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Designing Traffic Flow Management Strategies Under Uncertainty

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***Abstract*—This paper proposes a framework for designing and adapting strategic traffic management under uncertainty. A primary function of strategic traffic management is the development of traffic management initiatives to mitigate potential large-scale congestion. However, the associated longer planning horizon - 2-24 hours in advance of anticipated problems - means that congestion forecasts are highly uncertain. Furthermore, complex interactions exist between management initiatives and traffic propagation, producing a non-intuitive planning environment. The proposed adaptive planning framework captures these features, enabling quantitative design of traffic management initiatives that balance uncertainty with performance. Specifically, a decision tree is constructed to represent critical deviations in the forecast over the planning horizon. Corresponding decision points provide opportunities for management initiatives to be defined, and a genetic algorithm is employed to optimize the expected performance of the initiatives over the entire decision tree. Thus, this method identifies optimal strategies under forecast uncertainty, capturing the tradeoff between employing initiatives that may not be required and lost opportunities due to inaction. Performance of the adaptive design framework is compared with alternate design approaches, verifying the potential value of this new approach for real time decision making.**

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

A. Introduction

Strategic Traffic Flow Management (TFM) involves planning and executing a set of Traffic Management Initiatives (TMIs) to mitigate future (2-24 hours in advance) congestion. A TFM strategy may involve multiple TMIs, such as Ground Delay Programs (GDPs), Airspace Flow Programs (AFPs), single-point rate restrictions (e.g., Miles-in-Trail (MIT)), and reroutes, each requiring specific parameters to be set. Strategic TFM is challenging due to interconnectivity of the National Airspace System (NAS) and complex interaction effects of TMIs on traffic/congestion. Furthermore, some TMIs must be implemented hours before an event, as they require flights to be delayed prior to departure. At the same time, the forecasts identifying the constraints the TMIs address (e.g., airport arrival rate and airspace sector capacities) are uncertain, adding significant complexity to the strategic planning process.

The next generation of the United States (U.S.) Traffic Flow Management System (TFMS), intended for deployment by 2020, is expected to provide improved decision support capabilities, enabling improved TMI traffic impact estimates [1]. However, these tools will not help *design* effective plans under the uncertainties present in the strategic timeframe. The work described here aims to provide decision support that explicitly accounts for weather and demand prediction uncertainties, and can suggest and adaptively select among a variety of effective solutions (TMIs to use and their parameters) across a range of possible weather outcomes.

Analytical research on strategic TFM has been undertaken using both model-driven and data-based approaches. Initial research investigated the design of a single rate restriction [2], or in combination with a GDP [3]. Flow-based models such as [4], [5], and [6] have proved useful for strategizing TFM, because they allow computationally efficient simulations that can be used to analyze and optimize routing strategies in combination with GDPs. Linear dynamic system models, which can also capture the impact of uncertain demand propagation [7] and demand initialization [8], were developed to leverage control theory algorithms for restriction design. Alternatively, a probabilistic scenario tree approach was used in [9] to capture how individual flight reroutes and delays can be assigned under uncertain weather.

Cook [10] describes the development of a decision support system that integrates the stochastic weather and traffic forecasts to provide decision makers a GDP evaluation capability. This work represents a critical step forward as the prototype decision support capability was evaluated at San Francisco International Airport (SFO) [11]. However, for NAS-wide strategic TFM, new models and design approaches are needed.

Motivated by this need, several recent research directions (e.g. [12]), including our effort on Flow Contingency Management (FCM) [13], have sought to develop weather-impact forecasting and NAS-wide TMI evaluation software tools. However, efforts thus far have been focused on TMI plan evaluation or, at best, tuning of parameters.

Very recently, a few research efforts have formulated the traffic-management problem explicitly as a sequential decision-making problem, which acknowledges the possibility for adapting TMI plans with new information, and considered dynamic-programming-based solution approaches. Notably, Clare et al. [14] leveraged Model Predictive Control with Disturbance Feedback 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. While these studies are interesting from a theoretical perspective, the methods are distanced from current operational practice and have not yet gained traction for implementation.

As such, a formal approach for sequential decision making is needed that captures the quandary often faced by operators, namely, what TMIs must be implemented now in order to mitigate severe future congestion, given that these predictions are highly uncertain. Aggressive and immediate action may be required, but if the forecast (often, of severe convective weather) isn't realized, the actions taken will result in unnecessary traffic delays. However, if these actions aren't taken and the weather evolves as forecasted, large delays and undesirable traffic impacts will result. Balancing these choices, especially when high-impact forecasts have low likelihoods of occurrence, only complicates this process further.

To capture the traffic impact resulting from different forecasts realizations, the proposed model is represented by a decision tree. Each branch in the decision tree represents one or a cluster of forecast members, where clustering captures critical deviations between the forecasted outcomes. Decision points are co-located decision to provide opportunities to tailor the TMI strategy appropriately. The result captures the need for a single action at the given decision point and the different strategies that may be needed in the future. The TMI strategies associated with later decision points provides insight for stakeholders as to upcoming actions, and allows optimization to capture the impact of future outcomes on the current decision. As such, it represents a potentially powerful new approach for strategic TFM decision making.

