarios chosen from a long-duration historical archive must be considered. The model also must be enhanced to represent capacity reduction due to man-made disruptions. In general, man-made disruptions require different model types from weather disruptions. Specifically, while man-made disruptions also cause reductions in airspace and airport capacities, statistical models for the capacity reduction are often not appropriate. Instead, man-made disruptions typically result in capacity reduction profiles that are highly structured across a wide area (multiple Sectors and even Centers), while also being subject to a few parametric uncertainties that are not well modeled (e.g., launch delay in Space Vehicle operations). Thus, models that capture these specific capacity-reduction profiles, yet represent and allow evaluation of unknown (non-random) parameters, are needed. For our purposes here, we assume that these models for capacity reduction can be developed by leveraging domain expertise, and focus on evaluation and design using these models.

The evaluation of non-weather disruptions also requires new metrics and analyses for airspace system performance. Typically, in strategizing for severe weather, the performance of a TMI plan is measured in terms of expected delay or congestion costs. Reactive design for non-weather disruptions should be based on similar performance metrics. For proactive evaluation and design, delay and congestion costs are important. However, proactive rerouting may allow for many strategies that eliminate delays, some of which are preferred because of other cost considerations (e.g., fuel costs for airlines). These additional objectives should be accounted for in the proactive design. Additionally, for the proactive design, evaluation of costs across demand profiles and non-random parameter spaces is needed.

III. Evaluation of Non-Weather Disruptions: An Illustrative Example

We pursue performance evaluation of man-made disruptions to the airspace system, in the context of a small-scale case study. In the study, we explore the impact of the long-duration closure of a sector on system performance, the efficiency of a rerouting strategy, and the robustness of this strategy to demand uncertainties. A closure of this sort may result from e.g. an attack on Center facilities, unavailability of the Sector’s controllers, or a space-vehicle launch in the region of interest.

As shown in Figure 1, the small example contains four O-D subnetworks, and multiple sectors including $S_3$, $S_5$, and $S_6$ [3]. Nodes 1 and 2 represent origin airports, and nodes 11 and 16 represent destination airports. The routes that belong to the four O-D subnetworks (1-11, 1-16, 2-11, and 2-16) are marked with different colors. Numbers on the routes represent the flow fractions in individual subnetworks and the travel time (marked in purple). The other 12 nodes in this network are sector boundary points. They
are located on sector boundaries (marked by dashed lines), and represent where the flows merge and split.

The capacities of $S_3$ and $S_6$ are 4 and 3 per time interval ($15\text{min}$) respectively. The departure rate constraints of airports 1 and 2 are 8 and 7, and the arrival rate constraints of airports 11 and 16 are 3 and 4, respectively. We disable sector $S_5$ (marked using yellow dashed lines) with zero capacity over a span of 24 hours to capture a non-weather disruption. To reduce the congestion caused by the shutdown of $S_5$, we design a simple rerouting plan. In particular, the flows from airport 1 to nodes 4 and 6 are rerouted to node 7 to avoid the sector $S_5$. As such, flow fractions from airport 1 to nodes 4, 6, 7 in the subnetwork 1-11 are set to be 0, 0, 1, respectively. Similarily, the flows from airport 2 to nodes 9 and 10 are rerouted to node 12, and hence the flow fractions from airport 2 to nodes 9, 10, 12 to set be 0, 0, 1, respectively. We then evaluate the total backlogs (over a time span of 24 hours) before and after applying the rerouting strategy.

Traffic demands are uncertain for a proactive (planning-stage) evaluation. To evaluate the impact of traffic demands on system performance and rerouting strategy, we vary the traffic demands and repeat the above experiments. In particular, traffic demands at airports 1 and 2 are modeled using Poisson processes, with their mean values set to be $\{0.1, 0.5, 1, 1.5, 2, 2.5\}$ per 15 minutes. For each setting, we repeat the experiments for 10 times, and evaluate the minimum, mean, and maximum total backlogs. Other parameter settings are shown as follows.