To evaluate the performance of the proposed approach, this paper compares the results generated using three different optimization strategies. The first strategy provides an optimized TMI plan for each forecast member/cluster without regard to other forecast members/clusters. The results obtained through this approach provide a baseline of performance. However, the TMI plans developed for the different forecast members/clusters may be drastically different, resulting in the need for human decision makers to manually integrate the different results to identify a single action at the current decision point. As such, the optimized TMI strategy would be most useful when planning for a deterministic forecast, or when only a plan for a single forecast cluster (e.g., plan for the most likely) is required.

The second strategy provides a single TMI plan that is robust to all forecast members/clusters, removing the need to manually integrate multiple plans. The robust optimization takes into account all forecast member/cluster probabilities when developing the plan. A main drawback of this strategy is that the TMI plan is dominated by high probability scenarios and therefore would be most effective if the forecast variance is small and remains small over the time horizon of interest.

The adaptive strategy provides a bridge between these first two strategies, addressing the shortfalls noted for each. Specifically, by developing a single TMI plan at the initial decision point, manual integration of multiple TMI plans is not required. In addition, by capturing forecast divergence over the planning horizon, the optimized TMI plans can better address problems specific to potential future scenarios. As such, this strategy would work best when forecasts diverge along the planning horizon, creating an environment that captures the evolving nature of the forecast and enabling an improved strategic planning process.

This paper is organized as follows. Section II describes the adaptive planning framework, and Section III presents the evaluation and optimization approach used in this paper. Section IV illustrates the results on a sample problem, analyzing how adaptive development of the solution compares to more traditional approaches. Section V summarizes the findings and discusses the continuing research in this area.

II. Adaptive Planning Framework

The goal of the adaptive planning framework is to identify the current TMI strategy that best satisfies the range of goals while accounting for potential future actions that may be needed. The framework is premised on the idea that forecast uncertainty evolves over the planning horizon. Distinguished from a single solution that is robust to uncertainty, it leverages the agility available at future decision points while balancing opportunity loss due to inaction.

A. Constructing the Decision Tree

In the strategic TFM process, decisions are made at discrete points along the planning horizon. To capture this structure, the time horizon T is discretized into τ decision periods, labeled $t = 1, 2, \ldots, \tau$. To construct the decision tree, a forecast ensemble that spans the decision horizon is required. We assume a forecast ensemble with a finite number of equally probable members with identical initial states. Each member is assumed to track the forecasted quantity over the planning horizon, at the same resolution as the decision periods. We note that although an ensemble forecast often refers to a weather product, we generalize the terminology here to capture any forecast of information (e.g. traffic demand) relevant to the strategic TFM planning process.

The forecast ensemble is evaluated over each decision period to capture the timing of critical divergences between possible outcomes. During the first decision period, all forecasts are assumed to be convergent, providing a single decision point at the beginning of planning horizon. As such, the first decision period ($t = 1$) is represented by a single decision node, defined as the root of the tree.

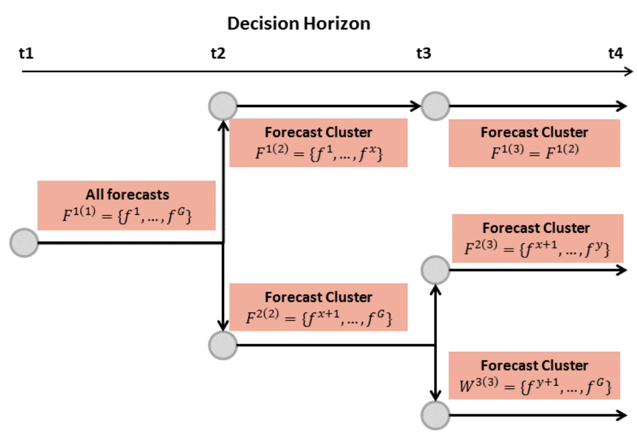

Figure 1. Illustration of Forecast Tree

In future decision periods, the forecasts may divide into sub-groups, or clusters, representing evolutionary differences over the decision horizon. For each cluster, a decision node is defined at the beginning of the decision period and the (directed) arcs connecting the nodes capture the subdivision. At the last decision period, each node represents a leaf in the tree. A branch is defined as the (directed) path between the root and a leaf. Figure 1 provides an illustration of the decision tree.

Forecast ensemble members are denoted as f^i, where $i = 1, 2, .. G$, and G is the number of ensemble members in the forecast. We define the set $F^{k(t)}$ to be the k^{th} forecast cluster in decision period t, i.e. the set containing the ensemble members in the cluster, where we use the labels $k(t) = 1(t), 2(t), \dots, K(t)$. The cluster labels $k(t)$ also indicate decision nodes, and arcs in the decision trees are specified by pairs of decision nodes or cluster labels. The sets $F^{k(t)}$ have the following properties:

- $F^{k(t)} \subseteq F^{1(1)} = \{f^1, \dots, f^G\}$, which states that in the first decision period all forecasts are contained in the same cluster (cluster 1) and at future decision points, the forecast cluster contains all or a subset of the forecasts.
- $F^{1(t)}, F^{2(t)}, \dots, F^{K(t)}\ are\ a\ partition\ of \{f^1, \dots, f^G\}$, i.e. all ensemble members are contained in one and only one cluster in a given decision point.
- $F^{k(t+1)} \subseteq F^{k(t)}\ iff\ (k(t), (k(t+1)) \in A$, where A is the set of all arcs in the decision tree. This final property ensures that a subsequent clustering can only contain forecasts that are present in the previous upstream cluster.

As each forecast member is assumed to be equally likely to occur, the probability of a forecast cluster ($p^{k(t)}$) is defined by the fraction of forecasts contained:

$$p^{k(t)} = \frac{|F^{k(t)}|}{|F^{1(1)}|},$$

where the notation $|F|$ indicates the cardinality of the set. We note that the assumption of all ensemble members being equal can be readily relaxed. The only requirement is that the sum of probabilities across each branch in the network add to one.

B. Representing TMI Decisions

TMIs are defined by specific parameters that dictate the implementation of flow restriction for congestion amelioration. Here, we focus on two types of TMIs: GDPs and AFPs. A GDP reduces the flow into a designated airport by delaying flights prior to departure. A GDP is defined by the designated airport, the start time of the action (at the local time of the designated airport), the duration or end time of the GDP, the desired number of arrival aircraft per hour (rate), and the set of departure airports whose flights will be affected by the TMI (scope or tier).

Similarly, an AFP reduces the flow into a region of airspace by delaying flights prior to departure. To define an AFP, a Flow Constrained Area (FCA) is constructed, which denotes a line or region of airspace and identifies intersecting flights or flows. An AFP is defined by this FCA, the start time of the constraint (again, at the local time), the duration or end time of the constraint and the desired number of (directional) crossing aircraft per hour (rate). Delays for flights or flows intersecting the AFP are assigned at their respective departure airports.

For each decision node in the tree, TMIs are selected to address the corresponding forecast cluster during that decision period. We denote the management plan corresponding to forecast cluster k at time t by $M^{k(t)}$. For each management plan, multiple TMIs (airport-specific GDP, FCA-specific AFP, etc.) may be defined and the implementation parameters for each must be specified. The implementation parameters are defined as follows. Each TMI may be included or not in the TMI plan. If it is included, the start time, duration, rate, and scope (if applicable), must also be specified. However, given that the TMI plan is only defined for the current decision period, these values are constrained.

The start time refers to the time the decision is enacted, which is limited to the current decision period. However, to better represent the lead time associated with some TMIs, the actual implementation time of the TMI can be delayed or offset. The offset on the start time would be specific to the TMI. For example, the lead time for a GDP is dependent on the scope of the GDP (i.e. the distance between the GDP airport and the departure airports impacted).

The duration of the TMI for each decision period is constrained by the beginning of the next decision period, and therefore intermediate tree nodes cannot have durations longer than the decision period. However, the duration can be extended as desired for the leaf nodes. Finally, the rate and tier (where applicable) provide the remaining TMI plan definition during the corresponding decision period.

C. Evaluating TMI Decisions under Uncertainty

To evaluate the performance of the TMI plans defined at each decision node, TMI strategies must first be constructed as the traffic impact is propagative (i.e. constraints at one time period modify conditions at subsequent time periods and therefore cannot be evaluated independently). For each branch in the tree, a TMI strategy is defined as the assembly of the TMI management plans associated with the nodes along each branch. The TMI strategy along the branch from the initial decision node to the leaf node $k(t)$ is denoted by $S^{k(\tau)}$.

This construction ensures that each forecast cluster (or directed tree arc) has the same TMIs included in the strategy for that time period. Furthermore, this structure easily captures the cost of switching or delaying actions. Switching costs occur when a TMI is included in a plan $M^{k(t)}$ but not in $M^{k(t+1)}$ (for$(k(t), (k(t+1)) \in A$). When offset implementation times are defined, these costs may be particularly significant. However, the cost of delaying a decision will result in the propagated congestion that occurs from not acting sooner, potentially requiring more restrictive TMIs to be implemented later. As such, the framework captures the critical tradeoffs associated with decision making in an uncertain environment.

The impact of the TMI strategy is quantified by a specified performance metric(s) or cost function. The cost function represents the cost incurred by the selected strategy for a particular ensemble member, i.e. assuming a particular deterministic forecast future. The cost profile of a TMI strategy is computed for each forecast associated with a branch of the decision tree, and defined as

$$C^i(t) = C(S^{k(\tau)}, f^i), \text{ for } t = 1, .., \tau$$

We notice that the cost profile specifies the cost at each decision period (which we call the cost function), for the given strategy and ensemble member.

Next, we define the objective profile for a branch of the scenario tree ($O^{k(t)}$) as the expected value of the cost profile over the forecast cluster.

$$O^{k(t)} = E\left[C\left(F^{k(t)}\right)\right] = \frac{\sum_{i \text{ s.t. } f^i \in F^{k(t)}} C^i(t)}{|F^{k(t)}|}, \text{ for } t = 1, .., \tau$$

The equation above averages the cost function for each forecast contained in set $F^{k(t)}$ for the decision period beginning at time t. The objective function for the entire tree is then defined as

$$O = \sum_t \alpha^t \sum_k p^{k(t)}\, O^{k(t)}$$

where α^t is an optional exponential fading factor that can be used to prioritize the expected value of certain time periods over others (for example, it may be desirable to reduce the contribution of the expected value at later decision periods). The probability $p^{k(t)}$ of each forecast cluster is used to weight the relative importance of each cluster in the overall objective.