Figure 1. Structure of a four O-D pair network.
As shown in Figure 2, the rerouting strategy reduces traffic backlogs. The result is consistent despite the variation of traffic demands. Several more observations are summarized here. When the mean traffic demands are relatively small (less than 1.5), the total backlogs after applying the rerouting strategy increase very slowly. This observation indicates that the rerouting strategy is robust, when demands are small. In addition, when the mean incoming flow rate is above 1.5 per time interval, the total traffic backlogs increase exponentially. This is understandable considering the saturation effect of sector capacities. Finally, the advantage of applying rerouting is reduced with the increase of traffic demands, as reflected by the faster growth of total backlog at higher demands when rerouting is applied. This is because rerouting will cause the increase of demand at other regions, and impair system performance when traffic demands are high. We leave to future work the comparison of multiple rerouting strategies that distribute the constrained flows in varied ways.

IV. Toward Proactive Design: A Routing Design Problem

The eventual goal of proactive design is to develop a playbook for addressing catalogued non-weather disruptions, so as to facilitate systematic and rapid implementation of management strategies upon occurrence of a disruption. In the long term, we envision developing strategies for diverse disruptions, including space-vehicle launches and landings a designated locations, UAS incursions in certain high-usage Sectors, and cyber- or physical-world attacks that interfere with the operations of an ARTCC. In this initial study, we conceptualize the proactive-design problem within the described modeling framework. Also, a mathematical formulation is developed and addressed for a canonical case, wherein a single major flow is rerouted at a particular waypoint to address the disruption.
Broadly, we are pursuing proactive designs that are based on re-routing traffic around capacity-restricted regions during non-weather disruption events. The optimization of TMI s that reroute traffic has already been studied in the context of the FCM framework, as well as in other work. This formulation can be adapted to the proactive design problem, but with several key enhancements and changes. As in the FCM framework, each re-routing procedure is modeled at selecting routing fractions for traffic on a major flow, over a duration of time: the decision variables are thus the routing fractions and the start and end times of each initiative. In FCM, these rerouting TMI s are optimized in tandem with flow-restriction TMI s (e.g., Airspace Flow Programs or AFPs, Ground Delay Programs or GDPs), with the aim of minimizing expected delay and congestion costs across the NAS on the day of operation. Designs have been obtained using a mix of heuristic and analytical methods. In contrast, for proactive design against non-weather disruptions, only the design of rerouting initiatives is considered, since we seek for advanced planning of traffic flows that largely eliminate delays (rather than trading off delay/congestion costs as is the case with flow-restriction TMI s). Since the design is proactive, more refined evaluation of a strategy’s performance for NAS stakeholders is also possible and dictated. Crucially, the design should account for financial costs incurred by rerouting (e.g., extra fuel costs), even when no additional delay is incurred. To account for these financial costs, an enhancement of the flow- and queuing- model is considered. Specifically, for each O-D pair, a cost is assigned to each route segment, which reflects the fuel cost incurred in traversing the route segment. These costs vary depending on weather conditions and other factors, and hence are naturally modeled statistically over a planning horizon. Likewise, at the planning horizon, distributional models are apt for demand as well as weather-related capacity reductions. These various statistical models can be extracted from archived historical data. The design problem of interest is thus to tune the selected set of rerouting TMI s (specifically their routing fractions and start/end times) so as to minimize a total cost, which incorporates both congestion/delay metrics and route-use costs. We seek specifically for a resilient design that optimizes the expected total cost over statistical demand and weather models derived from historical data. This resilient design is meant to serve as a playbook for rerouting for the specified man-made (non-weather) disruption, which then can be further refined on the day of operations using forecast data.