III. Evaluation and Optimization

The design goal pursued here is to optimize the TMI parameters at each decision node to minimize the objective function ($O^{k(t)}$), i.e. the expected cost of the strategies across the ensemble. This optimization requires 1) a method for clustering the forecast ensemble, 2) a tool for evaluating the cost for a given strategy and ensemble member, and 3) a means for strategy optimization. In this paper, the cost evaluation of a TMI strategy is achieved using a simulation of a flow-based queueing model of NAS-wide air traffic. Because the simulation-in-the-loop results in a non-analytical problem formulation, non-traditional approaches must be leveraged to optimize TMI values in the adaptive planning framework.

A. Designing the Decision Tree

Section II.A presented an approach for designing the decision tree for a general ensemble forecast. In this paper, we leverage an ensemble forecast for convective weather. Specifically, we use the Short Range Ensemble Forecast (SREF) to develop the adaptive planning decision tree. The SREF produces 21 deterministic weather trajectories that are each equally likely to occur and span the space of potential weather development [15]. Each ensemble member captures the spatial and temporal propagation of convective weather (defined by precipitation levels over a gridded area). We note that other SREF variables can be used to create forecasts of airport impact [16]; however these are included in the current analysis.

Leveraging the prediction of precipitation levels for each ensemble member, an estimate of capacity reduction can be obtained [17]. For each forecast of capacity reduction, a forecast of weather-impact can be derived by propagating demand through the NAS as permitted by constrained sector capacities. Using each of the 21 SREF ensemble members, 21 weather-impact scenarios can be defined.

In our previous work [18], weather-impact has been shown to be a superior metric for clustering ensemble members, by identifying clusters with similar responses to TMI strategies. To measure weather-impact similarity, a number of performance measures are evaluated. The first two metrics represent the spatial and temporal concentration of en route delays. The concentration metrics capture how the distribution of delays (centralized verses distributed) result in different TFM impacts. Delays for critical airports provide the remaining metrics of similarity, where differences between arrival and departure delays between the ensemble members signify potentially divergent strategies and therefore different groupings. A spectral clustering approach is employed [19] to obtain clusters of weather-impact scenarios.

The resulting clusters contain multiple weather-impact scenarios; however a single, representative scenario can be defined. For each cluster, the representative scenario is selected based on its similarity to scenarios in the cluster and its difference to scenarios in other clusters. Details regarding this approach can be found in [18, 20].

In this paper, we leverage this approach for comparing weather-impact ensemble members; however we evaluate similarity metrics separately for each decision period, as opposed to the entire time horizon. This distinction captures the evolution of weather-impact scenario clusters, defining the decision tree.

B. Evaluating TMI Strategies in FCM

In this paper, we utilize the queueing-network engine of the FCM capability to evaluate the cost of a TMI strategy [13]. Briefly, FCM is a framework for evaluating congestion and traffic across the NAS for selected traffic management strategies across weather futures. In FCM, a NAS-wide, fast-time simulation is used to identify the impact of restricted capacity and management initiatives on traffic flows. FCM employs a flow-based, multi-layered, network queuing model [21] to capture traffic flow and its restriction due to potentially-reduced capacities in en route sectors and airport resources. The model captures several types of TMIs and can evaluate the performance of different management strategies on the traffic. Figure 2

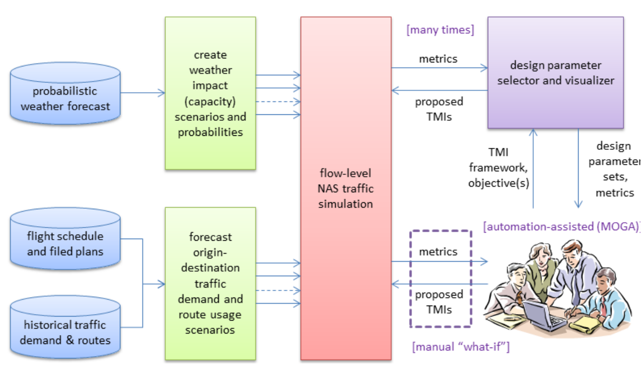

Figure 2. FCM Framework

depicts the simulation framework. Further details regarding specific components can be found in [22].

The FCM queueing model returns the 'backlog' or 'delay' associated at each resource in the network at each time period (15 minutes in FCM). Delays can be aggregated in time and/or by resource (airspace sector, airport, flow), capturing the differences in TFM impact under changing weather forecasts and TMI strategies. We note that the computed backlog delays do not necessarily represent delays in the operational environment, as tactical TFM and Air Traffic Control (ATC) actions would be undertaken to restrict aircraft from 'queuing' at the boundary of a sector. However, the delays do represent the severity of the problem that requires intervention.

The cost function used to evaluate a TMI strategy in FCM can be chosen to capture a variety of attributes. An in-depth discussion of potential metrics is needed, but beyond the scope of this paper. In this work, a cost function is selected that measures the tradeoff between en route (ED) and ground delay(GD). Using FCM, the simulation returns these values for each resource (en route airspace and terminal departure delay), and the metrics are aggregated for each resource over the decision period using the following equation.

$$C^i(t) = GD(S^{k(\tau)}, f^i) + 2 * ED(S^{k(\tau)}, f^i)$$

C. TMI Strategy Optimization

The adaptive planning framework proposed in this paper is a sequential decision-making problem [23, 24]. Sequential decision-making problems arise in many contexts, ranging from generation-unit scheduling for electric power networks, to industrial-process optimization and bandwidth scheduling in communication networks [25, 26, 27]. Sequential decision-making problems have also recently been of interest in the air traffic management space [9, 28, 29, 30]. In these contexts, designs that optimize or improve a performance measure are often sought. Many formulations are concerned with minimizing a performance cost over a receding look-ahead horizon for a Markov plant model; these problems are referred to as model predictive control or receding-horizon control problems [31]. Optimal design of sequential decisions may be challenging because the design space is high dimensional, the managed processes are uncertain, information availability for decision-making is complicated, and/or designs must account for future design freedom.