In this initial study, we have developed a mathematical formalization and theoretical analysis for the proactive design problem for the special case that a single rerouting initiative is being designed, which acts on a major flow. The idea here is understand how the major flow(s) affected by a non-weather disruption should be redistributed to avoid congestion while minimizing extraneous costs. For the formal analysis, we also focus on optimization during a single busy period with a specified average rate rather than a time-varying rate, to allow characterization of rerouting needs in the worst case. Formally, aircraft are assumed to arrive at the routing waypoint according to a Poisson process, with rate $\lambda$ (see [13,16,17,18] for justification for Poisson models for air traffic flow, which are often apt for flows that incorporate diverse OD pairs). The flow rate is not known at the planning horizon, and is rather modeled by a probability distribution which can be derived from archived data. Nominally, a route with ample capacity and low cost is available for the traffic flow, however this route is assumed to be blocked entirely due to the man-made disruption. There are $n$ alternative routes for the flow, labeled $i = 1, \ldots, n$. The bottleneck capacity rate available for the rerouted flow on each alternative route $i$ is denoted by $u_i$. Since these capacity rates depend on weather as well as other traffic flows, they will be subject to significant uncertainty at the planning horizon; thus, the bottleneck capacities $u_i$ are also modeled as random variables, whose probability distributions can be extracted from archived data. Finally, each alternative route $i$ incurs a differential preference cost $C_i$, which reflects fuel costs and other differential benefits/drawbacks for airlines in using the route. These costs are also uncertain at the planning horizon, since they depend on weather (e.g., jetstream position) and airlines’ operational needs. Here, a
distributional (statistical) model for the costs is assumed. For convenience (and without loss of
generality), the alternative routes are assumed ordered by preference, in the sense that \( E[C_1] \leq E[C_2] \leq \ldots \leq E[C_n] \).

The problem of interest is to design routing fractions at the waypoint, i.e. to select the percentage \( p_i \) of
the flow density allocated to each route in the airspace (where \( p_i \geq 0 \) and \( \sum_{i=1}^{n} p_i = 1 \)). The routing
fractions should be designed to optimize or reduce an expected cost metric, which reflects both
congestion costs and differential preference costs. The expected preference cost is naturally evaluated as

\[
O_p = E[\sum_{i=1}^{n} p_i C_i \lambda].
\]

Some further effort is needed to model the congestion cost. If traffic were routed according to the
selected routing fractions without any further management, congestion (if any) would be reflected in
capacity excesses in the bottleneck regions. In practice, further management actions would be taken to
avoid capacity excesses, whether via ground holding programs or airborne delays. Wherever the
management action is taken, it can be viewed as queueing aircraft and hence imposing backlog and
delay. If the rate of aircraft directed to the route is larger than the available capacity, the backlog and
hence delay will necessarily accumulate with time. If the rate of routed aircraft is smaller than the
capacity, then some backlog and delay will be incurred in smoothing the traffic flow, however average
values will reach an asymptote rather than accumulating. In a proactive design, it is natural to seek a
solution that avoids accumulating delays, provided that capacities are known with sufficient fidelity.
Here, we will focus on this case, and hence limit the flow rate on each route \( (p_i \lambda) \) to the route’s capacity.
In our previous work \[18\], we have made the argument that an M/D/1 queueing model can be used to
approximate the backlog and delay in this case. From the asymptotic analysis of M/D/1 queues, this
average backlog imposed on traffic to route \( i \) can then be approximated as

\[
B_i = \frac{(p_i \lambda)^2}{2u_i(u_i - p_i \lambda)}
\]

and the average delay can be approximated as

\[
D_i = \frac{(p_i \lambda)}{2u_i(u_i - p_i \lambda)}
\]

The congestion cost for the routing strategy can then be naturally defined as

\[
O_C = \sum_{i=1}^{n} E(B_i) = \sum_{i=1}^{n} E[\frac{(p_i \lambda)^2}{2u_i(u_i - p_i \lambda)}]
\]

Combining the expected congestion and preference costs, we can thus routing design problem as follows:

\[
\begin{align*}
\min_{p_1, \ldots, p_n} & \quad E[\sum_{i=1}^{n} p_i C_i \lambda] + \alpha \sum_{i=1}^{n} E[\frac{(p_i \lambda)^2}{2u_i(u_i - p_i \lambda)}] \\
\text{subject to} & \quad \sum_{i} p_i = 1, \quad p_i \lambda \leq u_i \text{ and } p_i \geq 0.
\end{align*}
\]
where the scalar parameter $\alpha$ weights the contribution of each cost. We are also crucially interested in finding the minimizing routing fractions, denoted $p_{i1}^*, ..., p_{in}^*$.

Even the very simplified routing design problem described above is quite challenging to resolve, because of the need to optimize a cost over an uncertain parameter space: the need for a robust design significantly complicates the analysis. We thus develop approximations for the minimizing solution, $p_{i1}^*, ..., p_{in}^*$, to gain insight into resilient routing policies for non-weather disruptions. Specifically, we develop an approximation from a certainty-equivalence perspective. That is, we find the optimal solution for specified flow rate, costs, and capacities, and then average these solutions over the uncertain parameter space as an approximation for the global optimum.

Let us first consider the optimization in the case that preference costs are of primary interest, and congestion costs are ignored ($\alpha = 0$). We note that the constraint on the flow on each route is still enforced ($p_i \lambda \leq u_i$). In this special case, it is easy to derive the optimal routing design for a given parameter set. Specifically, the optimal design uses the entire available capacities of the lowest preference-cost routes, until the entire flow is accounted for. Formally, the optimum can be computed via the following algorithm. First, the smallest $m$ is found such that $\sum_{i=1}^{m+1} u_i \geq \lambda$. Then, the routing fractions are designed as $p_{i1}^k = \frac{u_i}{\lambda}$ for $i=1, ..., m$, where the notation $p_{i1}^k$ indicates the certainty-equivalent optimum. For $i=m+1$, the routing fraction is chosen as $p_{i1}^k = \frac{\lambda - \sum_{i=1}^{m} u_i}{\lambda}$, and for $i=m+2, ..., n$, the routing fractions are set to zero. The optimal solution can then be approximated as the average of the $p_{i1}^k$ over the uncertain parameter space, which can be computed easily given distributions of the uncertain parameters. Thus, in the case where preference costs are of primary interest, optimal routing around a non-weather disruption requires selecting a small set of low-preference-cost alternatives that are just adequate to handle the excess traffic.

In the other extreme where congestion costs are the primary concern ($\alpha$ large), the certainty-equivalent optimal routing design has been derived in our previous work [18], using Lagrange multiplier techniques. Specifically, the optimal design is found to equalize the sensitivities of the per-route backlog with respect to the design parameters (routing fractions). This equality resolves to a quadratic equation which can be solved for the optimal routing fractions. The optimal design is highly distributed, with the flow being split among all available routes in a roughly proportional manner. The global optimum can then be approximated via averaging of the certainty-equivalent design over the uncertain parameter space.

In the general case, a Lagrange multiplier argument can also be brought to bear to find the certainty-equivalent design. Applying this argument, one finds that the optimal design is intermediate to the two extreme cases. In particular, the optimal solution assigns non-zero routing fractions to at least $m+1$ routes, but in general does not distribute the aircraft on all available routes. Additionally, the routing fractions for the lower-cost routes are enhanced compared to the congestion-cost-only optimal, and the sensitivities of the corresponding congestion cost to the routing fractions and also the capacity parameters are significantly enhanced. The solution can be shown to increasingly resemble the two extreme cases, as the weighting parameter $\alpha$ is made small and large, respectively. Thus, we see that rerouting solutions for non-weather disruptions can be tuned to use a small set of low preference-cost alternatives, but with the consequence of higher congestion cost and differential sensitivity. Details are excluded to time constraints, but will be included in a future version of this work.

In sum, this article has shown – via simulations and formal analysis – that rerouting strategies can be brought to bear to address non-weather disruptions. Further, proactive designs can be tuned to trade
off stakeholders’ preference costs with congestion/sensitivity concerns. We believe that these designs are a promising starting point for a playbook of strategies for diverse non-weather disruptions to the National Airspace System. However, significant further work is needed to 1) develop theoretical results on the design for a full suite of TMI, 2) understand the robustness of solutions to parametric variations, and 3) refine strategies on the day-of-operations based on forecast data.

Works Cited