Sequential decision-making problems including model-predictive control problems are often addressed using *dynamic-programming* techniques, which decompose high-dimensional optimization problems into a number of simpler sub-problems using Bellman's principle of optimality [24, 32]. The dynamic-programming approaches resolve to simple optimal-design algorithms in a few very special cases, for instance model predictive control problems with linear process models, quadratic costs, and additive Gaussian uncertainties. More typically, the dynamical programming approaches require numerical search over a space that grows exponentially in a look-ahead horizon. In these cases, a number of approximation techniques, such as certainty-equivalent design, can be brought to bear.

The problem formulation and approach presented in this paper entails several new challenges which necessitate new solution methods:

- Uncertainties are high-dimensional, correlated in space and time, transient in nature, and highly non-Gaussian.
- The design space is complex: some TMIs may be subject to implementation delays; design variables may include discrete-valued and continuous quantities; and design variables may have compatibility constraints.
- The queueing-network model for traffic does not admit an analytical description, and instead must be evaluated via simulation for each given TMI plan. The model is also highly nonlinear.
- Multiple objective functions may need to be considered in designing effective adaptive plans.

Because of these characteristics, there is no established algorithm for solving the posed optimization problem, and optimization necessarily entails a significant computational challenge. In this paper, we employ a genetic algorithm (GA) to identify the optimal TMI parameters at each decision point in the tree, where the objective function measures the expected performance of the resulting TMI strategies across all scenarios.

A GA is a heuristic optimization approach that mimics biological evolution [33]. Heuristic optimization approaches are often employed when optimizing a simulation-based model, as more traditional methods may not be applicable given 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. Although GAs have been shown to efficiently and effectively evaluate the search space for a number of problems, including TMI parameter design using the FCM simulation [20], there is no guarantee of finding an optimal solution.

A GA operates by defining a 'chromosome', where each 'gene' in a chromosome specifies a value for each design parameter from a range of values provided. A population consists of the number of individuals, each with a unique chromosome, 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. This "breeding" process continues until the specified set of generations has been evaluated or alternate termination criteria are satisfied. Further details regarding the specific GA implementation used in this analysis can be found in [34].

For the adaptive planning framework, the TMI parameters associated with each management plan ($M^{k(t)}$) are represented as a portion of the chromosome on the genome. Figure 3 illustrates a chromosome section for a TMI plan that consists of a single GDP and AFP. As shown, each TMI can be represented as 'on' or 'off'. If the TMI is off, the remaining TMI parameters are set to default values to eliminate redundant computation. If the TMI is on, the parameter values associated with each gene define the TMI plan. As there is a TMI plan for each weather cluster k at each time t, the final chromosome is the concatenation of each $M^{k(t)}$ chromosome.

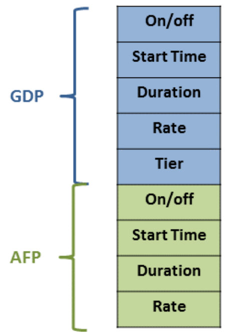

Figure 3. Example GA Chromosome Section

GAs optimize the chromosome by evaluating a fitness function. Each TMI strategy evaluation in FCM provides input into the fitness function; however the GA is optimizing the adaptive framework objective (O) which captures the expected performance of the TMI strategies represented as the values in the genome. We further note that by employing a GA, different objective functions, such as minimizing expected variance, or minimizing maximum cost could be readily evaluated. As such, the GA provides a valuable tool for analyzing and optimizing complex problems of this nature.

IV. RESULTS

To illustrate decision-making using the developed adaptive planning framework, we consider a historic day with significant weather impact and uncertainty. A decision tree is constructed by clustering weather-impact scenarios. TMI plans are identified at each decision point and the resultant TMI strategies are optimized for the entire tree. The strategies generated by the adaptive planning design approach are compared to two other approaches. The first approach is the independent optimization of a management strategy for each weather-impact branch presuming a perfect forecast, providing a baseline of optimal performance. The second approach provides a single, non-adaptive management plan (rather than a strategy tree) that is robust to all scenarios, thereby capturing the relative contributions (probabilities) of each branch in the objective function.

A. Example Problem

The example problem considered is based on the 0900Z SREF forecast from 28 July, 2014. The forecast ensemble predicts that severe convective weather is likely to traverse the northern portion of New York (N.Y.) state, avoiding the major N.Y. area airports, namely, Newark Liberty International Airport (EWR), John F. Kennedy International Airport (JFK), and LaGuardia Airport (LGA). However, a few of the ensemble members show this weather system tracking further south, creating the potential for moderate or severe traffic impact. The traffic is based on the first filed flight plan from this same day and is assumed to be deterministic in this simulation.

The planning horizon is defined to begin at 12Z and consists of three planning periods. Leveraging the weather-impact clustering approach described in Section III.A, the SREF ensemble members (pink boxes) are clustered into a decision tree as shown in Figure 4. Figure 4 also highlights the management decisions (blue boxes) associated with each decision point.

Each branch in the tree is referred to by the representative SREF ensemble member identified for each leaf (SREF 11, SREF 19, and SREF 21) and the probability of each member is provided. Although there are only three periods with decision points (12Z, 14Z, and 16Z), the tree and simulation extends until 22Z, permitting traffic impacts resulting from these decisions to be measured.

Figure 5 depicts a snapshot of the three SREF forecasts at 12Z. Viewing Figure 5, we see that SREF 11 predicts weather directly over the New York area airports. However, only 2 of 21 ensemble members show this impact, resulting in a probability of occurrence of only ~9.5%. SREF 19 represents

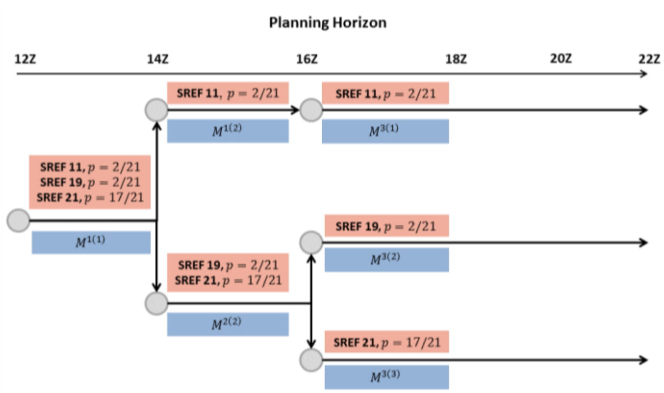

Figure 4. Decision Tree for 28 July, 2014

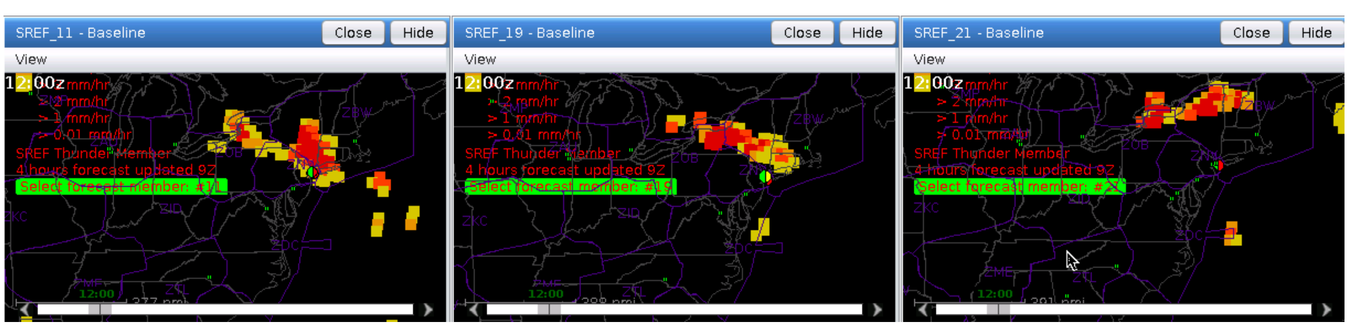

Figure 5. Snapshot of weather forecast at 12Z (red indicates heavier precipitation)

weather forecasts propagating just north of the New York area airports, resulting in a more moderate impact prediction than SREF 11. Again, the likelihood of this scenario is low (~9.5%). The most likely outcome (81%) is represented by SREF 21 which predicts the weather to traverse the northern New York State area. Although the lowest impact scenario is most likely, the severity of the high-impact scenarios warrants further consideration.

In order to design the optimal strategy using the GA as described above, the set of TMIs and their allowable parameters must first be defined. For this example, GDPs for the N.Y. area airports (EWR, JFK, and LGA), and Logan Airport (BOS) in Boston, Massachusetts are included in the strategy. Additionally, an AFP for FCAA08, which constrains north-bound flow along the eastern United States, is included. Figure 6 depicts the location of these TMIs, and Table 1 lists implementation parameters considered in the optimization. Again, we note that each TMI can be included or excluded from the TMI strategy.

Table 1. TMI Parameter Ranges

Airport/ Resource	Start Time (UTC)	Duration (Hr)	Hourly Rate
BOS	{12:00, 14:00, 16:00}	{2, 4, 6, 8}	{40, 55}
EWR	{12:00, 14:00, 16:00}	{2, 4, 6, 8}	{25, 40}
JFK	{12:00, 14:00, 16:00}	{2, 4, 6, 8}	{35, 50}
LGA	{12:00, 14:00, 16:00}	{2, 4, 6, 8}	{20, 30}
FCAA08	{12:00, 14:00, 16:00}	{2, 4, 6, 8}	{70, 90}

B. *Independent TMI Strategy Design*

To provide a performance baseline, the optimal TMI strategies for each of the three representative SREF scenarios are computed. The TMIs are defined based on the available parameters listed in Table 1. The objective function used for this design approach is the cost function $C^i(t)$ and not the objective function that considers expected performance, as it is a deterministic problem in this form. Table 2 presents the optimized strategy for the three SREF scenarios.

Table 2 indicates large differences in the optimal TMI strategies for the three SREF scenarios. In particular, scenario SREF 11 requires longer-duration and stronger TMIs than the

Figure 6. Geographic Location of TMIs

Table 2. Independent TMI Strategy Optimization

WI Scenario	TMIs	Decision Periods 12	14	16	18	20
SREF 11	BOS	55	55	55	55	
	EWR	40				
	JFK	35	35			
	LGA			30	30	30
	FCA	70				
SREF 19	BOS			55	55	
	EWR			25	25	
	JFK		50			
	LGA					
	FCA			70		
SREF 21	BOS					
	EWR	25	25	25		
	JFK					
	LGA					
	FCA					

other two scenarios. The optimized SREF 11 strategy (S11 O) has all TMIs except the GDP at LGA starting at 12Z, with the LGA GDP starting a couple of hours later. However, only the GDP at BOS is implemented for an extended duration, with the GDP at EWR and the AFP at FCAA08 implemented for 2 hours and the other initiatives for intermediate durations. These results indicate that the TMI strategy for S11 O aims to mitigate the en route congestion through immediate action, but balances ground delay costs by incrementally reducing the impact from the other TMIs.

Alternatively, the optimal TMI strategy for SREF 19 (S19 O) includes no TMIs at 12Z. Instead, TMIs are implemented later and for shorter periods of time. Finally, the optimal TMI strategy for SREF 21 contains a single GDP at EWR lasting 6 hours.

C. *Robust TMI Strategy Design*

As shown in Table 2, the independently optimizing the TMI strategy for each outcome is unlikely to identify a unified TMI strategy, even when simply viewing the current decision point (12Z). As strategic TFM decision making considers the impact of future outcomes, this design approach is unlikely to provide meaningful input into the decision making process. One alternative is to develop a single TMI plan or strategy that is robust to the forecast uncertainties, as discussed in [35].

The robust design approach develops a single TMI strategy that minimizes the expected cost across all scenarios. As such, it captures the performance range and the likelihood of each scenario. For this design approach, the objective function is the same as for the adaptive framework (capturing the expected performance), but all scenarios are clustered together for the entire planning horizon (i.e., a single plan is designed).

Table 3. Robust TMI Strategy Optimization

WI Scenario	TMIs	Decision Periods 12	14	16	18	20
All	BOS			40		
	EWR	25	25	25		
	JFK					
	LGA					
	FCA					

The TMI strategy designed using the robust approach, shown in Table 3, balances the relative cost functions for the three SREF scenarios, based on their likelihood of occurrence. This solution most closely resembles the optimized solution for SREF 21 (S21 O). In fact, the only deviation is the two hour GDP at BOS implemented at 16Z. The robust strategy is thus tailored to the most likely scenario, with only minor changes to slightly reduce the cost if the other scenarios are realized.

D. Adaptive TMI Strategy Design

The adaptive TMI strategy designs management plans for each decision node in the tree. Specifically, at each management design point (blue box in Figure 4) a TMI plan is defined. Given the TMI parameter constraints defined in Section II.B, the TMI parameter space is constructed differently than in Table 1, although the new parameter ranges are chosen to allow a similar range of resulting TMI strategies.

Specifically, at each decision node shown in Figure 4, the TMI plan can include each of the four GDPs and the AFP. If the TMI is included, the start time coincides with the beginning of the decision period. For all nodes with the exception of the leaf node, the duration corresponds to the length of the decision period. For the leaf nodes, the TMIs can have durations of 2, 4 or 6 hours, allowing these final decisions to implement TMIs for the duration of the simulation.

Table 4. Adaptive TMI Strategy Optimization

WI Scenario	TMIs	Decision Periods 12	14	16	18	20
SREF 11	BOS	40	40	40	40	
	EWR		25	25	25	25
	JFK			50	50	50
	LGA		30	30	30	
	FCA					
SREF 19	BOS	40		55	55	55
	EWR			40	40	
	JFK			35	35	
	LGA			20	20	20
	FCA			90	90	
SREF 21	BOS	40				
	EWR			40		
	JFK			35	35	
	LGA					
	FCA			90		

Table 4 shows the TMI strategy designed for each SREF scenario using the adaptive planning framework approach. Viewing Table 4, we see that the GDP at BOS is implemented at 12Z and note that this critical decision is made to mitigate the severe impact of SREF 11. The remaining TMIs defined for S11 O are delayed in the adaptive solution (S11 A) until 14Z, at which time SREF 11 forms a separate branch in the decision tree. However, we note that the TMIs parameters in the S11 A strategy are more restrictive than in the S11 O strategy, implying more restrictive TMIs are necessary at 14Z to compensate for the reduced restrictions at 12Z.

The adaptive strategies for SREF 19 (S19 A) and SREF 21 (S21 A) include the GDP for BOS at 12Z, as required by the adaptive framework, but do not include this (or any) TMIs at 14Z. Instead, the TMI strategies for these two scenarios delay further action until 16Z, when the TMI plans can be defined independently. This implies that the TMI plans at this decision point ($M^{2(2)}$) are dominated by the low impact and high probability of the SREF 21 scenario.

Viewing the entire TMI strategy for SREF 19 highlights a critical feature of the adaptive planning framework. Specifically, the GDP at BOS is implemented at 12Z, removed at 14Z, and re-implemented at 16Z, incurring a switching cost that negatively impacts performance. However, these costs are offset by the negative impact of continuing the GDP at BOS for SREF 21. Given the relative probabilities, the solution captures the preference to remove the BOS GDP, even if it must be re-implemented at 16Z to mitigate SREF 19.

E. TMI Strategy Cost Comparison

In this section, we examine the performance of the TMI strategies designed using each approach considered: Optimal (O), Robust (R), and Adaptive (A). Figure 7 provides the cost function ($C^i(t)$) corresponding to each TMI strategy designed for the three SREF scenarios.

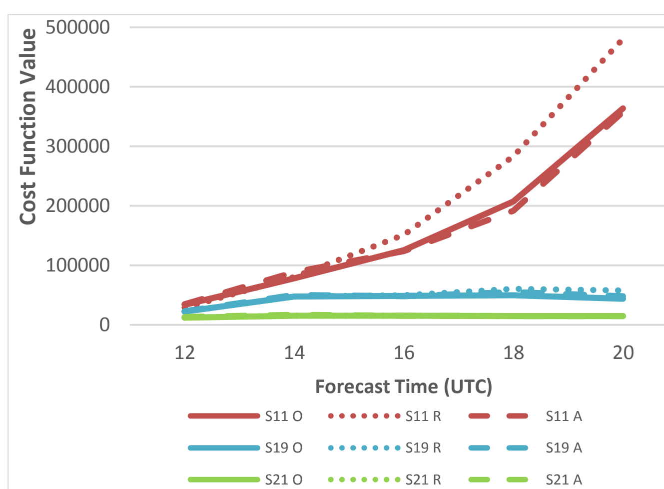

Figure 7. Cost Function ($C^i(t)$) vs. Time

Viewing Figure 7, we see that the TMI strategies for SREF 11 have the largest performance variance across design approach. Specifically, the TMI strategy designed using the robust approach (Table 3) results in the highest cost for this scenario as insufficient congestion mitigation is provided. However, the adaptive (A) TMI strategy has a similar cost profile to the optimal (O) strategy – which, recall, presumed a perfect forecast. Comparing the optimal (Table 2) and adaptive (Table 4) strategies for SREF 11, we note that the set of TMIs chosen is similar, but the adaptive strategy employs lower rates to compensate for delayed TMI implementation.

SREF 19 shows similar performance for both the optimal and adaptive strategies and a small degradation in performance for the robust strategy. Comparing the performance of the optimal (Table 2) and adaptive design approaches (Table 4) reveals that the adaptive strategy requires additional and extended TMIs to provide similar costs.

The performance of the TMI design approaches for SREF 21 result in cost variations that are indistinguishable in Figure 7. However, if we compare the TMI strategies developed by each of these design approaches, we note that the adaptive TMI strategy (Table 4) differs significantly from the other strategies (Tables 2 and 3). Specifically, by implementing the BOS GDP at 12Z, the sustained EWR GDP is unnecessary. Instead, a number of short and high rate restrictions are implemented in 16Z. This results shows that significantly different TMI strategies can obtain almost identical performance; the cumulative cost difference between the adaptive and optimized designs in this case is only 4.3%. This is a crucial aspect of the design problem that enables the adaptive planning framework to be leveraged in real world operational decision making.

The cost analysis shown in Figure 7 uses the cost function that quantifies the performance of the TMI strategy for a specific scenario. However, the GA for both the robust and adaptive design approaches evaluates the objective function (O), which measures the expected performance across the scenarios, capturing the relative likelihoods. Table 5 compares the cumulative cost incurred by each design approach for each SREF scenario and the overall GA objective function.

Table 5 again confirms that the adaptive solution outperforms the robust solution for SREF 11 and SREF 19 at the expense of the performance for SREF 21. However, even with the large probability associated with SREF 21, the expected value of the cumulative cost is reduced when the adaptive framework design approach is used. As such, in this example, effective mitigation of the high-impact scenario improves the expected performance over the range of forecast outcomes.

Table 5. Comparison of Expected Cost

	Probability	Robust	Adaptive
SREF_11	9.5%	57757	45274
SREF_19	9.5%	13876	13201
SREF_21	81%	4305	4450
Expected Cost		10307	9172

V. Conclusions

This paper describes a new adaptive design approach that captures the complex decision making environment associated with strategic TFM. The approach identifies discrete decision making opportunities in the planning environment and associates these points with critical deviations in the forecast futures. It then optimizes TFM decisions over forecast uncertainty, while capturing the flexibility available for future decision refinement. The decision structure in this approach is analogous to the human-driven, collaborative strategic TFM done in the US today, but suggests solutions based on quantitative forecasting and analysis. Thus it may provide a foundation for a future automated decision support capability that would improve the speed, performance, and consistency of strategic TFM.

However, much work remains to make this vision a reality. For TMI strategy designs to be relevant to decision makers, operationally-relevant objective functions that capture the complex trade-offs faced in the strategic TFM decision making process are needed. Similarly, it will be important to identify critical features in forecast deviations to refine the decision tree structure. Additional research is also needed to investigate potential areas of improvement in the optimization approach. These directions include methods for streamlining the search regions, for decreasing the computational burden via analytical solutions, and for identifying improved search algorithms.

Notice

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